



**NEW HORIZON
COLLEGE OF ENGINEERING**

Autonomous College Permanently Affiliated to VTU, Approved by AICTE & UGC
Accredited by NAAC with 'A' Grade, Accredited by NBA

**A PROJECT PHASE-1 REPORT
ON**

“NARCOTICS ELIMINATION THROUGH INTELLIGENT ULTRASOUND “

Submitted in partial fulfillment for the award of the degree of

**BACHELOR OF ENGINEERING
IN
COMPUTER SCIENCE AND ENGINEERING**

BY

**MADHUMITHA R (1NH16CS745)
ANKIT TYAGI (1NH14CS736)
AYUSH BHARDWAJ (1NH16CS739)**

Under the guidance of

P RAJITHA NAIR

Senior Assistant Professor,

Dept. of CSE

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(Autonomous Institution Affiliated to VTU & Approved by AICTE)**

Accredited by NAAC 'A', Accredited by NBA

Outer Ring Road, Panathur Post, Kadubisanahalli,

Bangalore – 560103



NEW HORIZON
COLLEGE OF ENGINEERING

Autonomous College Permanently Affiliated to VTU, Approved by AICTE & UGC
Accredited by NAAC with 'A' Grade.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

It is hereby certified that the project phase work entitled “**NARCOTICS ELIMINATION THROUGH INTELLIGENT ULTRASOUND**” is a bonafide work carried out by **MADHUMITHA R (1NH16CS745), ANKIT TYAGI (1NH14CS736) and AYUSH BHARDWAJ (1NH16CS739)** in partial fulfillment for the award of **Bachelor of Engineering in COMPUTER SCIENCE AND ENGINEERING** of the New Horizon College of Engineering during the year **2019-2020**. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said Degree.

.....
Signature of Guide
(Ms. P Rajitha Nair)

.....
Signature of HOD
(Dr. B. Rajalakshmi)

External Viva

Name of the Examiner

Signature with date

1.

.....

2.

.....

ABSTRACT

Surgery is not easy for everyone. It brings discomfort and often involves significant post-surgical pain. Currently, patient pain is frequently managed through the use of narcotics that bring a bevy of unwanted side effects.

Our solution aims to improve pain management through the use of indwelling catheters that block or mitigate pain at the source before the surgery begins. Pain management catheters reduce dependence on narcotics and speed up patient recovery.

In our solution, we identify and segment a collection of nerves called the Brachial Plexus (BP) in ultrasound images. Brachial plexus block remains the only practical alternative to general anaesthesia for significant surgery on the upper limb. It provides a superior quality of analgesia and avoids the common side-effects associated with general anaesthesia such as postoperative nausea and vomiting.

Our model can identify nerve structures in a dataset of ultrasound images of the neck. Doing so would improve catheter placement and contribute to a painless surgery. The dataset is a large training set of images where the nerve has been manually attributed by doctors. These doctors were trained by experts and instructed to attribute images where they felt confident about the existence of the BP nerve.

Keywords: Surgery, narcotics, Brachial Plexus, ultrasound, anaesthesia, postoperative nausea, pain management catheters

ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be impossible without the mention of the people who made it possible, whose constant guidance and encouragement crowned our efforts with success.

I have great pleasure in expressing my deep sense of gratitude to **Dr. Mohan Manghnani**, Chairman of New Horizon Educational Institutions for providing necessary infrastructure and creating good environment.

I take this opportunity to express my profound gratitude to **Dr. Manjunatha**, Principal NHCE, for his constant support and encouragement.

I am grateful to **Dr. Prashanth C.S.R**, Dean Academics, for his unfailing encouragement and suggestions, given to me in the course of my project work.

I would also like to thank **Dr. B. Rajalakshmi**, Professor and Head, Department of Computer Science and Engineering, for her constant support.

I express my gratitude to **Ms. P Rajitha Nair**, Senior Assistant Professor, my project guide, for constantly monitoring the development of the project and setting up precise deadlines. Her valuable suggestions were the motivating factors in completing the work.

Finally a note of thanks to the teaching and non-teaching staff of Dept of Computer Science and Engineering, for their cooperation extended to me, and my friends, who helped me directly or indirectly in the course of the project work.

MADHUMITHA R (1NH16CS745)

ANKIT TYAGI (1NH14CS736)

AYUSH BHARDWAJ (1NH16CS739)

CONTENTS

ABSTRACT	I
ACKNOWLEDGEMENT	II
LIST OF FIGURES	V
LIST OF TABLES	VI
1. INTRODUCTION	
1.1. DOMAIN INTRODUCTION	3
1.2. PROBLEM DEFINITION	7
1.3. OBJECTIVES	7
1.4. SCOPE OF THE PROJECT	8
2. LITERATURE SURVEY	
2.1. TECHNOLOGY	9
2.2. EXISTING SYSTEM	10
2.3. PROPOSED SYSTEM	12
2.4. METHODOLOGY TO BE FOLLOWED	13
3. REQUIREMENT ANALYSIS	
3.1. FUNCTIONAL REQUIREMENTS	15
3.2. NON FUNCTIONAL REQUIREMENTS	16
3.3. DOMAIN AND UI REQUIREMENTS	18
3.4. HARDWARE AND SOFTWARE REQUIREMENTS	19
4. DESIGN	
4.1. DESIGN GOALS	20
4.2. OVERALL SYSTEM ARCHITECTURE	21
4.3. PCA CLEANING	21
4.4. BATCH PROCESSING DIAGRAM	22
4.5. PROPAGATING MASKS DIAGRAM	22
4.6. USE CASE DIAGRAM	23
4.7. ALGORITHM	24

5. IMPLEMENTATION	
5.1. DATA PRE-PROCESSING	25
5.2. DATA POST_PROCESSING	26
5.3. U-NET ARCHITECTURE	27
5.4. REFINEMENT AND CONTROL	28
6. TESTING	
6.1. UNIT TESTING	29
6.2. SYSTEM TESTING	30
7. RESULTS	31
8. CONCLUSION	33
REFERENCES	34

LIST OF FIGURES

<u>Fig. No</u>	<u>Figure Description</u>	<u>Page No</u>
1.1	Supervised Learning	3
1.2	Unsupervised Learning	4
1.3	Reinforcement Learning	5
1.4	Semi Supervised Learning	6
2.1	Data features are raw sonogram images (left) and labels are mask annotations (right)	14
4.1	The basic flow of data through the CNN	20
4.2	Overall System Architecture	21
4.3	PCA Cleaning	21
4.4	Batch Processing Diagram	22
4.5	Propagating Masks Diagram	22
4.6	Use Case Diagram	23
4.7	Nerve Segmentation in frames from algorithm	24
4.8	Learning Rate and Loss in algorithm	24
5.1	U-Net Architecture	27
6.1	Levels of Testing	29
6.2	System Testing Types	30
7.1	Sample of predicted masks as the final output from the auto-encoder	32

LIST OF TABLES

<u>Table No</u>	<u>Table Description</u>	<u>Page No</u>
1.1	Features of the Project	8

CHAPTER 1

INTRODUCTION

From time to time, man has resorted to many methods in his search for relief of pain. Painless surgery is probably the greatest boon that has been granted to the patients and indirectly to surgeons.

General anesthesia is unconsciousness produced by medications. This allows for surgery and other treatments that would otherwise be too painful or difficult to tolerate. But essentially, *it's a medically induced coma, not sleep.*

General anesthetics are highly lipid soluble and can dissolve in every membrane, penetrate into organelles and interact with numerous cellular constituents. Their actions have long been considered rapid and fully reversible, with the pharmacodynamic time course of anesthesia dictated solely by the pharmacokinetic profiles of anesthetic uptake and elimination. But recent laboratory data call for a cautious reassessment of this assumption.

In the last decade, it has become apparent that anesthetics can affect gene expression, protein synthesis and processing, cause amnesia, and cellular function in poorly understood ways that provide plausible biochemical substrates for durable long-term effects in a number of tissues. While in most patients physiological homeostasis is restored soon following general anesthesia, anesthetics have potentially profound and long-lasting effects that, in animal models, appear particularly consequential in specific developmental periods and path physiological contexts.

Previous investigations involving hospitalized patients suggest that local anesthetic infused via perineural catheters decreases postoperative pain and narcotic requirements after a variety of procedures.

Our solution aims to improve pain management through the use of indwelling catheters that block or mitigate pain at the source before the surgery begins. Pain management catheters reduce dependence on narcotics and speed up patient recovery.

In our solution, we identify and segment a collection of nerves called the Brachial Plexus (BP) in ultrasound images. The brachial plexus is a complex network of nerves, extending from the neck to the axilla, which supplies motor and sensory fibres to the upper extremity. Brachial plexus block offers as optimal operating conditions for upper limb surgeries by producing complete muscular relaxation, maintaining hemodynamic stability and the associated sympathetic block. They also provide extended postoperative analgesia with minimal side effects.

Brachial plexus nerve blocks (BPNBs) for upper extremity surgery provide superior analgesia and reduce opioid consumption. Supraclavicular block anesthetizes the brachial plexus where it is in its most compact form, thus providing a complete and reliable block for upper extremity surgery. Ultrasound guided single injection (SI) and triple injection (TI) techniques were found to provide the same degree of surgical anesthesia at 30 minutes while the TI technique needed more time to perform.

Brachial plexus block remains the only practical alternative to general anaesthesia for significant surgery on the upper limb. It provides a superior quality of analgesia and avoids the common side-effects associated with general anaesthesia such as postoperative nausea and vomiting. It can be extremely useful in patients with significant co-morbidities such as severe respiratory and cardiovascular disease, morbid obesity and in those with potential airway difficulties.

In addition, it simplifies the management of other disease conditions such as diabetes mellitus, where perioperative fasting can be minimized, diet more easily reintroduced and conscious level continuously monitored. These blocks are therefore particularly useful in the ambulatory surgical setting for a wide variety of patients and procedures. For more complex major procedures, continuous catheter techniques allow prolongation of analgesic block with earlier mobilization, improved rehabilitation, and the potential to reduce hospital stay and improve functional outcome.

1.1 DOMAIN INTRODUCTION

The term AI was instituted in 1959 by Arthur prophet, Associate in nursing yank pioneer inside the field of workstation play and software engineering, and unequivocal that “it offers PCs the adaptability to discover while not explicitly programming”.

Furthermore, in 1997, Tom Mitchell gave a “well-presented” scientific and relative definition that “a worm is claimed to discover from ability E some undertaking T and a couple of execution live P, if its presentation, as estimated, P improves with ability”.

1.1.1 Classification of Machine Learning:

1) Supervised learning :

- When a calculation gains from model information and related target reactions that can comprise of numeric esteems or string marks, for example, classes or labels, so as to later foresee the right reaction when presented with new models goes under the classification of supervised learning.
- This methodology is without a doubt like human learning under the supervision of an instructor.

The instructor gives genuine guides to the understudy to remember, and the understudy at that point gets general standards from these particular models.

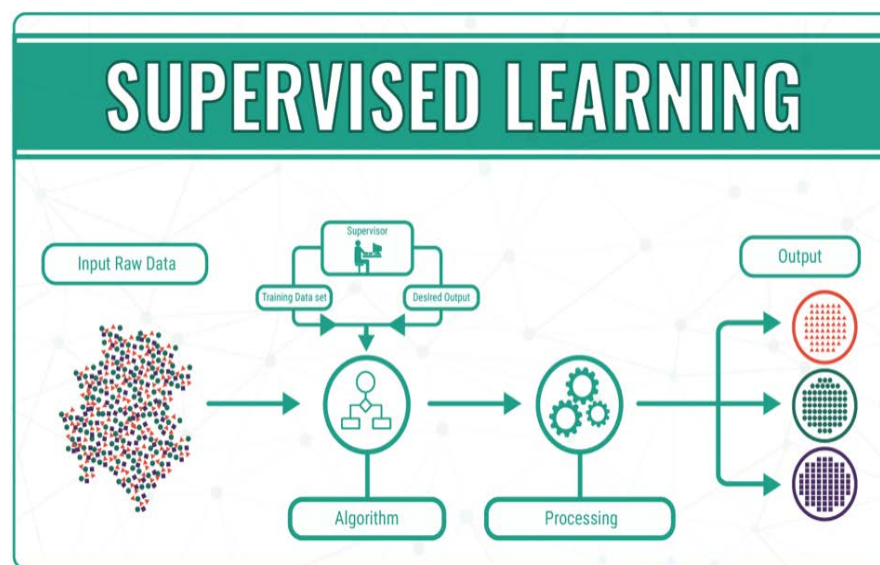


Fig. 1.1: Supervised Learning

2) Unsupervised Learning :

- When a calculation gains from plain models with no related reaction, leaving to the calculation to decide the information designs without anyone else.
- This kind of calculation will in general rebuild the information into something different, for example, new highlights that may speak to a class or another arrangement of un-connected qualities.
- They are very valuable in giving people experiences into the significance of information and new helpful contributions to directed AI calculations.
- As a sort of learning, it takes after the techniques people use to make sense of those specific articles or occasions are from a similar class, for example, by watching the level of similitude between objects.
- Some suggestion frameworks that you find on the web through promoting computerization depend on this sort of learning.

Technically, there are bound to be wrong answers, since there is a certain degree of probability. However, just like how we humans work, the strength of machine learning lies in its ability to recognize mistakes, learn from them, and to eventually make better estimations next time around.

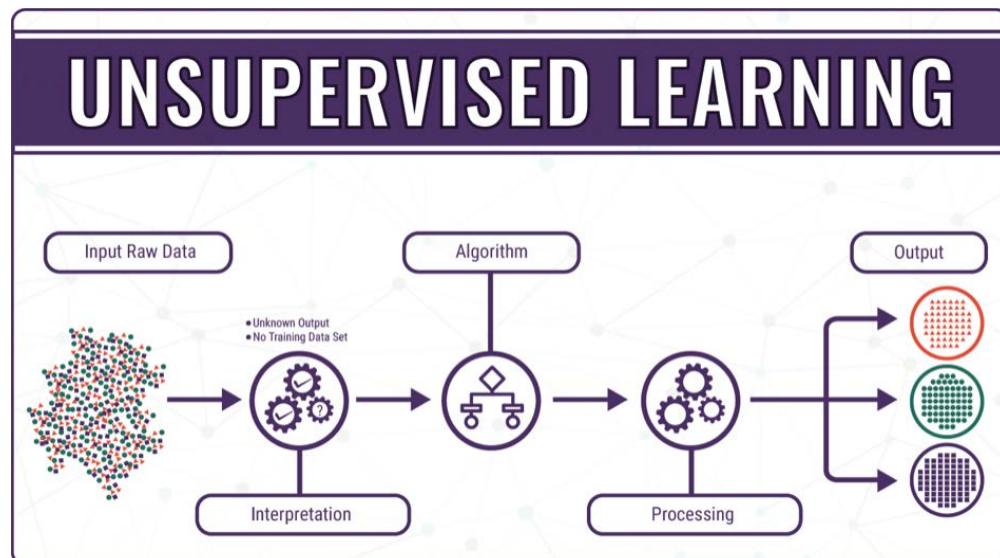


Fig. 1.2: Unsupervised Learning

3) Reinforcement Learning :

- When you present the calculation with models that need names, as in unsupervised learning.
- It is associated with applications for which the calculation must decide (so the item is prescriptive, not only engaging, as in unaided learning), and the choices bear results. In the human world, it is much the same as learning by experimentation.
- For this situation, an application gives the calculation instances of explicit circumstances, for example, having the gamer stuck in a labyrinth while maintaining a strategic distance from an adversary.
- The application tells the calculation the result of moves it makes, and learning happens while attempting to dodge what it finds to be dangerous and to seek after endurance.
- You can examine how the organization Google DeepMind has made a fortification learning program that plays old Atari's videogames. When viewing the video, see how the program is at first cumbersome and untalented however relentlessly improves with preparing until it turns into a victor.

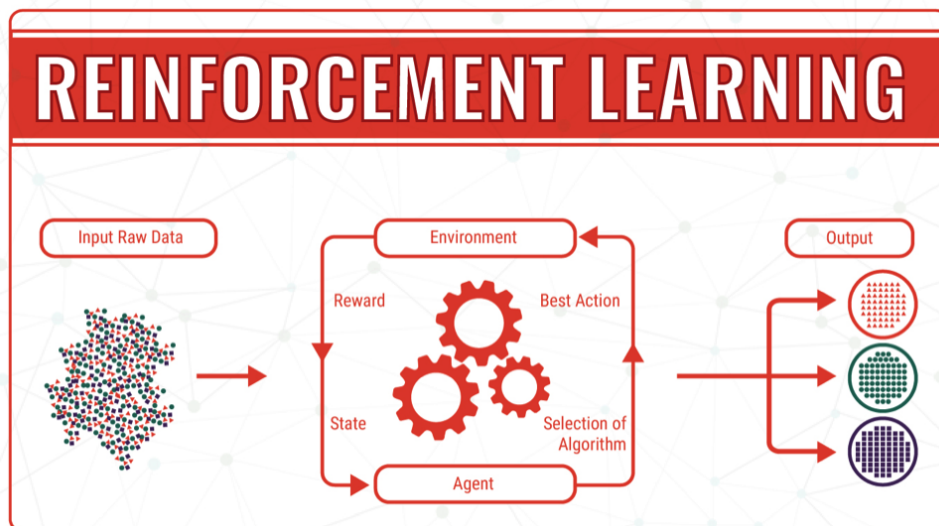


Fig. 1.3: Reinforcement Learning

4) Semi-supervised Learning :

- Where a deficient preparing sign is given: a preparation set with a few (regularly a considerable lot) of the objective yields missing.
- There is an uncommon instance of this guideline known as Transduction where the whole arrangement of issue occasions is known at learning time, then again, actually some portion of the objectives are absent.

A Semi-Supervised algorithm assumes the following about the data –

- **Continuity Assumption:** The algorithm assumes that the points which are closer to each other are more likely to have the same output label.
- **Cluster Assumption:** The data can be divided into discrete clusters and points in the same cluster are more likely to share an output label.
- **Manifold Assumption:** The data lie approximately on a manifold of much lower dimension than the input space. This assumption allows the use of distances and densities which are defined on a manifold.

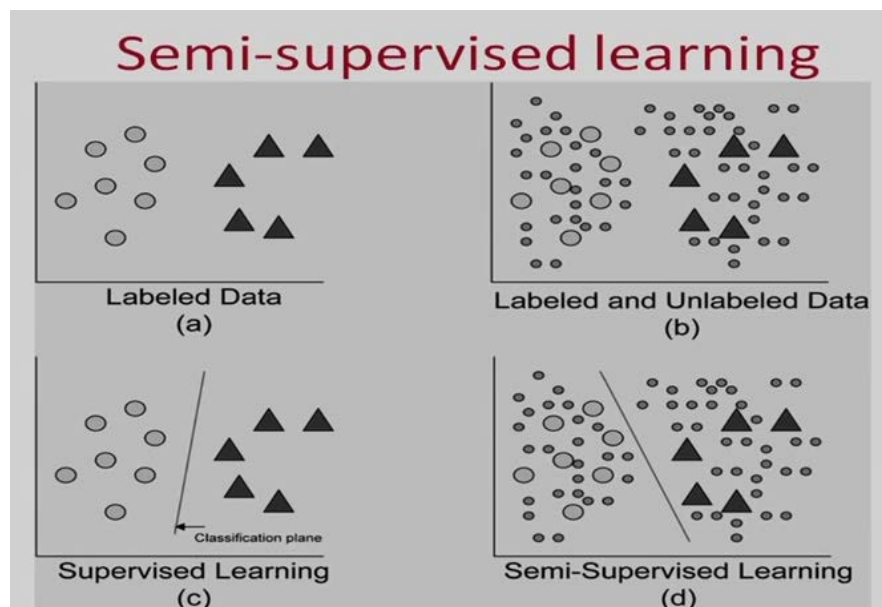


Fig. 1.4: Semi Supervised Learning

1.2 OBJECTIVES

The basic and specific objectives of this project are:

- To understand and realize the real world project, understand the problems associated in developing it and explore the appropriate solution to it.
- To think in a way so as to make the life simpler and easier with the available technology and resources.
- To become familiar with basic principles of AI towards problem solving, inference, perception, knowledge representation, and learning.
- To demonstrate awareness and a fundamental understanding of various applications of AI techniques in intelligent agents, expert systems, artificial neural networks and other machine learning models.
- To improve pain management through the use of indwelling catheters that block or mitigate pain at the source before the surgery begins.
- To identify and segment a collection of nerves called the Brachial Plexus (BP) through ultrasound images.
- To build a model that can identify nerve structures in a dataset of ultrasound images of the neck that would improve catheter placement and contribute to a painless surgery.

1.3 PROBLEM DEFINITION

- To develop a computerized AI application using Intelligent Ultrasound that eliminates narcotics and its side effects and improves pain management.
- The system should be able to identify nerve structures in a dataset of ultrasound images of the neck that would improve catheter placement and contribute to a painless surgery.
- The system should be able to check the validity of input data and give a feedback to the user in case of errors or inconsistency using exception handling.
- The system should be user friendly and convenient to use.

1.4 SCOPE OF THE PROJECT

The project scope is to develop and implement a computerized Artificial Intelligence application using Intelligent Ultrasound that eliminates narcotics and its side effects and improves pain management. The preferred solution is to improve pain management through the use of indwelling catheters that block or mitigate pain at the source before the surgery begins. The scope of the solution is limited to the development and implementation of the system specified.

Features	AI Application
Scalability of the Application	Medium
Level of UI	Polished
Users & Accounts	NIL
Dates & Locations: <ul style="list-style-type: none">- Calendaring- Display of custom maps	<div>✓</div> <div>✗</div>
Admin, Feedback & Analytics <ul style="list-style-type: none">- User Admin Pages- Usage Analytics- Crash Reporting- Performance Monitoring	<div>✓</div>
External APIs and Integrations <ul style="list-style-type: none">- Connect to one or more third party services	<div>✓</div>

Table 1.1: Features of the Project

CHAPTER 2

LITERATURE SURVEY

2.1 TECHNOLOGY

I. Healthcare Websites

1) Healthline.com

It's a website which publishes various articles on health tips and general body awareness. It has an article on the side effects of using anesthesia.

The article is written by Tim Newman who bachelor's degree in neuroscience at the U.K.'s University of Manchester and is currently a neurology adviser. He showed various long term and short term ill effects of using general anesthesia.

2) MedicalNews.com

It's a website which publishes daily news on healthy lifestyles and human body. The article referred is written by Adithya Cattamanchi. Dr. Adithya Cattamanchi specializes in pulmonary and critical care medicine.

He graduated from University of California, San Francisco. He works at Zuckerberg San Francisco General Hospital and Trauma Centre and is an associate professor of medicine at University of California, San Francisco.

It tells about how using anesthesia can lead to amnesia which can lead to temporary loss of memory and ability to recollect things of past and relating it which present. Amnesia is one of the biggest side effects of using general anesthesia.

3) MedlinePlus

MedlinePlus provides encyclopaedic information on health and drug issues, and provides a directory of medical services. MedlinePlus Connect links patients or providers in electronic health record (EHR) systems to related MedlinePlus information on conditions or medications.

II. Books

1) Clinical Anesthesia

Author: Bruce Cullen, Paul Barash, and Robert K. Stoelting

The chapters of this book brought us to the conclusion that General anesthesia is almost safe for most of the people. But this is not the case with old people or the surgeries which takes more time and is more sophisticated. In these cases we have to upgrade our temporary paralysis techniques by using regional anesthesia.

III. Videos

1) Brachial Plexus Block- Wikipedia

This is a video of a brachial plexus block; a portable ultrasound scanning device is used to track the Brachial Plexus nerves on neck and then the regional anesthesia is induced through the catheter.

2) YouTube

This videos tell what Brachial plexus nerves are and where they are located. It tells information about how these nerves can be used for paralysing an organ of human body. It gives information about various types of methods in which BP nerves can be blocked and how it is currently practiced by various doctors across the globe.

2.2 EXISTING SYSTEM

I. Base Papers

1) Intercostals nerve transfer to biceps motor branch in complete traumatic brachial plexus injuries

- The motivation behind this report is to basically assess our aftereffects of two intercostals nerve moves legitimately to the biceps engine branch in complete awful brachial plexus wounds. From January 2007 to November 2012, 19 patients were submitted to this kind of medical procedure, however just 15 of them had a follow-up for ≥ 2 years

2) Latest studies in the management of brachial plexus injuries

- The executives of brachial plexus damage are a requesting field of hand and furthest point medical procedure.
- With as of now accessible microsurgical strategies, useful increases are remunerating in upper plexus wounds. Nonetheless, treatment choices in the administration of thrash and analgesic appendage are as yet developing.
- Most recent three decades have seen huge improvements in the administration of these wounds, which incorporate a superior comprehension of the life systems, propels in the symptomatic modalities, joining of intra-usable nerve incitement methods, increasingly liberal utilization of nerve unites in crossing over nerve holes, and the expansion of new nerve moves, which specifically neurotise the objective muscles near the engine end plates.
- Fresher research chips away at the utilization of nerve allograft and safe modulators (FK 506) are under assessment in further improving the outcomes in nerve remaking.
- Direct re-implantation of separated spinal nerve roots into the spinal string is another territory of research in brachial plexus remaking.

3) Attractive reverberation imaging for recognizing root separations in horrendous grown-up brachial plexus wounds: convention for a precise survey of symptomatic exactness

- Adult brachial plexus wounds (BPI) are getting progressively normal. The remaking and forecast of pre-ganglionic wounds (root separations) are distinctive to different kinds of BPI damage.
- Preoperative attractive reverberation imaging (MRI) is being utilized to recognize root separations, yet the proofs from investigations of its demonstrative precision are clashing.
- Therefore, a precise survey is expected to address vulnerability about the exactness of MRI and to direct future research.

- We will lead a methodical pursuit of electronic databases close by reference following.
- We will avoid case reports, articles thinking about respective wounds and studies where the quantity of genuine positives, false positives, false negatives and genuine negatives can't be determined.
- The methodological nature of the included examinations will be surveyed utilizing a custom-made rendition of the QUADAS-2 apparatus.
- Where conceivable, a bi-variate model will be utilized for meta-examination to get outline sensitivities and specificities for both target conditions.
- We will examine heterogeneity in the presentation of MRI as indicated by field quality and the danger of predisposition if information licenses.

2.3 PROPOSED SYSTEM

Time is the most precious resource for skilled healthcare professionals. Both physicians and patients have a major incentive to adopt data-driven solutions that can improve the quality of medical care. The analysis of ultrasound images is a tedious task that drains thousands of valuable hours from physicians that could otherwise be spent on patient critical tasks. Applying machine learning to this domain has the potential to increase the productivity of physicians by automating exhausting tasks.

An opportunity to contribute in this field occurred with the 2016 Ultrasound Nerve Segmentation* competition on Kaggle.

The problem at hand is to identify a grouping of nerves known as the Brachial Plexus (BP) from raw ultrasound images. Physicians must identify these nerve structures before inserting a pain management catheter prior to a surgical procedure. The training set is provided by Kaggle and contains images where the nerve has been manually annotated and outlined by trained medical professionals. Each image in the training set contains a mask that highlights the BP nerve area.

2.4 METHODOLOGY TO BE FOLLOWED

- The challenge is to two-fold –
 - 1) Classify the presence of the BP Nerve; and
 - 2) Auto-encode a mask that outlines the nerve area.
- The available training data includes 5,635 sonogram images that have been manually annotated by medical professionals.
- Dataset - A large training set of images where the nerve has been manually attributed by doctors. These doctors were trained by experts and instructed to attribute images where they felt confident about the existence of the BP nerve.
- Important points about dataset:
 - 1) The dataset contains images where the BP is not present. Our algorithm predicts no pixel values in these cases.
 - 2) As with all human-labeled data, we do find noise, artifacts, and potential mistakes in the ground truth.
 - 3) Identical images do exist in the dataset. Revealed in EDA.
 - 4) Dataset uses run-length encoding (RLE) on the pixel values.
 - 5) The dataset consists of 5635 training images and their masks, and 5508 testing images
- About the data-
 - 1) **Train.zip** file contains the training set images, named according to subject_imageNum.tif. Every image with the same subject number comes from the same person. This folder also includes binary mask images showing the BP segmentations.
 - 2) **Test.zip** contains the test set images, named according to imageNum.tif. We predict the BP segmentation for these images. There is no overlap between the subjects in the training and test sets.
- Dataset Credits: Qure.ai - Deep learning products that fit your radiology workflow.

- The high dimensionality and requirement for image auto-encoding in this challenge is ideal for deep learning, particularly convolution neural networks. A variety of convolution neural network architectures have been applied to similar image recognition tasks with impressive levels of success.
- The image below, this nerve is distinguished by subtle patterns and is hardly prominent in to the untrained human eye.

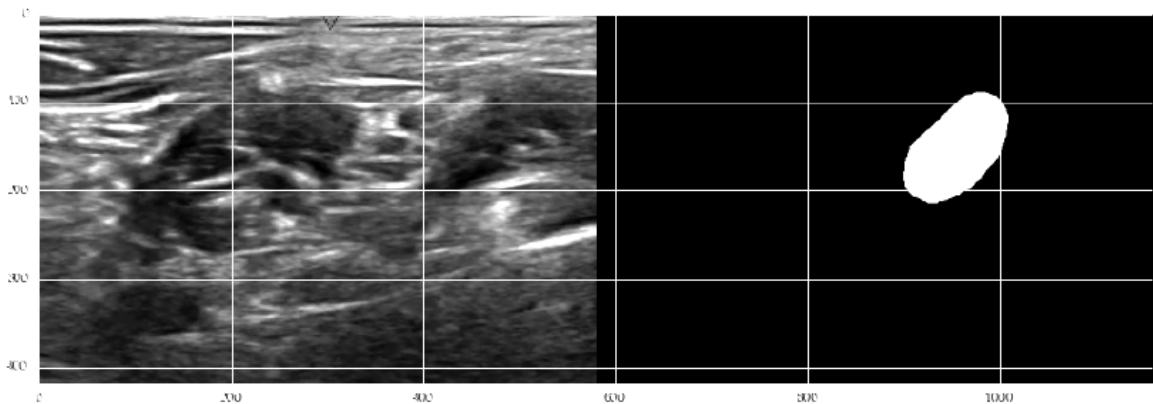


Fig 2.1: Data features are raw sonogram images (left) and labels are mask annotations (right)

- The following steps have been taken to approach this problem:
 - 3) Exploratory data analysis of the sonogram image data
 - 4) Train deep learning models to detect and encode the BP nerve
 - 5) Validate effectiveness of the model
 - 6) Benchmark results on the active Kaggle competition

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

A requirement is a portrayal of the administration that product must offer. A prerequisite can run from the significant level theoretical articulation of the sender's need to definite scientific practical necessity details.

I. What is a Functional Requirement?

In programming designing, a useful necessity characterizes a framework or its segment. It depicts the capacities a product must perform. A capacity is only inputs, its conduct, and yields. It very well may be a figuring, information control, business process, client collaboration, or whatever other explicit usefulness which characterizes what capacity a framework is probably going to perform. Utilitarian Requirements are likewise called Functional Specification. Practical programming necessities help you to catch the proposed conduct of the framework. This conduct might be communicated as capacities, administrations or assignments or which framework is required to perform.

II. Benefits of Functional Requirement

- Causes you to check whether the application is giving every one of the functionalities that were referenced in the useful necessity of that application
- A practical prerequisite archive causes you to characterize the usefulness of a framework or one of its subsystems.
- Practical prerequisites alongside necessity examination help distinguish missing prerequisites. They help unmistakably characterize the normal framework administration and conduct.
- Blunders trapped in the Functional prerequisite social affair stage are the least expensive to fix.
- Bolster client objectives, undertakings, or exercises.

III. Functional Requirement Of Project :

- The doctor should be able to upload the ultrasound image he wants locate BP nerve for.
- The algorithm should be able to interpret the image format supplied by the doctor.
- The algorithm should be able to pre-process the training dataset given.
- The algorithm should be able to rescale the images to smaller pixels to avoid memory overflow.
- The algorithm should be able to remove contradictory images, to remove the training images without a mask that were close to another training image with a mask.
- The algorithm should be able to use a PCA decomposition of the training masks and reconstruct the predicted mask using a limited number of principal components. This will seemed to help more consistently
- The algorithm should be able to perform the PCA cleaning successfully.
- The idea of using PCA to post-process came from the Eigenface concept. Basically, you consider your image as a big vector and you then do PCA on the training masks to learn “eigenmasks”.
- The doctor should able to see the marked BP nerve on the image with a good accuracy.

3.2 NON FUNCTIONAL REQUIREMENTS

I. What is a Non-Functional Requirement?

Fundamentally, Non-Functional requirements portray how the framework functions, while utilitarian necessities depict what the framework ought to do. This doesn't mean the last are increasingly significant, however most necessity gathering strategies centre around utilitarian prerequisites, so enormous holes in non-practical necessities are normal.

So what precisely would we say we are searching for here? All things considered, here are four instances of Non-Functional necessity, usability, reliability, performance, and supportability, just as a couple of top tips on every one.

1) Usability

- Organize the significant elements of the framework dependent on use designs.
- As often as possible utilized capacities ought to be tried for ease of use, as should intricate and basic capacities. Make certain to make a prerequisite for this.

2) Reliability

- Clients need to confide in the framework, significantly in the wake of utilizing it for quite a while.
- Your objective ought to be a long MTBF (mean time between disappointments).
- Make a necessity that information made in the framework will be held for various years without the information being changed by the framework.
- It's a smart thought to likewise incorporate necessities that make it simpler to screen framework execution.

3) Performance

- What should framework reaction times be, as estimated from any point, under what conditions?
- Are there explicit pinnacle times when the heap on the framework will be bizarrely high?
- Consider pressure periods, for instance, toward the month's end or related to finance dispensing.

4) Supportability

- The framework should be very healthy to keep up.
- Viability prerequisites may cover various degrees of documentation, for example, framework documentation, just as test documentation, for example which experiments and test plans will go with the framework.

II. Non-Functional Requirement Of Project :

- The project should be able to produce a good accuracy, minimum of 80% in order to locate the BP nerves with more credibility.
- The cleaning of images should be of good quality to ensure the core algorithm works well.
- The training of the machine should be fast, as in real-time scenarios, it requires more number of images to process per unit time.
- The process should be simple to understand by any user.
- The data of the algorithm should be kept safe so as to avoid any malicious access.
- Maintenance of the algorithm is required time to time to maintain a good experience for the users.
- The data images stored for training should be kept safe without any disturbance to their quality.
- A backup for the images and the algorithm should be kept to avoid any accidental deletion.
- The code should have proper comments, so that if any other user wants to modify it in future should be able to do so.
- In case of any failure or exceptions, proper error handling techniques should be available.
- The different units of the algorithm should be able to work together as a system efficiently.

3.3 DOMAIN AND UI REQUIREMENTS

I. Domain Requirements

- Looking for current problem and how it can be solved with Machine Learning.
- Looking for right dataset.
- Looking for a right IDE to develop.
- Knowledge of Machine Learning and basics of Deep Learning algorithms.

- Pre-processing the data so as to get maximum results.
- Reducing unrequited images from the dataset.
- Able to visualize the results using python libraries like seaborn, matplotlib.

II. UI Requirements

- User should be able to locate the various files like training and testing images and the python script.
- User should be able to easily create new files or merge two different files to support unit and system testing.
- It should be able to add various dependencies required for the project.
- The UI should be able to deploy the project on various open platforms for any suggestions.
- User should be able to see the visualizations from the UI only.
- User should be able to run the python script successfully.
- User should be given alerts during exceptions of any fault occurrences.

3.4 HARDWARE AND SOFTWARE REQUIREMENTS

I. Hardware Requirements

- **CPU:** intel i5 5th generation minimum
- **RAM:** 8GB/16GB for better performances.
- **SSD:** 128 GB for better experience.
- **Disk Storage:** 250GB free.
- **GPU:** GTX 1080

II. Software Requirements

- Python IDE
- Good internet connection.
- Python libraries being installed.

CHAPTER 4

DESIGN

4.1 DESIGN GOALS

CNNs excel at image recognition by applying a series of kernel filters to training images to detect important features. The filters are tied together to provide a modified version of the input image – a process which is then repeated for each subsequent layer.

After each batch of samples, the network will update the weights of features based on the target labels. The result is a graph of local connectivity patterns between a stack of convolution layers.

After running all training samples through the network, the process is repeated with the initial weights learned from the previous iteration or epoch.

The training samples will be fed to the network for multiple epochs, until the target metric (Dice Coefficient) reaches a plateau.

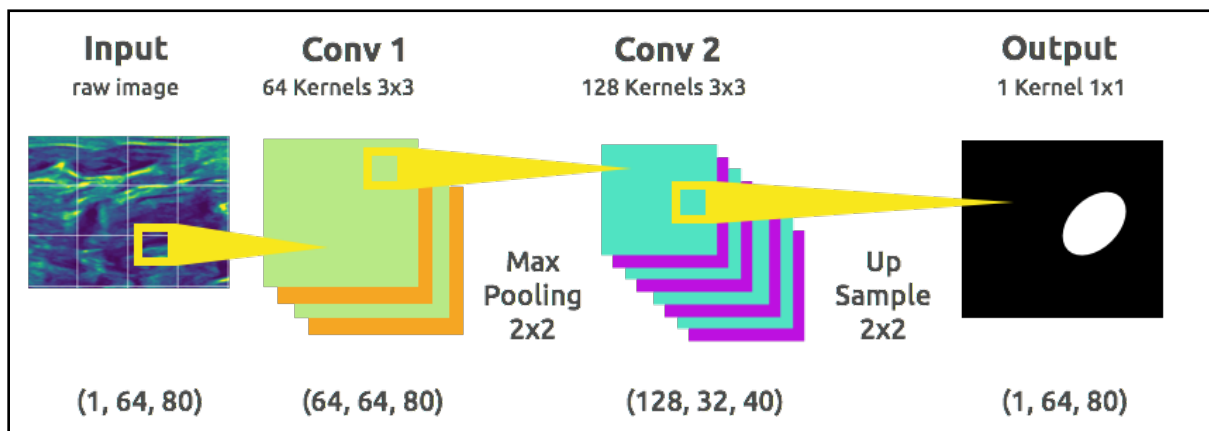


Fig. 4.1: The basic flow of data through the CNN

4.2 OVERALL SYSTEM ARCHITECTURE

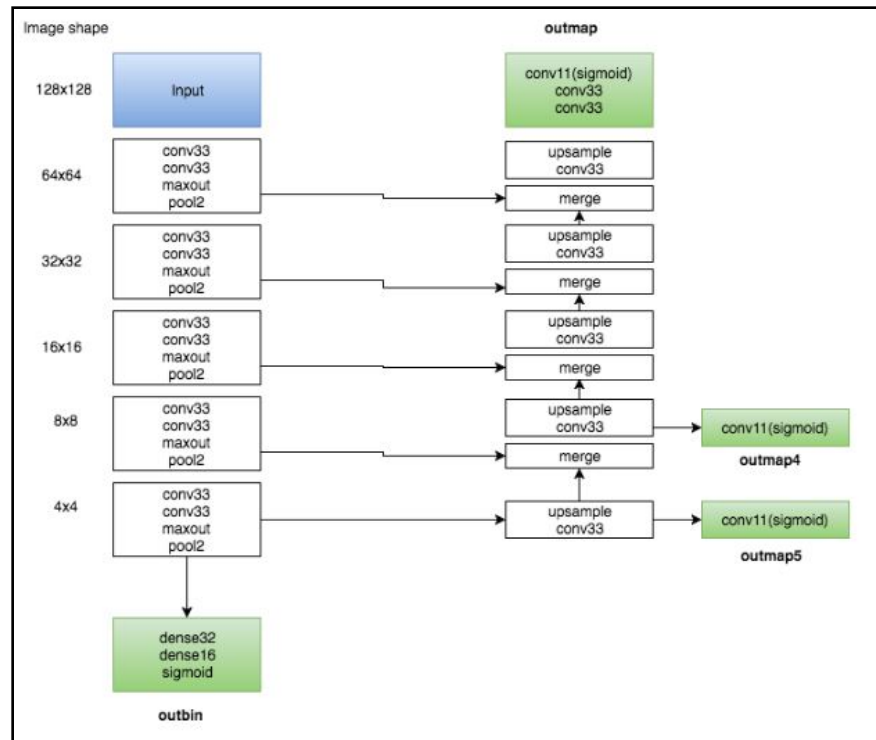


Fig. 4.2: Overall System Architecture

4.3 PCA CLEANING

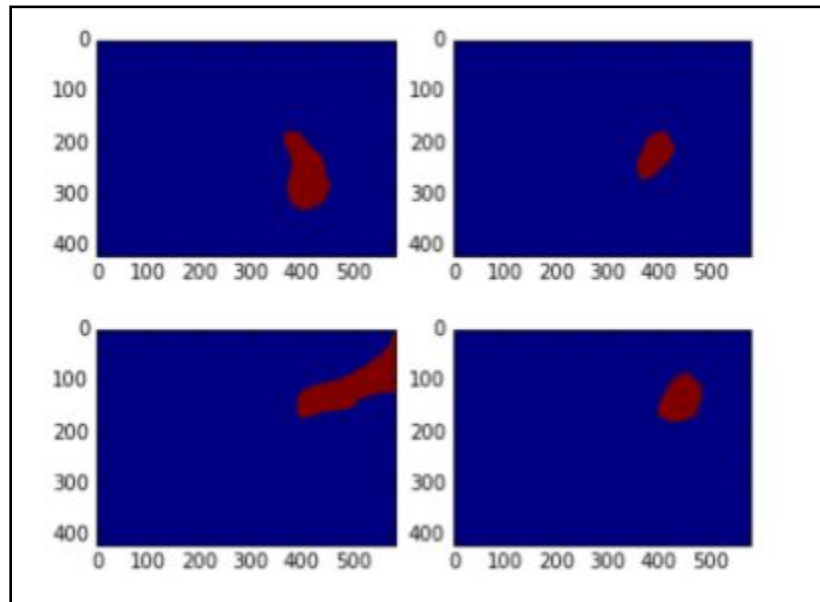


Fig. 4.3: PCA Cleaning

4.4 BATCH PROCESSING DIAGRAM

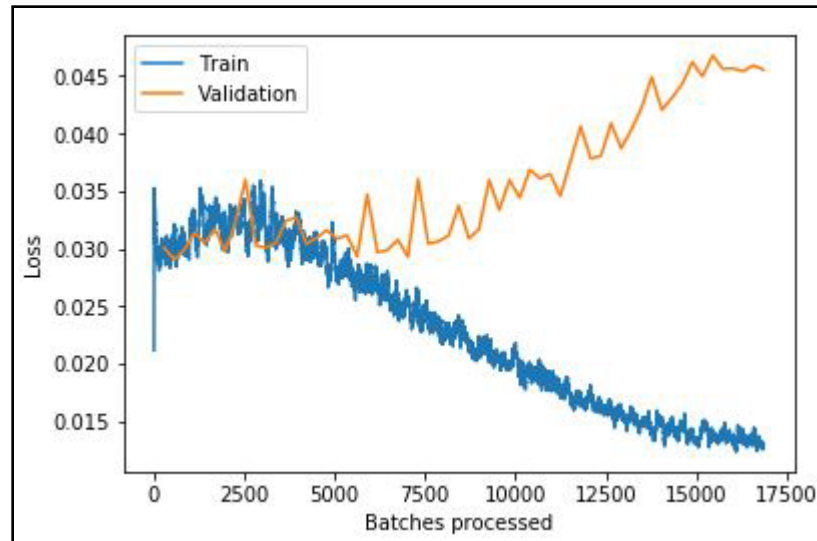


Fig. 4.4: Batch Processing Diagram

4.5 PROPAGATING MASKS DIAGRAM

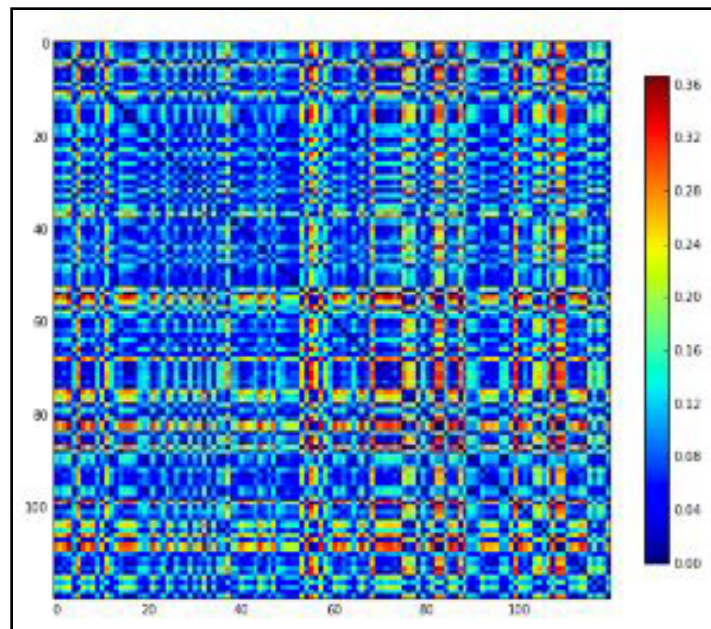


Fig. 4.5: Propagating Masks Diagram

4.6 USE CASE DIAGRAM

A UML use case diagram is the primary form of system/software requirements for a new software program underdeveloped. Use cases specify the expected behavior (what), and not the exact method of making it happen (how).

Use cases once specified can be denoted both textual and visual representation (i.e. use case diagram). A key concept of use case modeling is that it helps us design a system from the end user's perspective. It is an effective technique for communicating system behavior in the user's terms by specifying all externally visible system behavior.

A use case diagram is usually simple. It does not show the detail of the use cases:

- It only summarizes some of the relationships between use cases, actors, and systems.
- It does not show the order in which steps are performed to achieve the goals of each use case.

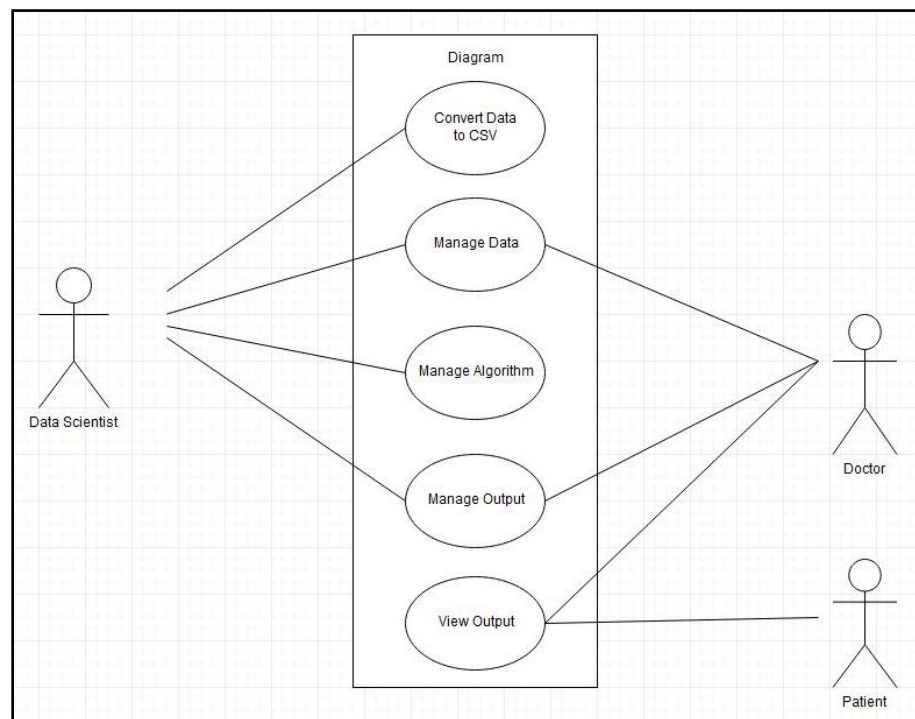


Fig. 4.6: Use Case Diagram

4.7 ALGORITHM

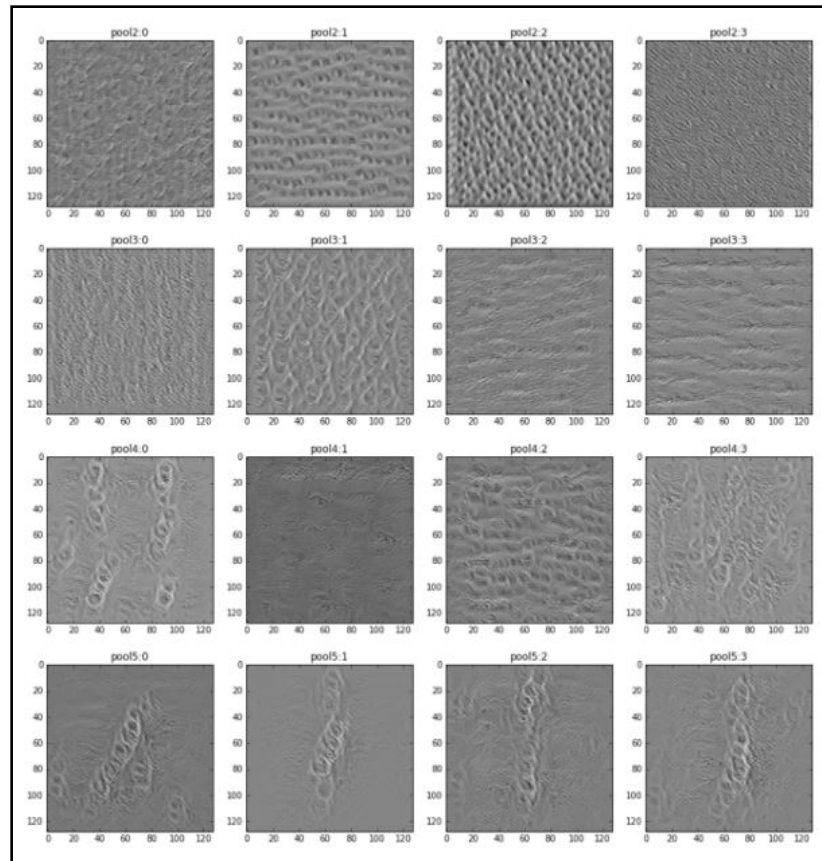


Fig. 4.7: Nerve Segmentation in frames from algorithm

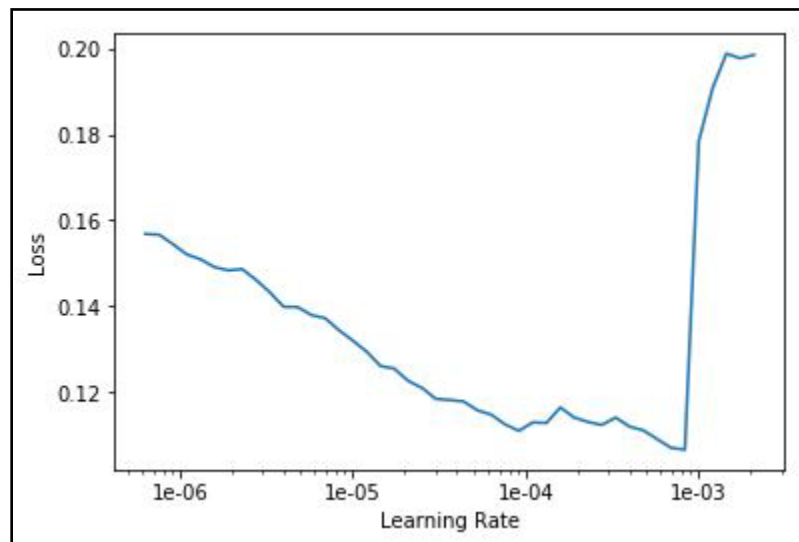


Fig. 4.8: Learning Rate and Loss in algorithm

CHAPTER 5

IMPLEMENTATION

5.1 DATA PRE-PROCESSING

Below is a summary of the pre-processing decisions and justification based on the exploratory data analysis.

- **Image scaling:** The images have a size of 580x420. Caused memory overflow while training. Rescaled images to 128x128. This also mean we stretched the images (the scale factor isn't the same for both axes), but this didn't seem to hinder performances much.
- **Removing contradictory images:** We decided to remove the training images without a mask that were close to another training image with a mask. We computed the similarity between two images by computing a signature for each image as follow : We divided the image in small 20x20 blocks and then compute a histogram of intensity in each block. All the histograms for the image are then concatenated into a big vector. These results in a distance matrix for all the training set images, which is then threshold to decide which images, should be removed. In the end, we kept 3906 training images (out of the 5500).
- **Architecture:** The model has 95000 parameters. We found difficult to train models with more parameters without over fitting and we got really good results with 50000 parameter models as well. We used some very simple data augmentation (small rotation, zoom, shear and translation) but it did not help performance.
- **Convert to Grayscale:** Sonogram images are black/white, so a grayscale conversion does not result in information loss.
- **Histogram Equalization:** Balancing the brightness and contrast adds clarity to the BP nerve feature in the images.
- **Gaussian Blur:** The images contain many sharp edges and shapes resembling the BP nerve that could result in false positives. A Gaussian blur filter softens these shapes.

- **Resize to 64x80:** Due to memory constraints, reducing the number of parameters is critical. The parameter count changes exponentially with changes to image dimensions.
- **Convert to Float32:** Pixel values are converted to float32 to run the code on a CUDA-enabled GPU.

5.2 DATA POST-PROCESSING

We tried three different post-processing approaches:

- Morphological close to remove small holes. This helped a bit.
- Fitting an ellipse to the mask and filling the ellipse. This didn't help during validation.
- Using a PCA decomposition of the training masks and reconstructs the predicted mask using a limited number of principal components. This seemed to help more consistently (although just a little bit).

- 1) **PCA cleaning** - The idea of using PCA to post-process came from the Eigenface concept. Basically, you consider your image as a big vector and you then do PCA on the training masks to learn “eigenmasks”.

To clean a predicted mask using this method, you project the cleaned mask on the subspace found by PCA and you then reconstruct using only the 20 (in my case) first principal components. This forces the reconstructed mask to have a shape similar to the training masks.

- 2) **Loss and mask percentage** - We tried using dice coefficient as a loss, but we always got better results by using binary cross-entropy. Lowering the thresholds to get higher number of predicted masks leads to too many false positive. So 49% of the images should have mask and we tried to optimize the threshold on the binary and mask output to get close to 49% predicted masks.

5.3 U-NET ARCHITECTURE

- The U-Net architecture is a neural network consisting of two separate paths of inputs. On the left contracting path, the inputs are gradually contracted with pooling, which is the typical pattern of most neural network architectures, such as the popular VGG and LeNet. The U-Net includes pairs of 3x3 unpadded convolutions, each followed by ReLU activation. After each pair of convolutions, a 2x2 max pooling layer is added for down sampling. After each pooling layer, the number of kernels in the following convolutions is doubled.
- On the right upward path, the inputs are gradually expanded with up sampling, and then concatenated to the corresponding convolution from the left path. After each concatenation (merge) layer, two additional 3x3 convolutions are applied. Finally, a 1x1 convolution is included to remap the tensor to the target output shape of 1x64x80.

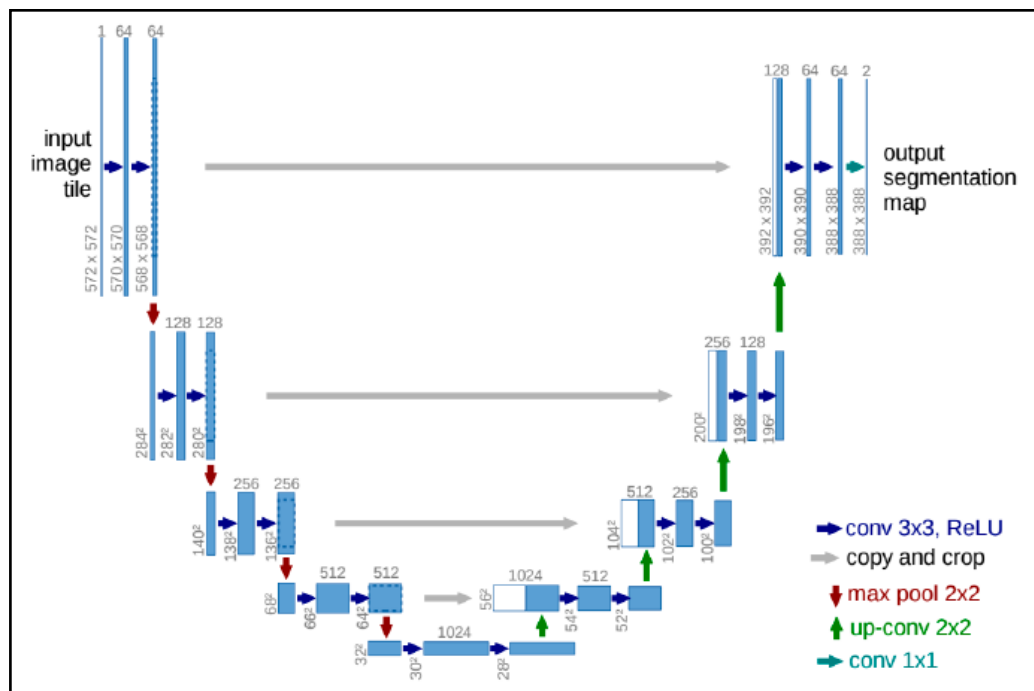


Fig. 5.1: U-Net Architecture

5.4 REFINEMENT AND CONTROL

- **Loss Function and Objective.** The loss function drives the refinement of weights for data features. After each batch of inputs, the mean of the output array across the entire feature map is calculated based on the loss function, in this case, the Dice Coefficient. By default, Keras does not support the Dice Coefficient as a loss function. It would be possible to use 'categorical cross entropy' as a loss function for this project, but it is not an optimal benchmark for the Kaggle competition.
- **Optimizer.** An optimizer is used to compute gradients for the loss function then apply gradients to tensor variables. There are many different approaches to neural network optimization, but Adaptive Momentum Estimation, or Adam, has proven to be optimal for this application. Adam is a stochastic gradient-based optimization that uses bias-correction and momentum.
- **The step size or learning rate** is the only important consideration for the optimizer in this implementation. If the learning rate is too high, the Dice Coefficient will converge quickly without generating a useful output, encoding only blank masks. On the other hand, a learning rate too small will cause the algorithm to plateau at a low Dice Coefficient, resulting in random noisy masks. For this data set a learning rate of 0.00001 produces a CNN that plateaus after approximately 20 epochs.

CHAPTER 6

TESTING

6.1 UNIT TESTING

UNIT TESTING is a level of programming testing where individual units/portions of an item are attempted. The explanation behind existing is to support that each unit of the item executes as arranged. A unit is the most diminutive testable bit of any item. It for the most part has one or two or three information sources and regularly alone yield. In procedural programming, a unit may be an individual program, work, system, etc.

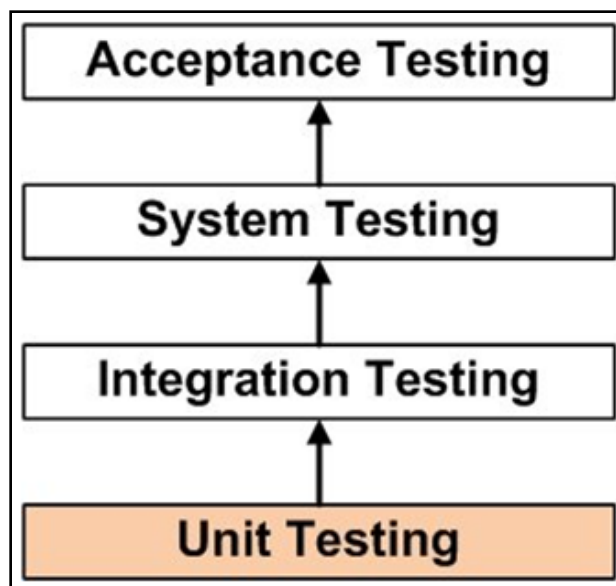


Fig. 6.1: Levels of Testing

I. Unit Testing in the Project:

- Loading the images successfully.
- Pre-processing the images successfully.
- Applying PCA cleaning.
- Training the machine.
- Testing with the image supplied to algorithm.

6.2 SYSTEM TESTING

System Testing is a discovery testing strategy performed to assess the total framework the framework's consistence against determined necessities. In System testing, the functionalities of the framework are tried from a start to finish viewpoint.

Framework Testing is typically done by a group that is autonomous of the improvement group so as to gauge the nature of the framework impartial.

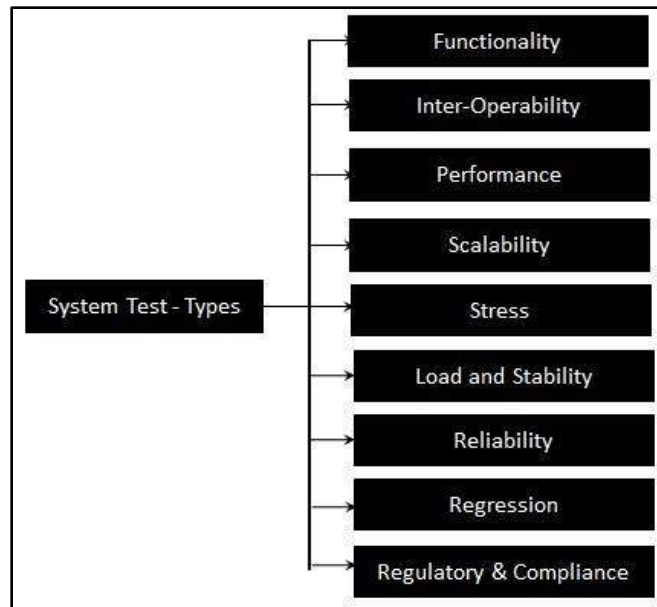


Fig. 6.2: System Testing Types

I. System Testing in the Project:

- Here we'll have all the various unit modules like, pre-processing , PCA cleaning, training machine with algorithm, predicting the result and visualization into a single unit and see how it works.
- Aim is to get a high accuracy and reliable model when the script is working as a single combined unit.
- The entire unit should interact with each other in a healthy manner and each proceeding unit should be able to parse the information provided by previous unit.
- The final result is the contribution of each unit, as all the units have equal importance in the project.

CHAPTER 7

RESULTS

Most CNNs are used for categorical classification – not auto-encoding. A classic example is the MNIST dataset, which includes handwritten digits that can be classified from 0 to 9. This type of network can be flattened down and run through a fully-connected layer that outputs a prediction for each of the 10 possible classes.

The nerve segmentation problem is inherently more complicated because the output tensor must retain its 4D shape (Batch, 1, 64, 80). The U-Net architecture generates a large amount of overlap and duplication that is likely excessive for something like the MNIST dataset. However, it excels at dealing with the noise and asymmetry found in the nerve segmentation images. It also provides an efficient method for down sampling the images, then up sampling back up to the required shape for auto-encoding. Simply up sampling the data after pooling would result in low resolution mask predictions. The U-Net provides an innovative way to deal with this problem by merging up sampled and down sampled layers, then running additional convolution layers after each step.

I. Sensitivity Analysis

To determine the robustness of the model, small random augmentations were introduced to the training data using the ImageDataGenerator class in Keras. Specifically, the following changes were introduced:

- Random rotations up to 10°
- Random width shifts of 10%
- Random height shifts up to 10%

These augmentations seem reasonable for real world applications, as sonogram images come in various sizes and orientations. A caveat that should be noted is that augmentation is only being applied on the feature images, which likely has a negative impact on auto-encoding. The result after 30 epochs in the U-Net model was a training Dice Coefficient 0.56.

Comparing the two models, the variance between the validation loss and training loss on the U-Net was much lower. The training Dice Coefficient loss for both the VGG-16 and U-Net achieved similar scores, but the U-Net validation loss was 0.025 lower. The loss trend on the VGG-16 also had a tendency to spike upwards at random, which is expected behaviour with over fitting. This leads to the conclusion that the U-Net model is superior at generalizing the complexity of the sonogram images.

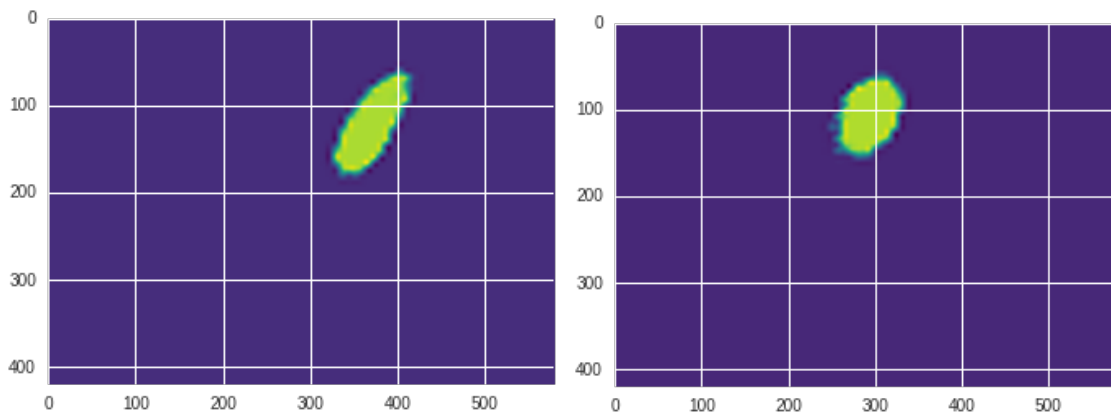


Fig. 7.1: Sample of predicted masks as the final output from the auto-encoder

Instead of submitting an exhaustive list of indices for our segmentation, the output is pairs of values that contain a start position and a run length. E.g. '2 5' implies starting at pixel 2 and running a total of 5 pixels (2, 3, 4, 5, 6). The metric checks that the pairs are sorted, positive, and the decoded pixel values are not duplicated.

CHAPTER 8

CONCLUSION

Overall, this was a very intriguing and challenging problem that required many hours of experimentation. We started this project without any experience using Keras and have come to appreciate the highly readable code that it produces. This was also a great introduction to Kaggle and we look forward to competing in upcoming challenges.

The initial exploratory data analysis became an extremely useful asset while approaching this problem. Understanding the expected shape and location of the image masks made it easier to validate the outputs of the auto-encoder and estimate if a certain output would achieve a high score on Kaggle. It also helped facilitate strategic pre-processing of the images based on feedback from neural network performance. Over the course of this project, much different architecture was attempted, but only the VGG-16 and U-Net exceeded the target benchmark. We went into this project expecting modifications to these architectures to yield better results, but found the defaults described in their respective papers to be optimal.

The most difficult aspect of the project was eliminating false positives. Ultimately, a naïve approach was taken by simply removing masks that did not meet a certain size threshold. This worked well for the competition, but may not be ideal in a real world medical imaging. Modifying the loss function and building a binary cross entropy classifier to detect blank/annotated masks were attempted, but did not manage to increase the Dice Coefficient.

Professional medical advice- Identifying the BP nerve is not an easy task for the untrained eye. When examining two images that seem to have similar features, one could be positive and the other negative. Gaining additional insight from a trained medical professional about specific patterns could provide clues for improved image pre-processing steps and algorithm tuning.

REFERENCES

- [1] Basics of Anaesthesia by Manuel Pardo MD and Ronald D. Miller MD MS
- [2] <https://www.healthline.com/health/side-effects-of-general-anesthesia>
- [3] <https://medlineplus.gov/anesthesia.html>
- [4] https://en.wikipedia.org/wiki/Brachial_plexus_block
- [5] <https://www.youtube.com/watch?v=qsjUz4IDSs>
- [6] <http://www.anzca.edu.au/patients/what-is-anaesthesia>
- [7] <https://onlinelibrary.wiley.com/journal/13652044>
- [8] <http://med.stanford.edu/anesthesia.html>
- [9] <https://www.anesthesiologynews.com/>