

University of Tartu
Faculty of Science and Technology
Institute of Technology

Heba Elshatoury

Classification of Alzheimer's Disease From MRI Images

Bachelor Thesis (12 ECTS)
Curriculum Science and Technology

Supervisors:

Egils Avots, MSc
Prof. Gholamreza Anbarjafari

Tartu 2019

Abstract

Classification of Alzheimer's Disease From MRI Images

In this thesis work machine learning techniques are used to classify MRI brain scans of people with Alzheimers Disease. This work deals with binary classification between Alzheimers Disease (AD) and Cognitively Normal (CN). Supervised learning algorithms were used to train a classifier using MATLAB Classification Learner App in which the accuracy is being compared. The dataset used is from The Alzheimers Disease Neuroimaging Initiative (ADNI). Histogram is used for all slices of all images. Based on the highest performance, specific slices were selected for further examination. Majority voting and weighted voting is applied in which the accuracy is calculated and the best result is 69.5% for majority voting.

CERCS: T111 Imaging, image processing

Keywords: Computer Vision, Machine Learning, Alzheimer's Disease, feature extraction, magnetic resonance imaging

Alzheimeri tõve klassifitseerimine MRI-piltidest

Käesolevas töös kasutatakse masinõppe meetodeid, et klassifitseerida Alzheimeri tõvega inimeste MRI aju skaneeringuid. Töös rakendatakse binaarset liigitust Alzheimeri tõve (AD) ja kognitiivse normaalsuse (CD) vahel. Kasutati juhendatud masinõppealgoritme, et treenida klassifikaatoreid MATLAB'i klassifikaatorite õpperakenduses (Classification Learner App), kus võrreldi algoritmi täpsust. Kasutatav andmestik pärineb ADNI andmebaasist (The Alzheimer's Disease Neuroimaging Initiative). Kõikidest piltidest võetud osadele arvutati histogrammid. Kõrgeima jõudluse põhjal valiti konkreetsed osad edasiseks uurimiseks. Võtteldi enamus ja kaalutud valikute täpsust ja parimaks tulemuseks saadi enamusvalikuid kasutades 69.5%.

CERCS: T111 Pilditehnika

Märksõnad: Arvutinägemine, masinõpe, Alzheimeri tõbi, Magnetresonantstomograafia

Acknowledgments

I would like to thank my supervisors Egils Avots and Prof. Gholamreza Anbarjafari for their support through out this thesis project.

I would like to thank The Alzheimer's Disease Neuroimaging Initiative (ADNI) for giving me access to their data.

Data used in the preparation of this thesis were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI was launched in 2003 as a public-private partnership, led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD). For up-to-date information, see www.adni-info.org.



Table of Contents

Abstract	2
Acknowledgments	3
List of Figures	6
List of Tables	7
Abbreviations and Acronyms	8
1 Introduction	9
1.1 Alzheimer’s disease	9
1.2 Problem Overview	10
1.3 Goals	10
1.4 Structure	11
2 Alzheimer’s detection	12
2.1 Data Magnetic Resonance Imaging (MRI)	12
2.2 Machine Learning	14
3 Literature Review	16
4 Problem Review	18
4.1 The Alzheimer’s Disease Neuroimaging Initiativ (ADNI)	18
4.2 Tools and Data format	20
5 Methodology	21
5.1 Dimensionality Reduction	21
5.1.1 Principal component analysis (PCA)	21
5.2 Histogram	22
5.3 Supervised learning algorithms:	23
5.4 3D Image Representation	26

6	Results	27
6.1	PCA implementation	27
6.2	Vectorized image histogram	27
6.3	Histogram of slices	28
7	Conclusion and Future Work	34
	References	35
	Appendix	39
7.1	Appendix A: Slices 1 - 160 accuracy (1)	40
7.2	Appendix B: Slices 1 - 160 accuracy (2)	43
7.3	Appendix C: Slices 1 - 160 accuracy from trained model	46
	License	47

List of Figures

1.1	Illustration of brain with and without Alzheimer's [1]	10
2.1	Summary of MCI and AD workup table illustrated by Judith N. and Wang S. [2, Table 1]	13
5.1	Flowchart of histogram based classification	22
5.2	Sigmoid function	24
5.3	Axial, Sagittal and Coronal planes shown from an image from the dataset used.	26
6.1	Representation of the histogram of the vectorized images	28
6.2	Maximum accuracy per slice for multiple classifiers	30
6.3	AD Image Slices 5, 10 & 15	30
6.4	CN Image Slices 5, 10 & 15	31
6.5	Maximum and minimum accuracy per slice for multiple classifiers	31
6.6	Comparison between Fine Tree, Medium Gaussian SVM and Medium kNN accuracy	32
6.7	AD and CN image slices 36, 37 and 38	33
6.8	Accuracy for majority and weighted vote	33

List of Tables

3.1	Comparison of classification between AD and healthy control subjects based on what is reported in the literature.	17
6.1	Accuracy for PCA results for different number of features	27
6.2	Accuracy for histogram of vectorized images with different classifiers comparing different numbers of features	28
6.3	Performance for slices 31 - 40 (Maximum in row being bold)	29
6.4	Performance for slices 31 - 40 (Maximum in column being bold)	32
6.5	Performance for testing data for slices 31 - 40 using trained model of slice 36 and 37	33

Abbreviations and Acronyms

AD - Alzheimer's Disease

CN - Cognitively Normal

PCA - Principal Component Analysis

SVM - Support Vector Machine

MRI - Magnetic Resonance Imaging

ADNI - Alzheimers Disease Neuroimaging Initiative

CT - Computed Tomography

NIfTI - Neuroimaging Informatics Technology Initiative

MCI - Mild Cognitive Impairment

1 Introduction

1.1 Alzheimer's disease

Alzheimer's Disease (AD) is a disease in the brain that causes memory loss, behaviour problems as well as problems with thinking. Symptoms of the disease usually show early signs that could later on develop and become fatal and affect daily activities [3]. Ron et al. (2007) [4] reported that in 2006 there were 26.6 million people affected by Alzheimer's Disease. They predict that in year 2050 there will be about 106.8 million patients of Alzheimer's [4]. AD is form of dementia which is a term that is used to describe decline in general brain functions like thinking or the ability to remember. Symptoms could be severe enough that it can affect daily activities. 60 to 80 percent of cases of dementia accounts to Alzheimer's Disease [5]. The majority of people with Alzheimer's Disease are 65 and older. As age increases risk of developing Alzheimer's Disease increase as well, meanwhile it's not a disease of old age as younger people can be pre-diagnosed as well. As announced by the Alzheimer's Association, there are about 50 million people worldwide whom are living with Alzheimer's Disease or other form of Dementia [6].

Alzheimer's is a progressive disease which means that over the years symptoms get worse. The disease can be divided into stages, during the early stages a person can have mild loss of memory, but later on as the symptoms progress, normal routine activities become difficult. There are three main stages of Alzheimer's disease which are mild (early stage), moderate (middle stage) and severe (late stage) [7], these stages vary from one patient to another based on the time it will take to develop to the next stage as well as the condition in each stage vary as well. Preclinical Alzheimer's disease is a term used for the time in which the brain of a person starts to change without any signs of the disease appearing [7]. Despite the efforts done to treat or cure Alzheimer's Disease, at the moment there is no cure for it. Research and efforts continue to find solutions to treat or prevent this disease and stop it from developing. There is treatment for symptoms which are available, those treatments can't prevent the progression of the disease but it can temporary slow the progression of symptoms of dementia. Efforts are made to improve the quality of life for people with Alzheimer's. Early diagnostic of the disease is critical to help people with Alzheimer's. Diagnostic of Alzheimer's Disease is made with the help of many specialists, tests and approaches using different tools. One of these tools are brain

imaging. One of the standard medical checkups is based on making a structural image of the brain using magnetic resonance imaging (MRI) or computed tomography (CT) [8].

Alzheimer's Disease causes the nerve cells in the brain to die leading to tissue loss in the brain. The brain of a person diagnosed by Alzheimer's Disease shrinks drastically, causing it to be not functioning properly as shown in figure 1.1 [1]. Research has shown that as Alzheimer's Disease progresses the brain of a patient would shrink in size, research using structural imaging of the brain show that some regions in the brain are more heavily affected for example the hippocampus area in the brain. The shrinkage of the hippocampus could be an easy sign of Alzheimers Disease. Although scientists still have not agreed about the standard in which a shrinkage should be considered in compared to the size of a brain for each individual [9].

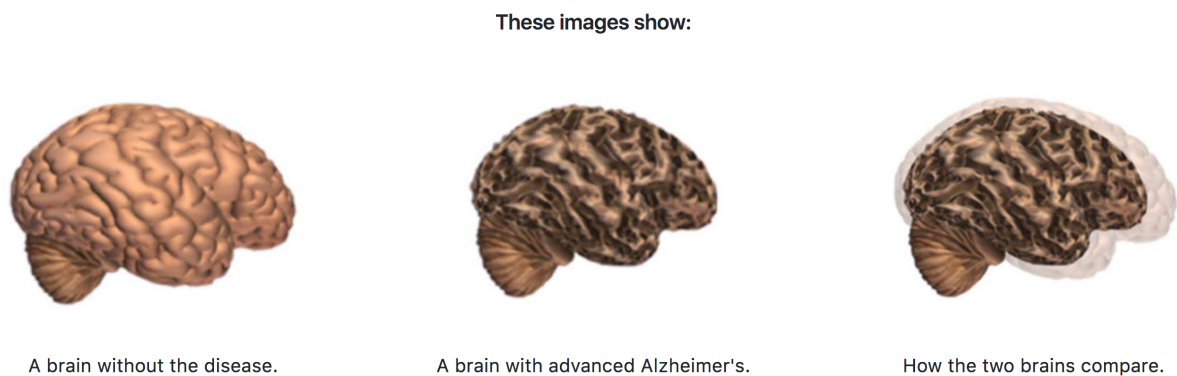


Figure 1.1: Illustration of brain with and without Alzheimer's [1]

1.2 Problem Overview

Alzheimer's Disease (AD) is a common disease that has no cure or treatment. There is a big interest and collective efforts for early diagnostic for this disease to improve the quality of life for those affected by this disease. In the recent years researchers have been using computational advancements and machine learning techniques for early diagnosis of AD using image processing and computer vision by finding biomarkers that indicate the presence of the disease from an early stage. Pattern Recognition and Machine Learning could help doctors in early detection of this disease. This thesis uses the ADNI dataset, which contains MRI scans of the brain which are suitable for statistical analysis using machine learning techniques.

1.3 Goals

The goal of this thesis is to analyze different machine learning techniques for classification of MRI brain scans for Alzheimer's Disease (AD) and Cognitively Normal (CN) subjects using

supervised learning. This research which includes improving methods for classification of AD and CN could help in early diagnostics of AD using computer vision and machine learning. These tools could be used by professionals to assist their decision in determining if a person is developing Alzheimer's Disease which could help improve the quality of life for the people affected and give them a chance to choose the way they want to be taken care of in the years were the disease progresses. Through this work the performance of multiple machine learning algorithms like Support Vector Machine (SVM), Logistic Regression, and Decision Trees among others are being compared. To deal with the large dimensionality of the used data, and to enhance the accuracy, different techniques like histogram representation and Principal Component Analysis (PCA) were being studied.

1.4 Structure

- Chapter 1 gave an overview of Alzheimer's Disease and introduced the problem definition followed by the objective of this project.
- In chapter 2 of this thesis Magnetic Resonance Imaging (MRI) is being explained and an overview of Machine Learning types, algorithms and methods is being presented.
- Chapter 3 is composed of literature review giving examples of previous research work done on this topic along with their methods and results.
- In chapter 4 provides information on the experiments that are done in this research work introducing the tools used to deal with the problem overview and also detailed information about the database used in this thesis is given in this chapter.
- Chapter 5 includes the methods used in this research work, how the large data was handled using dimensionality reduction techniques that are being described. The supervised learning algorithms used in this work are also presented in this chapter with a brief explanation. Also challenges met during this work are included at the end of this chapter.
- The results of this research work are presented in chapter 6 of the thesis, showing all the different results that has been obtained.
- In chapter 7 the analysis of the methods and results presented in earlier chapters are being discussed. Future work is also briefed.

2 Alzheimer's detection

There are several tests that are being done from physicians and specialists to determine if a person is diagnosed with Alzheimer's Disease or not. For the time being there isn't a specific test that could determine the condition on its own [8]. One of the first checkups would be that a doctor will ask about the patient's medical history. Determining if a family member has suffered from AD or other dementia and also ask about medications and make some physical examinations to exclude the possibility of another diseases that have the same symptoms like AD [8]. After these examinations if the doctor suspects that the patient might have mild cognitive impairment (MCI) or Alzheimer's, the doctor can then use the help of other specialists for example refer the patient to geriatrician, neurologist, neuropsychologist and geriatric psychiatrists. Those specialists can help in the diagnostic of Alzheimer's Disease by making extra examinations to determine the case [10]. The diagnostic process does not end here, a patient also undergo a mental status test in which one popular test is the Mini-Mental Status Test (MMSE) this test determines the patient ability to answer simple everyday mental tasks [8]. Genetic testing is also one of the tests that help determine whether a person has certain genes that could increase the risk of developing AD [8]. All these tests are followed by brain imaging that could determine if the brain shows any signs of AD using the scan of the patient's brain. Brain imaging techniques have helped a lot with the diagnostic of AD and other dementia types. It has become a necessary tool that doctors use as a guide to determine if the symptoms are of other diseases and not AD. Researchers are working on developing brain imaging techniques to have more information and more understanding of how AD affects the brain and also help in determining other causes. The diagnosis of AD and MCI has a similar workup in which a set of different tools and approaches are used by doctors, specialists and physicians to determine the detection of the disease for a patient [2]. Judith N. and Wang S. (2011) show a table of the workup for MCI and AD shown in figure 2.1 [2].

2.1 Data Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is a type of medical scanning that is used to generate medical images for the visualization of anatomy. MRI uses magnetic waves and radio waves to produce detailed images of the body's soft tissues and bones for diagnostic purposes or monitoring treatment progress. On the contrary to Computed Tomography (CT) and X-ray scans, MRI

Initial Dementia Workup.

Standard Workup	Depending on History and/or Availability	Research Tests
History	Neuropsychology testing	Genotyping
Patient	Laboratory studies	APOE
Informant	HIV	CSF or serum biomarkers
Cognitive screens	Lyme	β_{1-40}
MMSE	Heavy metal	β_{1-42}
MoCA*	Alcohol level, urine toxicology	Total τ
Office screens	MMA	Phosphorylated τ
GDS	Homocysteine	Imaging
	CSF	Functional MRI
Laboratory studies	Standard studies	β amyloid PET imaging
SMA-18, CBC	Cell count, protein, glucose, opening pressure	
TSH		
Vitamin B12		
Folic acid	HIV	
RPR	Syphilis	
Urinalysis and urine culture	Lyme	
Imaging	Imaging	
Head CT scan	^{18}F -FDG	
Brain MRI [†]	PET	

Abbreviations: AD, Alzheimer's disease; APOE, apolipoprotein E; CBC, complete blood count; CSF, cerebrospinal fluid; CT, computed tomography; FDG, fluorodeoxyglucose; GDS, Geriatric Depression Scale; HIV, human immunodeficiency virus; MCI, mild cognitive impairment; MMA, methylmalonic acid; MMSE, Mini-Mental State Examination; MoCA, Montreal Cognitive Assessment; MRI, magnetic resonance imaging; PET, positron emission tomography; RPR, rapid plasma reagin; SMA-18, sequential multiple analysis 18; TSH, thyroid-stimulating hormone.

* If suspicious for MCI or early AD.

[†] Preferred if no contraindication and patient can tolerate.

Figure 2.1: Summary of MCI and AD workup table illustrated by Judith N. and Wang S. [2, Table 1]

does not use ionizing radiation which makes MRI generate less hazards than CT scans [11]. A strong magnetic field is applied in a MRI scanner, when a body is placed in MRI machine the protons from water molecules in the tissues align to the magnetic vector along the MRI scanner axis which is processed to produce the MRI images. When the radio frequency is switched off, it takes time for the protons to return to equilibrium after excitation. The rate at which tissue relaxation occurs can be measured in two ways T1 which is the longitudinal relaxation time and T2 which is the transverse relaxation time [12]. The series of images produced from the MRI scanner of the body is composed of three-dimensional image composed of slices of the body that could then be analyzed by a professional in the field.

Structural imaging of the brain using Magnetic Resonance Imaging (MRI) has a big role in the diagnosis of AD. Doctors use MRI to determine if a patient show signs of MCI or AD as well as to check the possibility of other diseases like vascular and other non-Alzheimer neurodegeneration [13]. Brain imaging using MRI show how the brain has been damaged and what tissue areas are shrinking in an AD patient. Such brain scans show doctors specific regions of the brain that could be affected by AD for example the hippocampus and the entorhinal cortex which is another area in the brain that deals with memory which are both regions in the brain that show the progression of AD and MCI [13]. Machine Learning techniques for early detection of Alzheimer's Disease can assist doctors during the diagnosis period to help in the process.

This research work helps to investigate the classification of AD and CN to improve the research in the early detection of AD.

2.2 Machine Learning

Machine Learning is a branch of artificial intelligence in which the analysis of data is taken place without specific instructions that is given [14–16]. Machine Learning deals with training data to find patterns and decide or predict the outcome accordingly.

Supervised, Unsupervised and Reinforcement learning

In machine learning there are three main types supervised, unsupervised and reinforcement learning. Supervised learning can be divided into two categories, classification and regression [17]. Some of the common classification methods are Support Vector Machine (SVM), Naïve Bayes classifier and Nearest Neighbours. Some of the regression methods are Linear and Nonlinear Regression. In regression problems the output is predicted using a continuous function in order to map a continuous input [17]. In classification problems the results are predicted using a discrete output [17].

Supervised learning is a method in which the system is given a training data that is labeled and by giving an adequate amount of this training set the system can then categorize another set of test data based on the classification of the input data set. In supervised learning the output is known based on the input of the dataset [18]. One popular method that is used in supervised learning for classification and regression problems is Support Vector Machines (SVM) [19–22]. Another classifier used in supervised learning is Naïve Bayes classifier which assumes that each feature in the dataset is conditionally independent to make the model simpler [23].

K-nearest neighbour (kNN) algorithm is another machine learning and pattern recognition algorithm used in supervised learning program in which each data point or feature is classified based on its neighbor features by assigning a value for k that corresponds to the number of neighbor points that is taken into consideration, also known as clustering [23]. Random forest is another supervised learning classifier that works by choosing the best class based on combining multiple decision trees [24]. Random forest is part of the ensemble method which is a supervised learning algorithm which uses multiple trees for classification problem and then predict the output class based on popularity [24–26].

In unsupervised learning the output results is unknown and in this case clustering is used to group data based on relationships among the variables [18]. There is no feedback on the predicted results in unsupervised learning which make it more challenging than supervised learning. One of the most common algorithm used in unsupervised learning is neural networks. Neural Network is an algorithm that finds patterns and connection between features in a dataset

to learn and make conclusions using hidden layers of information [23].

Reinforcement learning is a type of machine learning that deals with taking a set of actions to maximize the reward [27]. Unlike supervised learning in reinforcement learning there are no labels given and the system needs to learn what is the best option based on experience [23]. Reinforcement learning is used in many applications for example game theory and control theory.

3 Literature Review

A lot of research is being done to help in early diagnosis of Alzheimer's Disease using machine learning techniques and computer vision for classification and early detection using MRI scans. Many researchers use a selection of features to assist the classification of binary class or multi-class for example classification of Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI) and Cognitively Normal (CN). In this section previous research results will be discussed and compared based on the method and performance that is addressed and table 3.1 show a comparison of results mentioned.

Zhang and Shen (2012) proposed a method with two components, a multi-class feature selection and a multi-model support vector machine. They performed their experiment on a data of 45 AD, 91 MCI and 50 healthy controls (HC) using MRI, FDG-PET, and cerebrospinal fluid (CSF) data from ADNI database. Results for AD vs HC in their experiment show an accuracy of 84.8% with MRI-based, 84.5% with PET-based and 80.5% with CSF-based [28]. By aiming to investigate magnetic resonance imaging (MRI) and cerebrospinalfluid (CSF) biomarkers, Westman et al. (2012) included 369 subjects from ADNI database with 96 AD, 162 MCI and 111 CTL (Healthy Controls) in their study. By combining CSF and MRI they got the best results for classifying AD vs CTL but as concerned with this paper they got 87% accuracy for MRI for distinguishing between AD and CTL using multivariate data analysis [29]. In a study that included 59 AD and 127 cognitively normal (CN) subjects Zhou et al. (2014) proposes classification of AD by combining MRI data and mini-mental state examination (MMSE). For feature selection they used FreeSurfer to calculate 55 volumetric variables. In the results without using MMSE an accuracy of 78.2% was achieved for AD vs CN and while using MMSE the accuracy was significantly improved to become 92.4% [30].

Gray et al. (2013) achieved 89% multi-modal classification accuracy between AD and healthy controls using MRI volumes, voxel-based FDG-PET signal intensities, CSF biomarker measures, and categorical genetic information joined together as features. Their study included 147 participants with 37 AD and 35 healthy controls (HC). The 89% accuracy was achieved using Random Forrest classifier [31]. In a research done by Papakostas et al. including 98 females from OASIS dataset in which Voxel-based morphometry (VBM) and Deformation-based morphometry (DBM) were used for classification of AD and Healthy Controls (HC). The study

resulted in 85% accuracy using MSD features from the VBM model of feature extraction [32]. Zhang, Wang et al. (2011) published their results for multi-model approach by combining MRI, PET and CSF as biomarkers for AD. Their study included 51 AD and 52 healthy controls. Combination of those 3 features yielded a robust accuracy of 93.2% [33].

Mahmood et al. proposed a method for classification of MRI images using feed forward multi-layer Neural Network in which the model was trained using 230 subjects from OASIS dataset. By reducing the features to 150 using PCA they were able to get an accuracy of 89.22% after testing the model on all 457 MRI subjects. When features was reduced to 100 the accuracy decreased to 86.47% [34]. Yi Ding et al. proposed a novel approach for feature selection using VBM and texture analysis for classification of AD and normal controls (CN). The dataset used in the study is from ADNI in which 54 AD and 58 NC patients were taken into account. Accuracy of 92.86% was achieved using SVM with RBF kernel for classification [35].

Table 3.1: Comparison of classification between AD and healthy control subjects based on what is reported in the literature.

Author	Algorithm	No. of subjects (AD/CN)	Accuracy	Additional
Zhang et al.	SVM	45/50	84.80%	MRI-based
Zhou et al.	SVM	59/127	92.4% / 78.2%	MMSE/without MMSE
Westman et al.	Multivariate analysis	96/111	87%	MRI
Gray et al.	Random Forrest	37/35	89%	MRI volumes voxel-based FDG-PET signal intensities CSF biomarker genetic information
Papakostas et al.	rbf-DAB-SVM	49/49	85%	VBM
Zhang et al.	SVM	51/52	93.20%	MRI+PET+CSF
Mahmood et al.	Neural Network	230 MR images	89.22%	MRI, PCA
Yi Ding et al.	SVM	54/58	92.86%	VBM analysis and texture analysis

4 Problem Review

In this chapter information about the dataset used in this research is being presented in the first section. In the second section the tools that is used in the experiments are explained as well as the format of the images is discussed. In this bachelor thesis two classes (i.e. diagnostic groups) were used for classification problem: Cognitively Normal (CN) and Alzheimer's Disease (AD).

4.1 The Alzheimer's Disease Neuroimaging Initiative (ADNI)

The data set used in this study is from The Alzheimer's Disease Neuroimaging Initiative (ADNI). ADNI is one of the projects archived in the Image & Data Archive (IDA) as part of the Laboratory of Neuroimaging (LONI) which collects clinical trials and research studies from neuroscience research [36]. It collects these studies for research purposes to manage and share the information available in this field. LONI IDA manages data collection to facilitate collaboration between scientists all over the world in the field of neuroscience [36].

For early detection of Alzheimer's disease (AD), ADNI uses biomarkers to develop clinical images to enable tracking of patients cognitive health by allowing the use of this data to researchers around the world. A biomarker is an indicator used to measure the state of a certain disease [37]. The goals of ADNI are early detection of AD, support research for prevention and treatment in very early detection of AD and making it easy for researchers and scientists around the world to use and access the data they have [37].

The collection of data in ADNI happened over 4 phases, ADNI-1,GO,-2 and -3 starting from 2004 until 2016 [36]. In those 4 phases the subjects taking part in ADNI study were either carried forward in the new phases for additional examination or new participants were also added to continue investigation of Alzheimer's Disease progression. Development of biomarkers for different outcomes were measured through out the 4 phases for example measurement for clinical trials, examining early stages of the disease, prediction of cognitive decline as well as study of functional imaging techniques in clinical trials [36].

During the ADNI study four states of the disease were examined which are CN, SMC, MCI and AD [37]. CN stands for Cognitively Normal and acted as control subjects in the ADNI study and the participants showed no signs of dementia. SMC stands for Significant Memory Concern

which was added in ADNI 2, participants in this category showed some memory concerns that could develop later on [37]. It fills the gap between CN and MCI. MCI stands for Mild Cognitive Impairment, participants in this category maintained daily activities but reported memory concerns either by themselves or by a clinician in this stage there was no sign of dementia [37]. Finally the last stage is AD which stands for Alzheimer's Dementia in which participants in this category had dementia due to Alzheimer's disease.

In this research work the dataset was taken from The Alzheimer's Disease Neuroimaging Initiative (ADNI), the images used for the purpose of this bachelor thesis was take from ADNI1 phase. The MRI images in ADNI has undergone some specific pre-processing steps, each MPRAGE image in the database at Laboratory of Neuroimaging (LONI) is accompanied with set of descriptions remarking the pre-processing that happened on each MRI image [38]. As of the description written on the ADNI website here are the corrections applied to the images used in this work [38]:

1. Gradwarp: gradwarp is a system-specific correction of image geometry distortion due to gradient non-linearity. The degree to which images are distorted due to gradient non-linearity varies with each specific gradient model. We anticipate that most users will prefer to use images which have been corrected for gradient non-linearity distortion in analyses.
2. B1 non-uniformity: this correction procedure employs the B1 calibration scans noted in the protocol above to correct the image intensity non-uniformity that results when RF transmission is performed with a more uniform body coil while reception is performed with a less uniform head coil.
3. N3: N3 is a histogram peak sharpening algorithm that is applied to all images. It is applied after grad warp and after B1 correction for systems on which these two correction steps are performed. N3 will reduce intensity non-uniformity due to the wave or the dielectric effect at 3T. 1.5T scans also undergo N3 processing to reduce residual intensity non-uniformity.

The ADNI database has also description about subjects for each scan regarding age, gender and diagnostic group. The participants enrolled in the ADNI study are between 55 and 90 years old [37]. They are recruited in 57 sites in the United States and Canada [39]. The participants in the study are subjected to a series of initial tests that are repeated in a yearly interval, some of the tests are clinical evaluation, neuropsychological tests, genetic testing, lumbar puncture, and MRI and PET scans [37]. The screening schedule of intervals over the years are Screening, Baseline, Month 3, 6, 12, 18, 24, 36, 48 and annual on-going check up [37].

4.2 Tools and Data format

MATLAB

MATLAB is a matrix-based language developed by MathWorks for technical computing. It is used for analyzing and visualizing data, developing algorithms, computational mathematics and creating models and applications. To know more about MATLAB visit this page:

<https://www.mathworks.com/products/matlab.html>

Throughout the work of this thesis, MATLAB was used for reading the MRI images and the classification. Prior to the classification multiple mathematical analysis were made, including vectorization, PCA and histogram representation.

Classification Learner App in MATLAB

In this bachelor work, classification learner app on MATLAB is being used to train different models and classify the dataset. The classification learner app can be used in training a model using supervised learning methods. It gives wide range of classification model types to analyze the training data and export a model for testing. Some of the training models are decision trees, support vector machines, logistic regression and ensemble classification among others. The classification learner app takes an input of my dataset that needed to be analyzed by supplying the array of observations while specifying the response (i.e. labels or classes) and applying principal component analysis if needed as well as selecting which features to include in the model. The accuracy of the training models chosen are being presented along with confusion matrix and ROC curves. The model can then be exported in MATLAB workspace to predict the output of the test data. For more information about the classification learner app please visit: <https://www.mathworks.com/help/stats/train-classification-models-in-classification-learner-app.html>

Neuroimaging Informatics Technology Initiative (NIFTI)

Images were downloaded in .nii NIFTI format. NIFTI stands for Neuroimaging Informatics Technology Initiative. This initiative is sponsored by the National Institutes of Health (NIH) to promote and support software tools in the field of neuroimaging [40]. In total the size of the images used in this study is 27.06 GB.

5 Methodology

In this chapter the approaches that have been used are being discussed. Dimensionality reduction techniques that were tested are presented. The machine learning algorithms that were used are explained.

5.1 Dimensionality Reduction

In machine learning it's generally dealing with large dataset. In large scale dataset a problem of high-dimensional data arise. In such cases a method called dimensionality reduction is being used to make it easier, faster or even possible to analyze this very large data samples. Dimensionality reduction can be done using feature selection and feature extraction [28]. Dimensionality reduction is important to reduce computation time and storage space. A disadvantage of dimensionality reduction could be the loss of some data.

The used dataset in this work has a problem of very high-dimensional data needs to be processed. Therefore, several dimensionality reduction methods needs to be applied to be able to process and analyze the data in hand. Each .nii file downloaded from ADNI dataset corresponds to one subject either AD or CN. For each subject the MR image represents a number of slices of images that make up the 3D structure of the brain. Each subjects brain is represented by a 192x192x160 pixels which makes each patients brain represented by roughly around 5 million pixels. Including multiple subjects in this study would yield a very large data that is very computationally expensive and would take very much time to process. Therefore dimensionality reduction is necessary for the continuation of this study.

5.1.1 Principal component analysis (PCA)

Principal component analysis (PCA) is a method used for dimension reduction, in which it converts a large set of data into a new smaller data while still retaining the information and the correlation in the original data set [41]. It's a mathematical procedure in which correlated variables are converted to principal components without losing much of the information in the original variables [23]. In PCA the first principal components keep the most variation that existed in the original data. Eigenvalues and eigenvectors are used in PCA to analyze the data [23]. More detailed mathematical treatment about PCA can be found in [41].

To deal with the large data of this dataset each image was vectorized which is the process of transforming a matrix into one vector array. Having to deal with MRI data of brain scans in which images are in 3-dimensional composed of slices. All images were re-sized to 192x192x160 which is the lowest resolution in the dataset. Each image was vectorized to be transformed to one vector array with 5898240 elements. In this research work after vectorization of images, PCA was applied for dimensionality reduction. The function *pca* in MATLAB was used.

5.2 Histogram

Histogram is the representation of a continuous data by showing the frequency distribution [42]. The distribution is shown in a bar plot in which the data is divided into bins [42]. Number of bins can be chosen according to application and needs. In this work images were converted to 8-bit images using function *uint8* in MATLAB. 8-bit images have intensity values of pixels in the range between 0 and 255. Applying histogram helped in the reduction of dimensions in the dataset in which the number of bins were chosen to represent the features. In this study 256 features were used corresponding to 256 bins.

Figure 5.1 show a flowchart of the steps taken for the experiment of histogram based classifica-

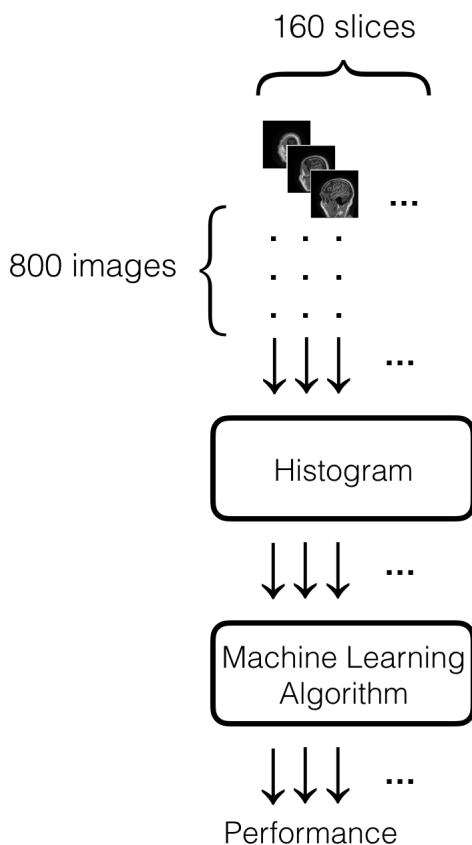


Figure 5.1: Flowchart of histogram based classification

tion. The approach is as follows, 800 images were used in which 400 AD and 400 CN subjects

are included in this study. For each subject the images are composed of 160 slices. The first slice was taken from all the 800 images and histogram was applied, then a machine learning algorithm was used to determine the accuracy of the performance for each batch. This process was repeated for 160 times compromising the number of slices in sagittal plane.

5.3 Supervised learning algorithms:

Multiple machine learning algorithms were being used in this study. SVM methods have been extensively used in many researches and studies and it yields promising results. Also other supervised learning algorithms that has been used in this study includes, Decision Trees, Logistic Regression, SVM, kNN and Ensemble.

While using the Classification Learner App in MATLAB 5-fold cross-validation was used. Cross-validation is used in which data is partitioned randomly as training data and test data to validate the performance of the model [43].

Decision Trees

Decision tree is a popular classification algorithm that uses a tree-like structure to predict the category of a new data point. The features of the dataset are known as attributes and the tree itself is built on nodes and branches. At each node, a certain attribute is examined and based on the result, it splits into 2 branches. The process is continued till a label is given and at that stage, the branch is called a leaf. [44]

Logistic Regression

Logistic Regression is a commonly used technique in binary classification problems. It usually makes use of the sigmoid function defined as:

$$y = \frac{1}{1 + e^{-x}} \quad (5.1)$$

This function can map the values of the used features into a probability value ranging between 0 and 1 as shown in figure 5.2. Classification is done using a certain threshold to label the data point as one of 2 classes. For example, if it's greater than 0.5, it's considered as one class and if it's less than 0.5 it's another class. [23]

Support Vector Machine (SVM)

Support Vector Machine (SVM) is an algorithm in machine learning used to solve classification and regression problems. SVM is more commonly used in classification challenges in supervised learning by classifying data with similar features and separating those which are

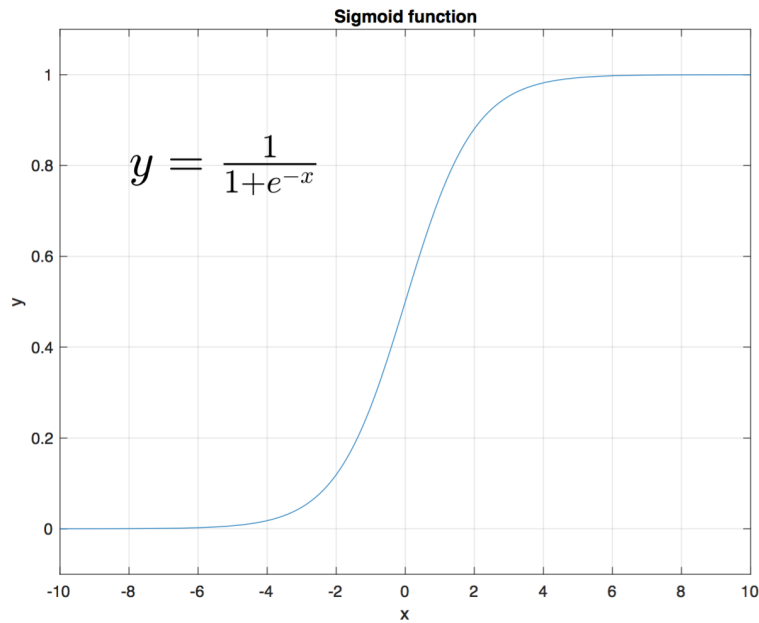


Figure 5.2: Sigmoid function

different. As described by Cortes and Vapnik, SVM works by finding a hyperplane in a number of dimension that corresponds to the number of features in a dataset [19]. Defining this hyperplane is concluded so that it specifies the boundaries to give us more certainty in the decision of classifying additional points in the dataset [23]. Classification in SVM is based on linear separation which might not yield good results and in such cases SVM performance can be improved by projecting on nonlinear function (kernel) [45]. The error is being minimized in SVM algorithm by maximizing the margin between the features and the hyperplane separating the two classes [45]. For mathematical description details of the algorithm, [19] includes the mathematical foundations.

k Nearest Neighbor (kNN)

Nearest Neighbor method is a machine learning algorithm in which data is classified based on the class of it's neighbors [46]. For one data point that has no class a sphere is drawn around it with k points included, the point is assigned the class with the largest class present in the other points inside the sphere [23]. In kNN algorithm the labels must be included in the data. Cover and Hart present detailed explanation of the algorithm [46].

Ensemble

Ensemble algorithm is a machine learning algorithm that uses multiple classifiers to make predictions on the data by combining the outcome of those classifiers [47]. Some of the main algorithms used in the ensemble method are bagging, boosting, AdaBoost and stacked generalization [48]. Bagging predictors divide the dataset into sets of training data and train the

same classifier on those sets; the predictions of each classifiers are combined in which the final prediction is based on majority voting [49]. Breiman gives detailed explanation of the algorithm [49]. Similar to bagging, boosting algorithm divides the training data into sets and make final predictions using majority voting. In boosting method majority voting is done on a number of weak classifiers in which it combines the predictions of those weak classifier to result in a strong classifier. AdaBoost method works by training a weak classifier on subsets of the training data in which the weight of the classifier is included in the hypothesis. [48] The output is the weighted vote of the predicted classes from the combined weak classifiers. Additional information on ensemble techniques are found in [48].

Majority Vote:

Majority vote is a process of combining all classifiers and making predictions based on the majority result of all the classifiers. It is a simple way of combining multiple classifiers outputs. [50] In case of this research work there is 2 classes, predictions of each algorithm is tested based on trained model. All the results are combined and a final prediction from the combined model is generated based on the majority of all the predictions using majority vote. For example the class is 1 if more than half the predictions of the algorithms are 1 and 0 if more than half the predictions are 0. In this thesis 22 classifiers were used in which the majority vote was done based on having more than 11 of the same class.

Weighted Vote:

Weighted vote was also applied in this research work by assigning a certain weight for each algorithm based on the accuracy of the trained model. The weights were used as counts for the labels for every test data point. The final prediction is based on the label that has the maximum counts. In this part 22 classifiers were used.

Binary classification problem:

In this study two classes were used for classification problem Cognitively Normal (CN) and Alzheimer's Disease (AD).

Problems during this research:

The curse of dimensionality, this term explains the case in which the number of features is way higher than the number of subjects in the dataset [51]. In this case feature selection must be applied to minimize the number of features used to classify the data and avoid this problem. This problem arose during the very beginning of this research work. After vectorization of images to be transformed to one vector array composed of 5898240 elements, this number is very large compared to the data points which were included in the first experiment.

5.4 3D Image Representation

The images used in this research is 3-dimensional MRI brain scans which can be viewed from three planes Axial, Sagittal and Coronal shown in figure 5.3.

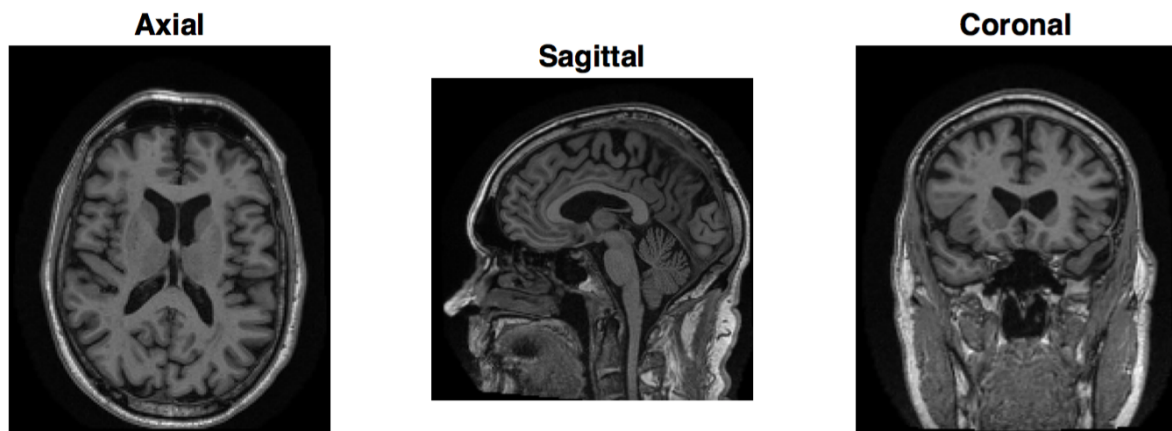


Figure 5.3: Axial, Sagittal and Coronal planes shown from an image from the dataset used.

6 Results

In this section the results of this research work is being presented. First, PCA was applied on the vectorized images for dimensionality reduction and accuracy of training data were obtained. Second, histogram was applied to vectorized images as technique to reduce data size by selecting multiple bin sizes and accuracy of different classifiers were compared with multiple features. Third, slices for all images were combined and histogram was applied. Accuracy of training data for multiple classifiers is presented and specific slices are selected for further investigation.

6.1 PCA implementation

In this section the results shown are done using 529 images with 193 AD and 336 CN.

Table 6.1 represents the accuracy of different classifiers for three set of features including 299, 385 and 422 features.

Table 6.1: Accuracy for PCA results for different number of features

res_AD_150_CN_150 (299 features)		res_AD_193_CN_193 (385 features)		res_AD_193_CN_230 (422 features)	
	Accuracy		Accuracy		Accuracy
Coarse Tree	55.70%	Medium Tree	53.40%	Medium Tree	55.30%
Logistic Regression	53.30%	Logistic Regression	51.30%	Logistic Regression	51.30%
Medium Gaussian SVM	51.30%	Linear SVM	50.00%	Medium Gaussian SVM	54.40%
Coarse KNN	52.00%	Cubic KNN	53.40%	Coarse KNN	53.70%
Bagged Trees Ensemble	59.00%	Subspace KNN Ensemble	62.70%	Subspace KNN Ensemble	60.00%

6.2 Vectorized image histogram

In this section the results shown are done using 484 images with 242 AD and 242 CN.

Figure 6.1 shows part of the histogram of vectorized images used in this section.

Table 6.2 shows the accuracy of different classifiers for classification of AD and CN vectorized images in which a comparison of the choice of bins (i.e. number of features as input for the classifier) are being represented along with the performance of each. The highest accuracy in

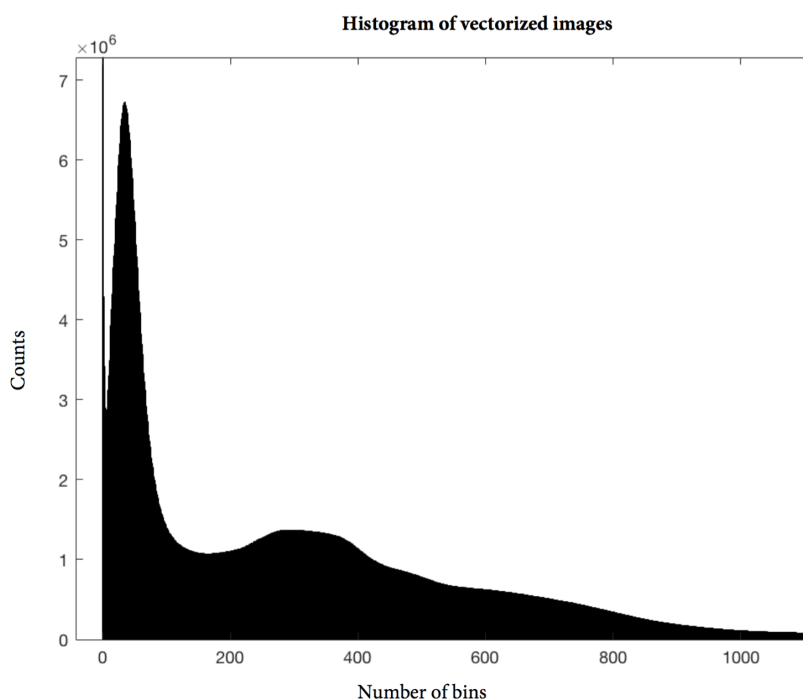


Figure 6.1: Representation of the histogram of the vectorized images

each column is in bold, Fine Gaussian SVM seem to have the highest accuracy when selecting different number of features. Highlighted in blue is the maximum accuracy in respect to each row which shows that the choice of 200 bins resulted in higher accuracy for the classification problem.

Table 6.2: Accuracy for histogram of vectorized images with different classifiers comparing different numbers of features

484 images (242 AD + 242 CN)	Accuracy					
	200 bins	300 bins	400 bins	600 bins	700 bins	1000 bins
Fine Tree	59.70%	61.40%	58.90%	62.60%	57.40%	56.80%
Linear Discriminant	57.20%	51%	52.50%	46.90%	44.80%	52.90%
Logistic Regression	55.80%	49%	50.40%	49%	45.70%	51.40%
Linear SVM	57.40%	59.30%	58.50%	57.60%	57.20%	59.50%
Quadratic SVM	65.70%	65.70%	67.10%	65.50%	63.60%	64.30%
Cubic SVM	60.30%	66.50%	63.40%	63%	65.70%	61.40%
Fine Gaussian SVM	65.90%	69.40%	69.80%	66.10%	65.70%	66.30%
Mediam Gaussian SVM	62.80%	61.40%	60.30%	57.60%	56.40%	57.40%
Coarse Gaussian SVM	51.70%	52.30%	53.10%	53.50%	51.90%	52.30%
Fine KNN	66.10%	66.70%	65.10%	63.80%	62.80%	63.80%
Medium KNN	63.20%	57.90%	62.40%	59.50%	61.40%	59.70%
Ensemble Boosted Trees	66.10%	65.30%	65.50%	65.90%	63%	66.50%

6.3 Histogram of slices

In this section the results shown are done using 800 images with 400 AD and 400 CN where the 3-dimensional images were represented in sagittal plane. Table 6.3 shows part of the results for

the run of 800 subjects for 160 slices, the number of features used is 256 which are the number of bins used in getting the histogram of the images. Performance accuracy of all 160 slices was being studied, full table can be find in appendix A in which multiple algorithms were used in the Classification Learner App in MATLAB in which Fine Tree, Logistic Regression, Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM, Fine KNN, Medium KNN and ensemble Boosted Trees were being compared in regard to accuracy.

Table 6.3 below shows comparison of slices between 31 and 40 in which highlighted in blue is the highest accuracy for each classifier in regard to the whole row from slice 1 to 160 in which slices 36 and 37 shows the highest accuracy in 6 classifiers.

Table 6.3: Performance for slices 31 - 40 (Maximum in row being bold)

800 images (400 AD + 400 CN)	Accuracy									
Slice number	31	32	33	34	35	36	37	38	39	40
Fine Tree	58.20%	56.00%	54.00%	54.40%	55.00%	51.20%	52.40%	54.40%	53.80%	51.70%
Logistic Regression	48.80%	48.80%	46.60%	50.10%	52.40%	54.10%	51.70%	52.10%	49.50%	52.40%
Linear SVM	54.10%	57.00%	53.60%	56.90%	59.10%	61.10%	57.90%	59.00%	57.10%	57.80%
Quadratic SVM	59.80%	60.90%	55.60%	60.50%	58.60%	61.80%	62.00%	57.80%	60.00%	59.20%
Cubic SVM	58.80%	57.50%	58.80%	61.00%	59.00%	63.50%	62.10%	58.90%	57.80%	59.90%
Fine Gaussian SVM	54.00%	55.00%	55.00%	56.10%	55.10%	52.50%	56.10%	57.20%	56.00%	52.20%
Mediam Gaussian SVM	59.20%	60.90%	59.60%	61.30%	61.60%	62.30%	64.00%	61.40%	62.30%	61.30%
Coarse Gaussian SVM	54.80%	56.80%	56.40%	56.20%	57.60%	58.90%	58.00%	57.00%	56.60%	56.00%
Fine KNN	57.20%	56.60%	57.20%	57.90%	58.10%	59.10%	61.40%	57.50%	58.40%	57.00%
Medium KNN	57.10%	57.60%	58.00%	55.50%	57.80%	62.10%	58.60%	59.20%	59.80%	55.60%
Ensemble Boosted Trees	60.00%	61.50%	57.10%	58.10%	61.50%	58.60%	58.80%	58.00%	57.40%	56.80%

In figure 6.2 the maximum accuracy for 160 slices for 800 subjects (400 AD and 400 CN) is plotted for multiple classifiers mentioned earlier in this document. Figure 6.2 show that the accuracy for the slices in the beginning and towards the end have lower accuracy in the classification between AD vs CN implying that these slices are not a good examination for the classification problem giving into account that in those slices the brain hasn't been shown yet and then gradually appears. Below in figure 6.3 and figure 6.4 an example is shown for slices number 5, 10 and 15 for one of the subjects which shows no sign of the brain in the images yet which explains why the accuracy is very low for the classification problem in the early slices, same case is for the slices towards the end.

In figure 6.5 the maximum and minimum accuracy for 160 slices for 800 subjects (400 AD and 400 CN) is plotted for multiple classifiers mentioned earlier in this document.

Table 6.4 below shows comparison of slices between 31 and 40 in which the highest accuracy is in bold showing the maximum of each column. It can be shown from this table that Medium Gaussian SVM preformed highest with most of the slices. Table 6.4 is the same as Table 6.3 the only difference is the highest accuracy highlighted in respect to the column or the row. Table 6.4 is part of the results and the full table can be shown in the appendix B.

Figure 6.6 shows the comparison of the performance of three classifiers from the data from table

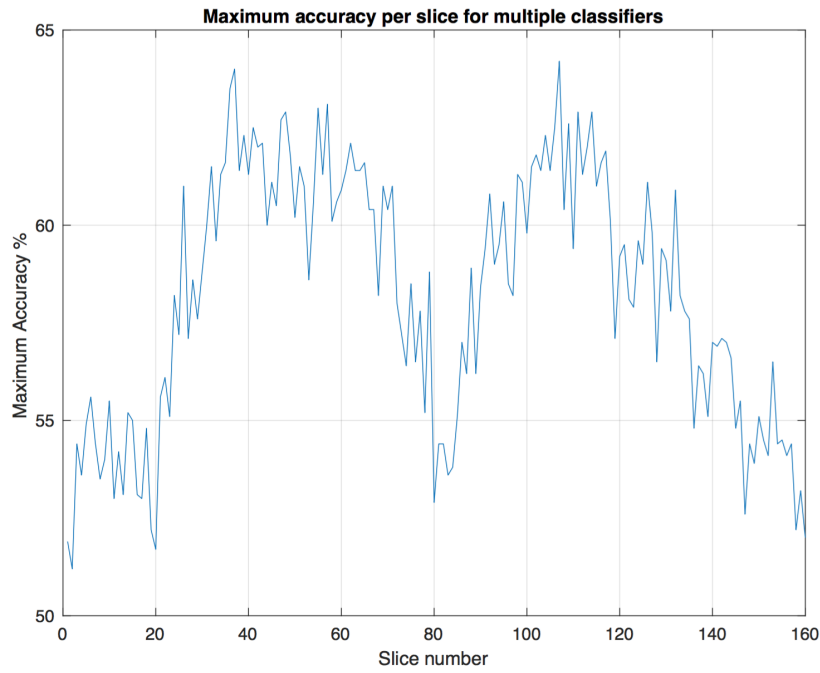


Figure 6.2: Maximum accuracy per slice for multiple classifiers

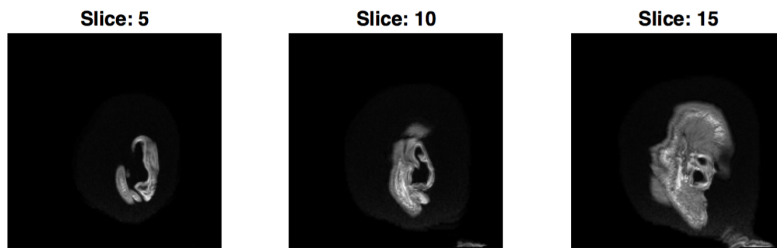


Figure 6.3: AD Image Slices 5, 10 & 15

6.4. Figure 6.6 shows the accuracy of Fine Tree, Medium Gaussian SVM and Medium kNN for the 160 slices. As shown in the figure Medium Gaussian SVM has the highest accuracy in most points.

Slices 36 and 37 are considered for further inspection since as shown earlier from table 6.3 and 6.4 the accuracy is the highest in those two slices in the classification between AD and CN. Therefore, Medium Gaussian SVM for the trained model for slices 36 and 37 was used for testing all other slices giving the following results in table 6.5.

Table 6.5 show the highest accuracy highlighted in blue for trained model for slice 36 and 37 which is used to test all other 160 slices. After testing the data for other slices using trained model of slice 36 using Medium Gaussian SVM classifier an accuracy of 70.75% for slice number 35 achieves highest accuracy. Respectively for trained model of slice 37 an accuracy of 70.87% was achieved for slice 36 as testing data. Full table of all slices used as testing data can



Figure 6.4: CN Image Slices 5, 10 & 15

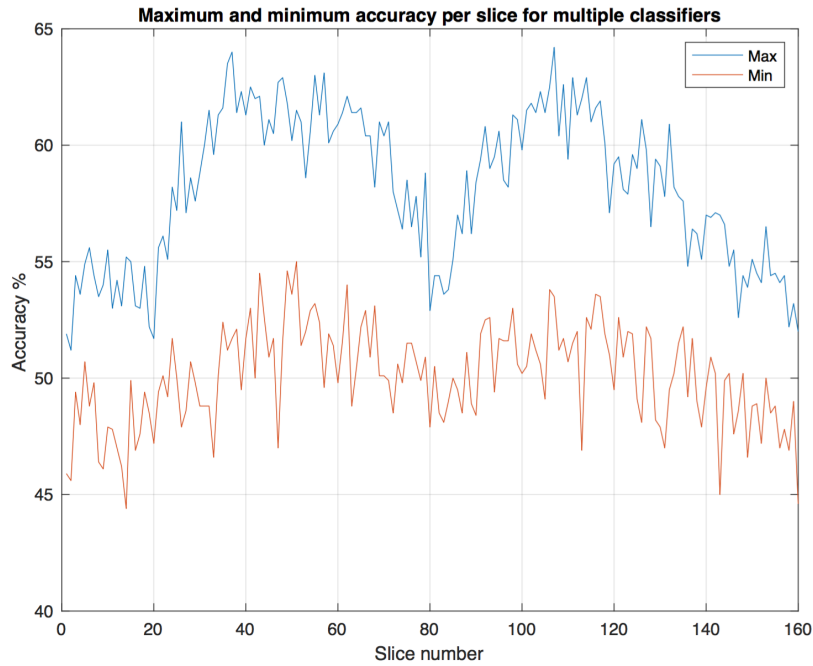


Figure 6.5: Maximum and minimum accuracy per slice for multiple classifiers

be found in the appendix C for trained model of slice 36 and 37.

Figure 6.7 show slices 36, 37 and 38 that are taken for further investigation as training data showed the highest accuracy in the classification between AD and CN in those slices.

Histograms of slice 36 and 37 for all the 800 images were concatenated in one matrix of 800 rows and 512 columns (corresponding to number of features). The dataset was divided into 600 images as training data and 200 images as testing data both divided equally into AD and CN. Training was done using the classification learner app in MATLAB and all classifiers were used with all the 512 features. The corresponding model for each classifier was saved and tested against the test data. A matrix of all predictions for the test data using all trained models was formed. Majority voting was applied for all the predictions and the results were compared to actual data labels. The accuracy of the majority vote for slice 36 and 37 is 69.5%. The same procedure was done for concatenating slices 36, 37 and 38. For slices 36, 37 and 38 the number

Table 6.4: Performance for slices 31 - 40 (Maximum in column being bold)

800 images (400 AD + 400 CN)	Accuracy									
Slice number	31	32	33	34	35	36	37	38	39	40
Fine Tree	58.20%	56.00%	54.00%	54.40%	55.00%	51.20%	52.40%	54.40%	53.80%	51.70%
Logistic Regression	48.80%	48.80%	46.60%	50.10%	52.40%	54.10%	51.70%	52.10%	49.50%	52.40%
Linear SVM	54.10%	57.00%	53.60%	56.90%	59.10%	61.10%	57.90%	59.00%	57.10%	57.80%
Quadratic SVM	59.80%	60.90%	56.60%	60.50%	58.60%	61.80%	62.00%	57.80%	60.00%	59.20%
Cubic SVM	58.60%	57.50%	58.80%	61.00%	59.00%	63.50%	62.10%	58.90%	57.80%	59.90%
Fine Gaussian SVM	54.00%	55.00%	55.00%	56.10%	55.10%	52.50%	56.10%	57.20%	56.00%	52.20%
Medium Gaussian SVM	59.20%	60.90%	59.60%	61.30%	61.60%	62.30%	64.00%	61.40%	62.30%	61.30%
Coarse Gaussian SVM	54.80%	56.80%	56.40%	56.20%	57.60%	58.90%	58.00%	57.00%	56.60%	56.00%
Fine KNN	57.20%	56.60%	57.20%	57.90%	58.10%	59.10%	61.40%	57.50%	58.40%	57.00%
Medium KNN	57.10%	57.60%	58.00%	55.50%	57.80%	62.10%	58.60%	59.20%	59.80%	55.60%
Ensemble Boosted Trees	60.00%	61.50%	57.10%	58.10%	61.50%	58.60%	58.80%	58.00%	57.40%	56.80%

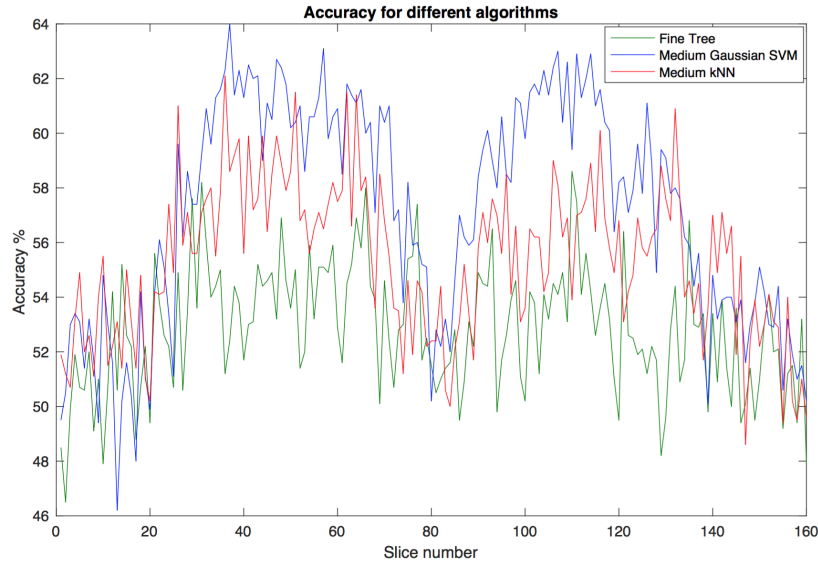


Figure 6.6: Comparison between Fine Tree, Medium Gaussian SVM and Medium kNN accuracy

of features is 768 and the accuracy of majority vote is in this case 64.5%. Weighted voting was also applied for all the predictions based on the accuracy of the trained model and the results were compared to actual data labels. The accuracy of the weighted vote for slice 36 and 37 is 67.5%. For slices 36, 37 and 38 the accuracy of weighted vote is 63.5%. Figure 6.8 shows a comparison of the results for majority vote and weighted vote for concatenation of slices 36, 37 and slices 36, 37, 38.

Table 6.5: Performance for testing data for slices 31 - 40 using trained model of slice 36 and 37

Slice 36			Slice 37	
Slice number	Medium Gaussian SVM (Accuracy%)		Slice number	Medium Gaussian SVM (Accuracy%)
31	60.5		31	58.125
32	62.125		32	61.625
33	65.5		33	63.25
34	68.375		34	65.125
35	70.75		35	67.5
36	80.125		36	70.875
37	69.25		37	80
38	69		38	69.75
39	67.75		39	68.75
40	65.75		40	68.125

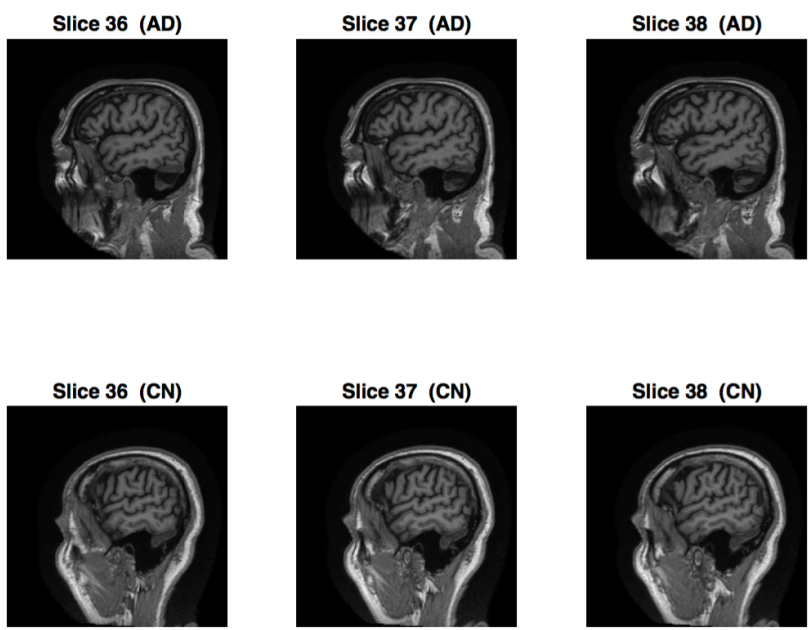


Figure 6.7: AD and CN image slices 36, 37 and 38

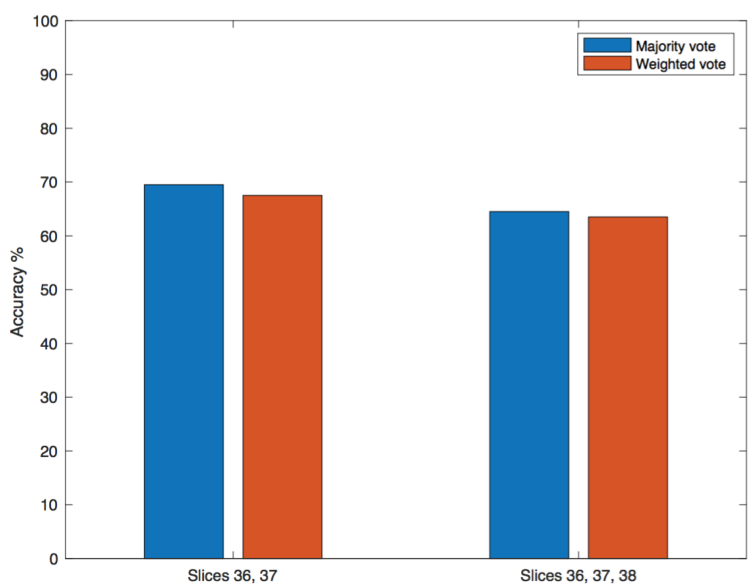


Figure 6.8: Accuracy for majority and weighted vote

7 Conclusion and Future Work

In this thesis different machine learning algorithms were tested for classification of AD and CN. Images of MRI brain scans were obtained from ADNI database in the format of NIfTI files. Each file consisted of 160 slices each of 192 by 192 pixels and therefor dimensionality reduction was needed. PCA was implemented and yielded a low accuracy. PCA experiment did not show improvement with increasing data points. Multiple experiments were being conducted with multiple number of data points with gradual increase but the accuracy was relatively not changing with different number of features. The vectorized images from the previous experiment were used to research applying histograms and comparing different choices of bins (i.e. features). The results in this part show promising results when the number of bins is 400 in which the accuracy is 69.8% for Fine Gaussian SVM algorithm which shows the highest accuracy.

The third main experiment of this research work is classification of slices using histogram for data representation. Accuracy for different slices were investigated in which certain slices showed most promising results. Slices 36 and 37 were selected based on accuracy results for further examination. Histogram of slices resulted in accuracy of 69.5% for classification by concatenating histogram of slices 36 and 37 as well as slices 36, 37 and 38 and using majority voting technique. The data was divided into training data and testing data. The same procedure was done to calculate the weighted vote and compare it to the actual labels. The weighted vote for slice 36 and 37 resulted in accuracy of 67.5%.

This research work proves the potential of using classical machine learning approaches for classification of Alzheimer's Disease and healthy brain. Based on results in this research work and previous work presented in the literature, AD can be detected using various machine learning methods in which with further research and development it could be used in real medical applications.

In continuation of this research work, deep neural network will be implemented to assess the performance of the classification problem. The use of other biomarkers in order to improve the accuracy of classification will be tested to help in the research of detection of Alzheimer's Disease in its early stage.

References

- [1] Alzheimer's Disease & Dementia. Alzheimer's Association. https://www.alz.org/alzheimers-dementia/what-is-alzheimers/brain_tour_part_2. Accessed: 18-04-2019.
- [2] Judith Neugroschl and Sophia Wang. Alzheimer's disease: diagnosis and treatment across the spectrum of disease severity. *Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine*, 78(4):596–612, 2011.
- [3] Alzheimer's Disease & Dementia. Alzheimer's Association. http://www.alz.org/alzheimers_disease_what_is_alzheimers.asp. Accessed: 14-02-2019.
- [4] Ron Brookmeyer, Elizabeth Johnson, Kathryn Ziegler-Graham, and H Michael Arrighi. Forecasting the global burden of alzheimer's disease. *Alzheimer's & dementia*, 3(3):186–191, 2007.
- [5] Alzheimer's Disease & Dementia. Alzheimer's Association. <https://www.alz.org/alzheimers-dementia/what-is-dementia>. Accessed: 14-02-2019.
- [6] Alzheimer's Disease & Dementia. Alzheimer's Association. https://www.alz.org/alzheimer_s_dementia. Accessed: 18-04-2019.
- [7] Alzheimer's Disease & Dementia. Alzheimer's Association. <https://www.alz.org/alzheimers-dementia/stages>. Accessed: 18-04-2019.
- [8] Alzheimer's Disease & Dementia. Alzheimer's Association. https://www.alz.org/alzheimers-dementia/diagnosis/medical_tests. Accessed: 25-04-2019.
- [9] Alzheimer's Disease & Dementia. Alzheimer's Association. https://www.alz.org/alzheimers-dementia/research_progress/earlier-diagnosis. Accessed: 20-04-2019.
- [10] National Institute on Aging. National Institutes of Health (NIH). How Is Alzheimer's Disease Diagnosed? <https://www.nia.nih.gov/health/how-alzheimers-disease-diagnosed>. Accessed: 25-04-2019.

- [11] Keith A Johnson, Nick C Fox, Reisa A Sperling, and William E Klunk. Brain imaging in alzheimer disease. *Cold Spring Harbor perspectives in medicine*, 2(4):a006213, 2012.
- [12] Abi Berger. How does it work?: Magnetic resonance imaging. *BMJ: British Medical Journal*, 324(7328):35, 2002.
- [13] Giovanni B Frisoni, Nick C Fox, Clifford R Jack Jr, Philip Scheltens, and Paul M Thompson. The clinical use of structural mri in alzheimer disease. *Nature Reviews Neurology*, 6(2):67, 2010.
- [14] Stefano A Bini. Artificial intelligence, machine learning, deep learning, and cognitive computing: what do these terms mean and how will they impact health care? *The Journal of arthroplasty*, 33(8):2358–2361, 2018.
- [15] Iman Beheshti, Norihide Maikusa, Hiroshi Matsuda, Hasan Demirel, and Gholamreza Anbarjafari. Histogram-based feature extraction from individual gray matter similarity-matrix for alzheimers disease classification. *Journal of Alzheimer’s Disease*, 55(4):1571–1582, 2017.
- [16] Iman Beheshti, Norihide Maikusa, Morteza Daneshmand, Hiroshi Matsuda, Hasan Demirel, and Gholamreza Anbarjafari. Classification of alzheimers disease and prediction of mild cognitive impairment conversion using histogram-based analysis of patient-specific anatomical brain connectivity networks. *Journal of Alzheimer’s Disease*, 60(1):295–304, 2017.
- [17] James A Nichols, Hsien W Herbert Chan, and Matthew AB Baker. Machine learning: applications of artificial intelligence to imaging and diagnosis. *Biophysical reviews*, 11(1):111–118, 2019.
- [18] Rahul C Deo. Machine learning in medicine. *Circulation*, 132(20):1920–1930, 2015.
- [19] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.
- [20] Fatemeh Noroozi, Dorota Kaminska, Tomasz Sapinski, and Gholamreza Anbarjafari. Supervised vocal-based emotion recognition using multiclass support vector machine, random forests, and adaboost. *Journal of the Audio Engineering Society*, 65(7/8):562–572, 2017.
- [21] Tõnis Uiboupin, Pejman Rasti, Gholamreza Anbarjafari, and Hasan Demirel. Facial image super resolution using sparse representation for improving face recognition in surveillance monitoring. In *2016 24th Signal Processing and Communication Application Conference (SIU)*, pages 437–440. IEEE, 2016.

- [22] Christer Loob, Pejman Rasti, Iris Lüsi, Julio CS Jacques Junior, Xavier Baró, Sergio Escalera, Tomasz Sapinski, Dorota Kaminska, and Gholamreza Anbarjafari. Dominant and complementary multi-emotional facial expression recognition using c-support vector classification. In *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*, pages 833–838. IEEE, 2017.
- [23] Christopher M Bishop. *Pattern recognition and machine learning*. springer, 2006.
- [24] Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.
- [25] Fatemeh Noroozi, Tomasz Sapiński, Dorota Kamińska, and Gholamreza Anbarjafari. Vocal-based emotion recognition using random forests and decision tree. *International Journal of Speech Technology*, 20(2):239–246, 2017.
- [26] Iris Lüsi, Sergio Escalera, and Gholamreza Anbarjafari. Human head pose estimation on sase database using random hough regression forests. In *Video Analytics. Face and Facial Expression Recognition and Audience Measurement*, pages 137–150. Springer, 2016.
- [27] Trishan Panch, Peter Szolovits, and Rifat Atun. Artificial intelligence, machine learning and health systems. *Journal of global health*, 8(2), 2018.
- [28] Daoqiang Zhang, Dinggang Shen, Alzheimer’s Disease Neuroimaging Initiative, et al. Multi-modal multi-task learning for joint prediction of multiple regression and classification variables in alzheimer’s disease. *NeuroImage*, 59(2):895–907, 2012.
- [29] Eric Westman, J-Sebastian Muehlboeck, and Andrew Simmons. Combining mri and csf measures for classification of alzheimer’s disease and prediction of mild cognitive impairment conversion. *Neuroimage*, 62(1):229–238, 2012.
- [30] Qi Zhou, Mohammed Goryawala, Mercedes Cabrerizo, Jin Wang, Warren Barker, David A Loewenstein, Ranjan Duara, and Malek Adjouadi. An optimal decisional space for the classification of alzheimer’s disease and mild cognitive impairment. *IEEE Transactions on Biomedical Engineering*, 61(8):2245–2253, 2014.
- [31] Katherine R Gray, Paul Aljabar, Rolf A Heckemann, Alexander Hammers, Daniel Rueckert, Alzheimer’s Disease Neuroimaging Initiative, et al. Random forest-based similarity measures for multi-modal classification of alzheimer’s disease. *NeuroImage*, 65:167–175, 2013.
- [32] George A Papakostas, Alexandre Savio, Manuel Graña, and Vassilis G Kaburlasos. A lattice computing approach to alzheimer’s disease computer assisted diagnosis based on mri data. *Neurocomputing*, 150:37–42, 2015.

- [33] Daoqiang Zhang, Yaping Wang, Luping Zhou, Hong Yuan, Dinggang Shen, Alzheimer's Disease Neuroimaging Initiative, et al. Multimodal classification of alzheimer's disease and mild cognitive impairment. *Neuroimage*, 55(3):856–867, 2011.
- [34] Rigel Mahmood and Bishad Ghimire. Automatic detection and classification of alzheimer's disease from mri scans using principal component analysis and artificial neural networks. In *2013 20th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 133–137. IEEE, 2013.
- [35] Yi Ding, Cong Zhang, Tian Lan, Zhiguang Qin, Xinjie Zhang, and Wei Wang. Classification of alzheimer's disease based on the combination of morphometric feature and texture feature. In *2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pages 409–412. IEEE, 2015.
- [36] ADNI. About ADNI. <http://adni.loni.usc.edu/about/>. Accessed: 02-05-2019.
- [37] ADNI. Background Rationale. <http://adni.loni.usc.edu/study-design/>. Accessed: 02-05-2019.
- [38] ADNI. MRI Pre-processing. <http://adni.loni.usc.edu/methods/mri-tool/mri-analysis/#mri-pre-processing-container>.
- [39] ADNI. MRI Pre-processing. <http://adni.loni.usc.edu/study-design/#study-objective-container>.
- [40] National Institutes of Health (NIH). Neuroimaging Informatics Technology Initiative. <https://nifti.nih.gov/>. Accessed: 25-04-2019.
- [41] I.T. Jolliffe. *Principal Component Analysis*. Springer, 2002.
- [42] R. C. Gonzalez and R. E. Woods. *Digital Image Processing Second Edition*. Upper Saddle River, New Jersey 07458: Prentice-Hall, Inc., 2002.
- [43] Assess Classifier Performance in Classification Learner. Mathworks. <https://www.mathworks.com/help/stats/assess-classifier-performance.html>. Accessed: 02-05-2019.
- [44] Carl Kingsford and Steven L Salzberg. What are decision trees? *Nature biotechnology*, 26(9):1011, 2008.
- [45] Shun-ichi Amari and Si Wu. Improving support vector machine classifiers by modifying kernel functions. *Neural Networks*, 12(6):783–789, 1999.
- [46] Thomas M Cover and Peter E Hart. Nearest neighbor pattern classification. *IEEE transactions on information theory*, 13(1):21–27, 1967.

- [47] Thomas G Dietterich. Ensemble methods in machine learning. In *International workshop on multiple classifier systems*, pages 1–15. Springer, 2000.
- [48] Robi Polikar. Ensemble based systems in decision making. *IEEE Circuits and systems magazine*, 6(3):21–45, 2006.
- [49] Leo Breiman. Bagging predictors. *Machine learning*, 24(2):123–140, 1996.
- [50] Louisa Lam and Ching Y Suen. A theoretical analysis of the application of majority voting to pattern recognition. In *Proceedings of the 12th IAPR International Conference on Pattern Recognition, Vol. 3-Conference C: Signal Processing (Cat. No. 94CH3440-5)*, volume 2, pages 418–420. IEEE, 1994.
- [51] Gregory Ditzler, Gail Rosen, and Robi Polikar. Information theoretic feature selection for high dimensional metagenomic data. In *Proceedings 2012 IEEE International Workshop on Genomic Signal Processing and Statistics (GENSIPS)*, pages 143–146. IEEE, 2012.

Appendix

7.1 Appendix A: Slices 1 - 160 accuracy (1)

Full table of accuracy of slices 1 - 160 using histogram (Highest accuracy in row is being bold and highlighted in blue are the maximum in the whole 160 slices)

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	1	2	3	4	5	6	7	8	9	10
Fine Tree	48.50%	46.50%	49.90%	51.90%	50.70%	50.60%	52.00%	49.10%	51.00%	47.90%
Logistic Regression	45.90%	50.00%	52.40%	49.80%	51.90%	49.90%	51.00%	49.80%	50.90%	51.20%
Linear SVM	49.90%	50.90%	54.40%	52.80%	51.90%	53.20%	51.70%	49.60%	50.50%	51.20%
Quadratic SVM	46.50%	48.60%	51.50%	49.00%	53.20%	55.60%	51.60%	49.40%	49.60%	51.60%
Cubic SVM	49.80%	48.90%	53.40%	48.00%	54.50%	52.60%	54.40%	47.50%	48.40%	54.00%
Fine Gaussian SVM	45.90%	45.60%	50.90%	51.10%	50.70%	53.00%	49.80%	46.40%	50.00%	50.10%
Mediam Gaussian SVM	49.50%	50.50%	53.00%	53.40%	53.10%	51.40%	53.20%	51.70%	49.40%	54.80%
Coarse Gaussian SVM	49.80%	48.10%	53.00%	53.60%	52.40%	52.20%	51.00%	48.80%	46.10%	48.80%
Fine KNN	50.10%	48.60%	49.40%	49.80%	51.00%	48.80%	50.60%	53.10%	47.50%	53.10%
Medium KNN	51.90%	51.20%	50.70%	53.20%	54.90%	52.00%	52.60%	51.10%	54.00%	55.50%
Ensemble Boosted Trees	48.90%	50.00%	53.80%	52.10%	51.90%	50.60%	53.80%	53.50%	51.70%	52.90%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	11	12	13	14	15	16	17	18	19	20
Fine Tree	50.70%	54.20%	50.60%	55.20%	52.60%	52.20%	48.80%	50.70%	52.20%	49.40%
Logistic Regression	48.20%	49.60%	50.70%	47.00%	52.40%	49.20%	49.60%	53.50%	52.00%	47.40%
Linear SVM	48.60%	52.20%	49.10%	46.90%	52.10%	52.50%	50.00%	54.40%	51.00%	47.50%
Quadratic SVM	49.40%	51.70%	51.90%	45.20%	50.90%	49.80%	51.20%	53.80%	52.20%	51.70%
Cubic SVM	47.80%	47.90%	51.10%	44.40%	53.20%	50.00%	53.00%	53.40%	49.20%	50.50%
Fine Gaussian SVM	51.40%	50.60%	52.00%	47.40%	51.90%	46.90%	50.00%	52.60%	49.00%	51.50%
Mediam Gaussian SVM	53.00%	51.60%	46.20%	50.20%	51.60%	50.40%	48.00%	54.20%	51.10%	49.90%
Coarse Gaussian SVM	48.90%	47.00%	48.00%	50.00%	49.90%	49.50%	47.60%	49.40%	50.70%	47.20%
Fine KNN	51.00%	51.20%	50.90%	51.10%	52.10%	50.20%	52.80%	53.20%	50.60%	51.20%
Medium KNN	51.50%	52.20%	53.10%	51.40%	55.00%	53.10%	51.40%	54.80%	51.00%	50.20%
Ensemble Boosted Trees	50.10%	52.10%	49.50%	49.60%	52.00%	49.90%	50.10%	50.60%	48.50%	49.60%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	21	22	23	24	25	26	27	28	29	30
Fine Tree	55.60%	53.80%	52.60%	52.20%	50.70%	54.90%	50.60%	53.50%	57.60%	53.60%
Logistic Regression	49.40%	50.10%	49.20%	51.70%	53.10%	47.90%	48.60%	50.70%	49.80%	48.80%
Linear SVM	51.10%	50.40%	51.40%	53.60%	50.00%	53.10%	51.20%	52.50%	52.20%	50.40%
Quadratic SVM	54.40%	54.80%	54.00%	55.60%	55.00%	53.60%	52.80%	58.20%	56.00%	58.80%
Cubic SVM	50.20%	54.90%	54.10%	56.20%	57.20%	57.60%	54.10%	55.60%	57.10%	56.90%
Fine Gaussian SVM	52.90%	53.50%	52.10%	56.90%	54.20%	56.00%	57.10%	54.00%	53.90%	54.40%
Mediam Gaussian SVM	54.20%	56.10%	55.10%	53.40%	51.10%	59.60%	56.20%	58.60%	57.40%	57.40%
Coarse Gaussian SVM	49.50%	50.40%	52.80%	54.20%	51.90%	55.20%	54.20%	52.80%	53.00%	53.50%
Fine KNN	53.40%	51.50%	53.10%	58.20%	55.80%	58.10%	56.60%	58.10%	55.60%	56.10%
Medium KNN	54.20%	54.10%	54.20%	57.40%	54.90%	61.00%	55.90%	57.10%	55.60%	55.60%
Ensemble Boosted Trees	52.50%	56.10%	52.60%	56.60%	53.50%	54.10%	55.10%	54.10%	57.00%	54.40%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	31	32	33	34	35	36	37	38	39	40
Fine Tree	58.20%	56.00%	54.00%	54.40%	55.00%	51.20%	52.40%	54.40%	53.80%	51.70%
Logistic Regression	48.80%	48.80%	46.60%	50.10%	52.40%	54.10%	51.70%	52.10%	49.50%	52.40%
Linear SVM	54.10%	57.00%	53.60%	56.90%	59.10%	61.10%	57.90%	59.00%	57.10%	57.80%
Quadratic SVM	59.80%	60.90%	55.60%	60.50%	58.60%	61.80%	62.00%	57.80%	60.00%	59.20%
Cubic SVM	58.60%	57.50%	58.80%	61.00%	59.00%	63.50%	62.10%	58.90%	57.80%	59.90%
Fine Gaussian SVM	54.00%	55.00%	55.00%	56.10%	55.10%	52.50%	56.10%	57.20%	56.00%	52.20%
Mediam Gaussian SVM	59.20%	60.90%	59.60%	61.30%	61.60%	62.30%	64.00%	61.40%	62.30%	61.30%
Coarse Gaussian SVM	54.80%	56.80%	56.40%	56.20%	57.60%	58.90%	58.00%	57.00%	56.60%	56.00%
Fine KNN	57.20%	56.60%	57.20%	57.90%	58.10%	59.10%	61.40%	57.50%	58.40%	57.00%
Medium KNN	57.10%	57.60%	58.00%	55.50%	57.80%	62.10%	58.60%	59.20%	59.80%	55.60%
Ensemble Boosted Trees	60.00%	61.50%	57.10%	58.10%	61.50%	58.60%	58.80%	58.00%	57.40%	56.80%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	41	42	43	44	45	46	47	48	49	50
Fine Tree	53.00%	53.10%	55.20%	54.40%	54.60%	54.90%	53.20%	56.90%	54.60%	53.60%
Logistic Regression	55.50%	50.00%	55.40%	52.60%	50.90%	51.70%	47.00%	51.60%	55.00%	55.60%
Linear SVM	59.10%	58.80%	60.10%	58.20%	56.80%	56.80%	54.10%	58.90%	60.00%	58.60%
Quadratic SVM	57.60%	58.80%	59.20%	60.00%	59.00%	57.90%	58.90%	61.00%	55.50%	58.90%
Cubic SVM	61.40%	59.90%	61.00%	58.10%	60.00%	60.20%	59.10%	62.90%	57.00%	60.20%
Fine Gaussian SVM	54.80%	56.40%	54.50%	56.20%	55.60%	53.20%	54.90%	57.60%	55.20%	53.80%
Mediam Gaussian SVM	62.50%	62.00%	62.10%	59.00%	61.10%	60.50%	62.70%	62.40%	61.80%	60.20%
Coarse Gaussian SVM	55.80%	56.90%	57.80%	55.80%	55.80%	55.60%	56.80%	56.80%	56.60%	55.80%
Fine KNN	58.00%	55.00%	55.40%	56.50%	59.50%	56.10%	57.60%	57.40%	54.90%	58.00%
Medium KNN	59.90%	57.20%	57.60%	59.90%	56.40%	58.50%	59.90%	58.90%	57.90%	58.60%
Ensemble Boosted Trees	59.90%	58.40%	56.10%	59.10%	58.60%	58.80%	60.50%	60.20%	60.80%	60.20%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	51	52	53	54	55	56	57	58	59	60
Fine Tree	55.00%	51.40%	52.00%	55.90%	53.20%	55.10%	55.10%	54.90%	55.90%	52.90%
Logistic Regression	56.00%	54.10%	53.10%	52.90%	53.80%	52.40%	49.60%	51.90%	51.40%	49.80%
Linear SVM	59.80%	58.80%	58.60%	59.20%	63.00%	59.40%	58.00%	60.00%	57.00%	58.00%
Quadratic SVM	58.80%	60.50%	56.80%	59.60%	59.80%	58.90%	58.20%	58.50%	58.50%	57.00%
Cubic SVM	60.50%	59.50%	58.40%	57.10%	56.50%	59.10%	57.10%	60.10%	58.40%	56.40%
Fine Gaussian SVM	55.90%	53.90%	53.80%	54.80%	53.40%	54.80%	54.40%	53.90%	54.90%	51.50%
Mediam Gaussian SVM	60.40%	61.00%	58.60%	60.60%	60.60%	61.30%	63.10%	59.80%	60.60%	60.90%
Coarse Gaussian SVM	57.60%	57.20%	57.20%	57.20%	56.90%	57.80%	57.00%	56.90%	58.50%	56.80%
Fine KNN	58.00%	55.80%	56.40%	60.00%	56.80%	60.60%	56.90%	57.00%	56.50%	54.60%
Medium KNN	61.50%	56.80%	57.20%	55.60%	56.50%	57.10%	56.50%	57.40%	58.20%	57.50%
Ensemble Boosted Trees	57.40%	58.10%	57.50%	58.80%	59.50%	58.50%	59.80%	57.80%	58.00%	56.90%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	61	62	63	64	65	66	67	68	69	70
Fine Tree	51.60%	54.50%	55.20%	56.90%	55.80%	58.00%	54.40%	53.90%	50.10%	54.60%
Logistic Regression	54.80%	54.00%	48.80%	50.40%	56.60%	52.90%	50.90%	53.90%	54.50%	54.40%
Linear SVM	61.40%	59.50%	60.50%	58.00%	57.40%	60.00%	58.90%	58.20%	59.00%	59.00%
Quadratic SVM	58.50%	59.80%	56.50%	56.60%	60.20%	59.50%	56.40%	58.10%	57.40%	54.50%
Cubic SVM	57.10%	58.20%	56.40%	56.20%	56.60%	58.80%	54.60%	55.60%	58.60%	55.00%
Fine Gaussian SVM	51.70%	56.10%	52.90%	52.60%	52.20%	56.00%	53.00%	53.10%	51.50%	50.10%
Mediam Gaussian SVM	58.50%	61.80%	61.40%	61.10%	61.60%	60.00%	60.40%	57.10%	61.00%	60.40%
Coarse Gaussian SVM	56.90%	58.10%	58.40%	57.60%	57.60%	57.80%	57.60%	54.50%	55.40%	56.90%
Fine KNN	55.60%	59.50%	56.60%	56.90%	52.90%	56.80%	54.90%	53.60%	56.10%	57.90%
Medium KNN	57.90%	61.50%	56.60%	61.40%	57.90%	58.40%	56.00%	53.60%	58.50%	56.80%
Ensemble Boosted Trees	56.60%	62.10%	60.60%	58.50%	59.60%	60.40%	58.40%	57.90%	57.90%	56.50%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	71	72	73	74	75	76	77	78	79	80
Fine Tree	52.40%	50.70%	52.80%	53.00%	55.40%	55.50%	57.40%	51.70%	52.50%	51.50%
Logistic Regression	49.90%	48.50%	51.10%	49.80%	51.50%	55.10%	50.70%	51.50%	50.90%	47.90%
Linear SVM	58.10%	55.10%	52.20%	54.80%	57.00%	55.40%	54.60%	54.10%	53.90%	49.60%
Quadratic SVM	56.20%	52.60%	52.20%	54.20%	58.50%	56.00%	52.80%	52.10%	55.90%	49.10%
Cubic SVM	56.10%	51.70%	50.60%	52.20%	56.10%	56.50%	52.40%	53.00%	54.40%	50.10%
Fine Gaussian SVM	52.20%	51.60%	53.60%	53.40%	52.20%	51.50%	53.80%	49.90%	52.00%	50.50%
Mediam Gaussian SVM	61.00%	56.80%	57.20%	53.80%	58.20%	55.90%	56.00%	55.20%	55.10%	50.20%
Coarse Gaussian SVM	56.20%	52.90%	54.20%	53.80%	52.50%	54.20%	54.80%	55.10%	53.80%	52.10%
Fine KNN	50.60%	52.40%	52.60%	53.40%	56.40%	54.00%	57.80%	51.40%	58.80%	51.90%
Medium KNN	55.50%	53.60%	53.50%	51.20%	54.60%	51.90%	54.60%	54.20%	52.20%	52.40%
Ensemble Boosted Trees	53.20%	58.00%	55.50%	56.40%	55.10%	53.80%	57.00%	53.60%	56.00%	52.90%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	81	82	83	84	85	86	87	88	89	90
Fine Tree	50.50%	51.00%	51.40%	51.60%	52.80%	49.50%	50.90%	53.10%	52.20%	54.90%
Logistic Regression	51.60%	48.50%	53.10%	51.70%	50.60%	53.80%	48.50%	51.10%	51.90%	48.40%
Linear SVM	52.40%	52.60%	50.60%	51.60%	51.50%	55.50%	51.90%	53.60%	53.60%	56.10%
Quadratic SVM	52.00%	49.00%	49.50%	49.00%	52.20%	56.40%	53.60%	52.40%	56.20%	55.20%
Cubic SVM	53.20%	50.90%	48.10%	50.70%	54.10%	52.50%	55.00%	56.40%	54.40%	56.80%
Fine Gaussian SVM	52.90%	50.70%	48.10%	50.20%	50.00%	51.50%	50.90%	53.40%	48.90%	53.50%
Mediam Gaussian SVM	52.80%	52.20%	53.20%	52.00%	54.60%	57.00%	56.20%	55.90%	56.10%	58.40%
Coarse Gaussian SVM	54.40%	53.20%	51.90%	53.80%	52.60%	54.90%	54.20%	55.10%	52.40%	54.10%
Fine KNN	54.10%	53.50%	53.60%	52.90%	54.90%	51.10%	49.80%	52.20%	51.40%	54.90%
Medium KNN	52.40%	54.40%	50.60%	50.00%	52.10%	53.10%	55.20%	53.40%	51.70%	55.80%
Ensemble Boosted Trees	52.80%	54.00%	52.50%	52.60%	55.10%	53.00%	55.50%	58.90%	56.10%	57.50%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	91	92	93	94	95	96	97	98	99	100
Fine Tree	54.50%	54.40%	56.50%	49.80%	51.70%	52.60%	53.90%	54.60%	51.10%	50.20%
Logistic Regression	51.90%	52.50%	52.60%	49.40%	53.60%	53.90%	52.40%	53.00%	50.60%	51.60%
Linear SVM	58.50%	57.80%	56.80%	59.10%	59.80%	56.90%	57.20%	59.10%	60.60%	58.10%
Quadratic SVM	57.20%	55.80%	54.90%	54.90%	57.10%	57.80%	53.00%	54.10%	56.50%	56.40%
Cubic SVM	56.10%	57.10%	56.60%	55.20%	57.10%	55.60%	53.80%	55.20%	53.90%	57.60%
Fine Gaussian SVM	52.50%	53.80%	54.20%	52.60%	52.80%	51.60%	51.60%	53.40%	51.40%	50.40%
Mediam Gaussian SVM	59.40%	60.10%	59.00%	58.00%	60.60%	58.50%	58.20%	61.30%	61.10%	59.80%
Coarse Gaussian SVM	57.40%	55.60%	53.20%	56.60%	56.40%	56.60%	56.10%	58.60%	57.80%	56.40%
Fine KNN	55.40%	58.10%	55.00%	56.60%	53.00%	56.90%	55.60%	57.40%	55.00%	54.10%
Medium KNN	57.10%	56.00%	57.60%	57.00%	56.60%	58.50%	54.10%	56.80%	53.10%	53.60%
Ensemble Boosted Trees	57.60%	60.80%	57.40%	59.50%	58.60%	56.50%	55.00%	57.60%	56.50%	57.10%

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	101	102	103	104	105	106	107	108	109	110	
Fine Tree	54.20%	53.80%	51.20%	54.10%	53.20%	54.50%	54.10%	54.90%	53.10%	58.60%	
Logistic Regression	53.90%	51.90%	53.90%	50.60%	49.10%	55.20%	53.50%	52.80%	51.70%	50.70%	
Linear SVM	60.20%	59.20%	60.50%	56.80%	57.40%	59.80%	59.20%	57.80%	59.10%	56.00%	
Quadratic SVM	57.20%	58.50%	57.80%	57.60%	60.60%	60.90%	64.20%	60.20%	59.50%	56.10%	
Cubic SVM	57.90%	57.80%	55.60%	57.80%	60.00%	62.50%	63.50%	57.00%	60.40%	56.80%	
Fine Gaussian SVM	50.50%	53.40%	53.00%	52.40%	52.50%	53.80%	55.40%	51.20%	55.10%	54.10%	
Mediam Gaussian SVM	61.50%	61.80%	61.40%	62.30%	61.40%	62.40%	63.00%	60.40%	62.60%	59.40%	
Coarse Gaussian SVM	58.20%	57.90%	57.80%	57.20%	55.80%	57.40%	56.80%	55.10%	55.60%	54.00%	
Fine KNN	54.20%	57.20%	54.40%	54.90%	55.20%	56.80%	57.60%	54.90%	56.00%	56.80%	
Medium KNN	56.50%	56.20%	56.20%	54.20%	54.90%	59.00%	58.10%	56.20%	56.90%	53.90%	
Ensemble Boosted Trees	61.10%	58.20%	59.20%	57.50%	57.40%	57.90%	62.00%	58.10%	58.80%	56.90%	

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	111	112	113	114	115	116	117	118	119	120	
Fine Tree	57.50%	54.10%	55.60%	54.20%	52.60%	53.60%	54.50%	53.20%	51.00%	49.50%	
Logistic Regression	51.50%	52.80%	46.90%	52.60%	52.10%	53.90%	54.20%	51.90%	51.90%	54.00%	
Linear SVM	58.20%	57.40%	58.80%	58.50%	58.60%	59.90%	57.60%	58.00%	55.90%	58.60%	
Quadratic SVM	57.60%	57.60%	61.10%	59.50%	56.50%	59.50%	58.90%	56.40%	56.10%	59.20%	
Cubic SVM	61.10%	57.50%	58.10%	60.10%	59.60%	60.40%	59.10%	55.50%	56.60%	59.20%	
Fine Gaussian SVM	53.60%	52.00%	57.20%	53.60%	53.20%	57.00%	54.10%	52.80%	54.50%	53.40%	
Mediam Gaussian SVM	62.90%	61.30%	62.00%	62.90%	61.00%	61.60%	60.40%	60.10%	56.40%	58.20%	
Coarse Gaussian SVM	55.00%	56.40%	56.50%	57.80%	57.00%	55.20%	53.50%	54.20%	55.90%	56.00%	
Fine KNN	57.20%	56.00%	57.00%	56.60%	55.40%	58.40%	56.00%	55.50%	53.50%	54.60%	
Medium KNN	57.00%	57.10%	57.60%	58.90%	56.40%	60.10%	56.90%	55.80%	54.90%	56.80%	
Ensemble Boosted Trees	61.00%	59.60%	59.00%	60.10%	58.20%	61.10%	61.90%	57.40%	57.10%	58.50%	

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	121	122	123	124	125	126	127	128	129	130	
Fine Tree	56.40%	52.60%	52.50%	51.90%	52.10%	51.20%	52.20%	51.70%	48.20%	49.60%	
Logistic Regression	54.00%	54.00%	52.00%	54.00%	49.10%	48.10%	52.20%	52.10%	52.90%	47.90%	
Linear SVM	59.50%	58.10%	55.50%	58.50%	57.00%	57.80%	59.10%	56.10%	58.80%	56.50%	
Quadratic SVM	58.50%	55.20%	55.00%	57.60%	58.40%	57.10%	57.90%	54.10%	57.10%	53.10%	
Cubic SVM	58.20%	55.60%	54.80%	57.50%	59.00%	58.00%	57.20%	54.60%	56.50%	53.20%	
Fine Gaussian SVM	52.60%	51.10%	53.50%	53.20%	55.40%	52.40%	53.80%	53.00%	53.80%	52.20%	
Mediam Gaussian SVM	58.40%	57.10%	57.90%	59.60%	57.80%	61.10%	58.90%	54.90%	59.40%	59.10%	
Coarse Gaussian SVM	55.10%	54.80%	54.20%	55.10%	56.20%	55.50%	55.60%	55.40%	56.60%	55.80%	
Fine KNN	52.90%	50.90%	54.40%	55.40%	55.40%	55.20%	56.90%	54.40%	58.00%	56.00%	
Medium KNN	53.10%	54.20%	54.80%	56.90%	55.80%	55.50%	56.20%	56.50%	58.80%	57.60%	
Ensemble Boosted Trees	56.10%	58.00%	56.20%	55.60%	53.60%	57.00%	59.80%	55.20%	54.00%	56.10%	

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	131	132	133	134	135	136	137	138	139	140	
Fine Tree	52.80%	54.40%	50.90%	51.70%	56.80%	53.00%	52.90%	53.40%	49.80%	53.40%	
Logistic Regression	47.00%	50.40%	50.20%	51.50%	52.20%	49.20%	53.80%	50.60%	50.10%	49.60%	
Linear SVM	54.80%	51.40%	52.60%	54.90%	52.20%	52.80%	51.70%	51.00%	49.00%	53.50%	
Quadratic SVM	56.10%	49.50%	53.90%	56.50%	55.50%	54.00%	54.40%	53.50%	50.00%	53.80%	
Cubic SVM	56.10%	52.10%	54.40%	57.80%	57.60%	54.80%	54.90%	54.60%	50.50%	54.80%	
Fine Gaussian SVM	54.00%	54.60%	51.40%	53.80%	52.40%	49.80%	53.10%	51.60%	53.40%	53.80%	
Mediam Gaussian SVM	57.80%	58.00%	57.60%	56.20%	55.90%	54.40%	55.60%	52.50%	50.10%	54.80%	
Coarse Gaussian SVM	55.10%	56.10%	55.00%	52.40%	54.00%	53.90%	53.10%	49.00%	47.90%	51.90%	
Fine KNN	57.50%	57.80%	58.20%	54.80%	57.50%	50.70%	56.40%	53.50%	55.10%	54.40%	
Medium KNN	56.80%	60.90%	57.60%	54.00%	54.60%	53.40%	54.50%	51.70%	53.60%	57.00%	
Ensemble Boosted Trees	56.40%	58.50%	55.90%	51.60%	54.20%	52.10%	55.50%	56.20%	53.00%	54.50%	

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	141	142	143	144	145	146	147	148	149	150	
Fine Tree	50.90%	53.90%	51.40%	50.00%	53.60%	49.40%	50.10%	51.40%	49.50%	51.00%	
Logistic Regression	51.40%	52.50%	45.00%	49.90%	51.90%	47.60%	49.20%	52.60%	46.60%	50.70%	
Linear SVM	53.40%	50.90%	52.00%	51.20%	50.20%	51.60%	50.50%	54.40%	51.20%	49.10%	
Quadratic SVM	52.10%	53.10%	50.40%	50.70%	54.80%	49.20%	52.40%	53.00%	49.80%	50.90%	
Cubic SVM	54.50%	53.10%	53.40%	54.60%	52.10%	54.40%	52.50%	53.40%	49.60%	50.20%	
Fine Gaussian SVM	56.90%	53.40%	54.50%	53.60%	52.60%	54.00%	52.60%	51.70%	51.10%	53.00%	
Mediam Gaussian SVM	53.20%	53.90%	54.00%	54.00%	53.10%	53.90%	51.60%	53.00%	53.80%	55.10%	
Coarse Gaussian SVM	52.40%	50.20%	52.00%	51.40%	51.90%	51.60%	52.60%	53.60%	52.40%	50.00%	
Fine KNN	56.10%	55.10%	57.00%	55.00%	53.90%	53.20%	52.20%	52.00%	51.60%	48.80%	
Medium KNN	54.90%	57.10%	55.60%	56.60%	51.90%	55.50%	48.60%	52.40%	53.90%	52.20%	
Ensemble Boosted Trees	54.20%	55.00%	54.00%	53.60%	54.50%	49.20%	50.50%	50.20%	51.90%	52.80%	

800 Images (400 AD + 400 CN)		Accuracy									
Slice number	151	152	153	154	155	156	157	158	159	160	
Fine Tree	53.00%	54.10%	52.00%	52.10%	49.20%	51.20%	51.50%	49.40%	53.20%	47.90%	
Logistic Regression	48.90%	47.20%	50.20%	51.70%	50.70%	47.00%	47.80%	48.90%	49.00%	44.60%	
Linear SVM	53.80%	49.20%	51.00%	53.00%	49.60%	51.90%	50.00%	48.80%	52.00%	52.00%	
Quadratic SVM	50.20%	52.00%	56.50%	50.90%	49.40%	51.70%	50.90%	50.20%	50.50%	47.80%	
Cubic SVM	51.10%	52.00%	53.00%	48.50%	48.80%	50.20%	49.50%	46.90%	49.10%	46.40%	
Fine Gaussian SVM	49.50%	52.20%	55.40%	53.10%	51.60%	51.00%	52.80%	49.20%	50.40%	48.90%	
Mediam Gaussian SVM	54.20%	53.00%	52.90%	54.40%	50.60%	53.20%	51.90%	51.00%	51.50%	50.20%	
Coarse Gaussian SVM	51.40%	49.00%	50.00%	52.40%	54.50%	54.10%	54.40%	52.20%	52.50%	51.90%	
Fine KNN	53.20%	53.50%	53.60%	50.60%	49.10%	49.50%	48.40%	47.10%	51.40%	48.60%	
Medium KNN	53.00%	54.10%	53.10%	52.90%	49.40%	54.00%	50.20%	49.50%	51.00%	49.60%	
Ensemble Boosted Trees	54.50%	51.10%	52.60%	53.90%	51.60%	52.00%	50.50%	51.40%	51.10%	49.60%	

7.2 Appendix B: Slices 1 - 160 accuracy (2)

Full table of accuracy of slices 1 - 160 using histogram (Highest accuracy in column is in bold)

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	1	2	3	4	5	6	7	8	9	10
Fine Tree	48.50%	46.50%	49.90%	51.90%	50.70%	50.60%	52.00%	49.10%	51.00%	47.90%
Logistic Regression	45.90%	50.00%	52.40%	49.80%	51.90%	49.90%	51.00%	49.80%	50.90%	51.20%
Linear SVM	49.90%	50.90%	54.40%	52.80%	51.90%	53.20%	51.70%	49.60%	50.50%	51.20%
Quadratic SVM	46.50%	48.60%	51.50%	49.00%	53.20%	55.60%	51.60%	49.40%	49.60%	51.60%
Cubic SVM	49.80%	48.90%	53.40%	48.00%	54.50%	52.60%	54.40%	47.50%	48.40%	54.00%
Fine Gaussian SVM	45.90%	45.60%	50.90%	51.10%	50.70%	53.00%	49.80%	46.40%	50.00%	50.10%
Medium Gaussian SVM	49.50%	50.50%	53.00%	53.40%	53.10%	51.40%	53.20%	51.70%	49.40%	54.80%
Coarse Gaussian SVM	49.80%	48.10%	53.00%	53.60%	52.40%	52.20%	51.00%	48.80%	46.10%	48.80%
Fine KNN	50.10%	48.60%	49.40%	49.80%	51.00%	48.80%	50.60%	53.10%	47.50%	53.10%
Medium KNN	51.90%	51.20%	50.70%	53.20%	54.90%	52.00%	52.60%	51.10%	54.00%	55.50%
Ensemble Boosted Trees	48.90%	50.00%	53.80%	52.10%	51.90%	50.60%	53.80%	53.50%	51.70%	52.90%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	11	12	13	14	15	16	17	18	19	20
Fine Tree	50.70%	54.20%	50.60%	55.20%	52.60%	52.20%	48.80%	50.70%	52.20%	49.40%
Logistic Regression	48.20%	49.60%	50.70%	47.00%	52.40%	49.20%	49.60%	53.50%	52.00%	47.40%
Linear SVM	48.60%	52.20%	49.10%	46.90%	52.10%	52.50%	50.00%	54.40%	51.00%	47.50%
Quadratic SVM	49.40%	51.70%	51.90%	45.20%	50.90%	49.80%	51.20%	53.80%	52.20%	51.70%
Cubic SVM	47.80%	47.90%	51.10%	44.40%	53.20%	50.00%	53.00%	53.40%	49.20%	50.50%
Fine Gaussian SVM	51.40%	50.60%	52.00%	47.40%	51.90%	46.90%	50.00%	52.60%	49.00%	51.50%
Medium Gaussian SVM	53.00%	51.60%	46.20%	50.20%	51.60%	50.40%	48.00%	54.20%	51.10%	49.90%
Coarse Gaussian SVM	48.90%	47.00%	48.00%	50.00%	49.90%	49.50%	47.60%	49.40%	50.70%	47.20%
Fine KNN	51.00%	51.20%	50.90%	51.10%	52.10%	50.20%	52.80%	53.20%	50.60%	51.20%
Medium KNN	51.50%	52.20%	53.10%	51.40%	55.00%	53.10%	51.40%	54.80%	51.00%	50.20%
Ensemble Boosted Trees	50.10%	52.10%	49.50%	49.60%	52.00%	49.90%	50.10%	50.60%	48.50%	49.60%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	21	22	23	24	25	26	27	28	29	30
Fine Tree	55.60%	53.80%	52.60%	52.20%	50.70%	54.90%	50.60%	53.50%	57.60%	53.60%
Logistic Regression	49.40%	50.10%	49.20%	51.70%	53.10%	47.90%	48.60%	50.70%	49.80%	48.80%
Linear SVM	51.10%	50.40%	51.40%	53.60%	50.00%	53.10%	51.20%	52.50%	52.20%	50.40%
Quadratic SVM	54.40%	54.80%	54.00%	55.60%	55.00%	53.60%	52.80%	58.20%	56.00%	58.80%
Cubic SVM	50.20%	54.90%	54.10%	56.20%	57.20%	57.60%	54.10%	55.60%	57.10%	56.90%
Fine Gaussian SVM	52.90%	53.50%	52.10%	56.90%	54.20%	56.00%	57.10%	54.00%	53.80%	54.40%
Medium Gaussian SVM	54.20%	56.10%	55.10%	53.40%	51.10%	59.60%	56.20%	58.60%	57.40%	57.40%
Coarse Gaussian SVM	49.50%	50.40%	52.80%	54.20%	51.90%	55.20%	54.20%	52.80%	53.00%	53.50%
Fine KNN	53.40%	51.50%	53.10%	58.20%	55.80%	58.10%	56.60%	58.10%	55.60%	56.10%
Medium KNN	54.20%	54.10%	54.20%	57.40%	54.90%	61.00%	55.90%	57.10%	55.60%	55.60%
Ensemble Boosted Trees	52.50%	56.10%	52.60%	56.60%	53.50%	54.10%	55.10%	54.10%	57.00%	54.40%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	31	32	33	34	35	36	37	38	39	40
Fine Tree	58.20%	56.00%	54.00%	54.40%	55.00%	51.20%	52.40%	54.40%	53.80%	51.70%
Logistic Regression	48.80%	48.80%	46.60%	50.10%	52.40%	54.10%	51.70%	52.10%	49.50%	52.40%
Linear SVM	54.10%	57.00%	53.60%	56.90%	59.10%	61.10%	57.90%	59.00%	57.10%	57.80%
Quadratic SVM	59.80%	60.90%	55.60%	60.50%	58.60%	61.80%	62.00%	57.80%	60.00%	59.20%
Cubic SVM	58.60%	57.50%	58.80%	61.00%	59.00%	63.50%	62.10%	58.90%	57.80%	59.90%
Fine Gaussian SVM	54.00%	55.00%	55.00%	56.10%	55.10%	52.50%	56.10%	57.20%	56.00%	52.20%
Medium Gaussian SVM	59.20%	60.90%	59.60%	61.30%	61.60%	62.30%	64.00%	61.40%	62.30%	61.30%
Coarse Gaussian SVM	54.80%	56.80%	56.40%	56.20%	57.60%	58.90%	58.00%	57.00%	56.60%	56.00%
Fine KNN	57.20%	56.60%	57.20%	57.90%	58.10%	59.10%	61.40%	57.50%	58.40%	57.00%
Medium KNN	57.10%	57.60%	58.00%	55.50%	57.80%	62.10%	58.60%	59.20%	59.80%	55.60%
Ensemble Boosted Trees	60.00%	61.50%	57.10%	58.10%	61.50%	58.60%	58.80%	58.00%	57.40%	56.80%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	41	42	43	44	45	46	47	48	49	50
Fine Tree	53.00%	53.10%	55.20%	54.40%	54.60%	54.90%	53.20%	56.90%	54.60%	53.60%
Logistic Regression	55.50%	50.00%	55.40%	52.60%	50.90%	51.70%	47.00%	51.60%	55.00%	55.60%
Linear SVM	59.10%	58.80%	60.10%	58.20%	56.80%	56.80%	54.10%	58.90%	60.00%	58.60%
Quadratic SVM	57.60%	58.80%	59.20%	60.00%	59.00%	57.90%	58.90%	61.00%	55.50%	58.90%
Cubic SVM	61.40%	59.90%	61.00%	58.10%	60.00%	60.20%	59.10%	62.90%	57.00%	60.20%
Fine Gaussian SVM	54.80%	56.40%	54.50%	56.20%	55.60%	53.20%	54.90%	57.60%	55.20%	53.80%
Medium Gaussian SVM	62.50%	62.00%	62.10%	59.00%	61.10%	60.50%	62.70%	62.40%	61.80%	60.20%
Coarse Gaussian SVM	55.80%	56.90%	57.80%	55.80%	55.80%	55.60%	56.80%	56.80%	56.60%	55.80%
Fine KNN	58.00%	55.00%	55.40%	56.50%	59.50%	56.10%	57.60%	57.40%	54.90%	58.00%
Medium KNN	59.90%	57.20%	57.60%	59.90%	56.40%	58.50%	59.90%	58.90%	57.90%	58.60%
Ensemble Boosted Trees	59.90%	58.40%	56.10%	59.10%	58.80%	58.80%	60.50%	60.20%	60.80%	60.20%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	51	52	53	54	55	56	57	58	59	60
Fine Tree	55.00%	51.40%	52.00%	55.90%	53.20%	55.10%	55.10%	54.90%	55.90%	52.90%
Logistic Regression	56.00%	54.10%	53.10%	52.90%	53.80%	52.40%	49.60%	51.90%	51.40%	49.80%
Linear SVM	59.80%	58.80%	58.60%	59.20%	63.00%	59.40%	58.00%	60.00%	57.00%	58.00%
Quadratic SVM	58.80%	60.50%	56.80%	59.60%	59.80%	58.90%	58.20%	58.50%	58.50%	57.00%
Cubic SVM	60.50%	59.50%	58.40%	57.10%	56.50%	59.10%	57.10%	60.10%	58.40%	56.40%
Fine Gaussian SVM	55.90%	53.90%	53.80%	54.80%	53.40%	54.80%	54.40%	53.90%	54.90%	51.50%
Medium Gaussian SVM	60.40%	61.00%	58.60%	60.60%	60.60%	61.30%	63.10%	59.80%	60.60%	60.90%
Coarse Gaussian SVM	57.60%	57.20%	57.20%	57.20%	56.90%	57.80%	57.00%	56.90%	58.50%	56.80%
Fine KNN	58.00%	55.80%	56.40%	60.00%	56.80%	60.60%	56.90%	57.00%	56.50%	54.60%
Medium KNN	61.50%	56.80%	57.20%	56.60%	56.50%	57.10%	56.50%	57.40%	58.20%	57.50%
Ensemble Boosted Trees	57.40%	58.10%	57.50%	58.80%	59.50%	58.50%	59.80%	57.80%	58.00%	56.90%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	61	62	63	64	65	66	67	68	69	70
Fine Tree	51.60%	54.50%	55.20%	56.90%	55.80%	58.00%	54.40%	53.90%	50.10%	54.60%
Logistic Regression	54.80%	54.00%	48.80%	50.40%	56.60%	52.90%	50.90%	53.90%	54.50%	54.40%
Linear SVM	61.40%	59.50%	60.50%	58.00%	57.40%	60.00%	58.90%	58.20%	59.00%	59.00%
Quadratic SVM	58.50%	59.80%	56.50%	56.60%	60.20%	59.50%	56.40%	58.10%	57.40%	54.50%
Cubic SVM	57.10%	58.20%	56.40%	56.20%	56.60%	58.80%	54.60%	55.60%	58.60%	55.00%
Fine Gaussian SVM	51.70%	56.10%	52.90%	52.60%	52.20%	56.00%	53.00%	53.10%	51.50%	50.10%
Medium Gaussian SVM	58.50%	61.80%	61.40%	61.10%	61.80%	60.00%	60.40%	57.10%	61.00%	60.40%
Coarse Gaussian SVM	56.90%	58.10%	58.40%	57.60%	57.60%	57.80%	57.60%	54.50%	55.40%	56.90%
Fine KNN	55.60%	59.50%	56.60%	56.90%	52.90%	56.80%	54.90%	53.60%	56.10%	57.90%
Medium KNN	57.90%	61.50%	56.60%	61.40%	57.90%	58.40%	56.00%	53.60%	58.50%	56.80%
Ensemble Boosted Trees	56.60%	62.10%	60.60%	58.50%	59.60%	60.40%	58.40%	57.90%	57.90%	56.50%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	71	72	73	74	75	76	77	78	79	80
Fine Tree	52.40%	50.70%	52.80%	53.00%	55.40%	55.50%	57.40%	51.70%	52.50%	51.50%
Logistic Regression	49.90%	48.50%	51.10%	49.80%	51.50%	55.10%	50.70%	51.50%	50.90%	47.90%
Linear SVM	58.10%	55.10%	52.20%	54.80%	57.00%	55.40%	54.60%	54.10%	53.90%	49.60%
Quadratic SVM	56.20%	52.60%	52.20%	54.20%	58.50%	56.00%	52.80%	52.10%	55.90%	49.10%
Cubic SVM	56.10%	51.70%	50.60%	52.20%	56.10%	56.50%	52.40%	53.00%	54.40%	50.10%
Fine Gaussian SVM	52.20%	51.60%	53.60%	53.40%	52.20%	51.50%	53.80%	49.90%	52.00%	50.50%
Medium Gaussian SVM	61.00%	56.80%	57.20%	53.80%	58.20%	55.90%	56.00%	55.20%	55.10%	50.20%
Coarse Gaussian SVM	56.20%	52.90%	54.20%	53.80%	52.50%	54.20%	54.80%	55.10%	53.80%	52.10%
Fine KNN	50.60%	52.40%	52.60%	53.40%	56.40%	54.00%	57.80%	51.40%	58.80%	51.90%
Medium KNN	55.50%	53.60%	53.50%	51.20%	54.60%	51.90%	54.60%	54.20%	52.20%	52.40%
Ensemble Boosted Trees	53.20%	58.00%	55.50%	56.40%	55.10%	53.80%	57.00%	53.60%	56.00%	52.90%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	81	82	83	84	85	86	87	88	89	90
Fine Tree	50.50%	51.00%	51.40%	51.60%	52.80%	49.50%	50.90%	53.10%	52.20%	54.90%
Logistic Regression	51.60%	48.50%	53.10%	51.70%	50.60%	53.80%	48.50%	51.10%	51.90%	48.40%
Linear SVM	52.40%	52.60%	50.60%	51.60%	51.50%	55.50%	51.90%	53.60%	53.60%	56.10%
Quadratic SVM	52.00%	49.00%	49.50%	49.00%	52.20%	56.40%	53.60%	52.40%	56.20%	55.20%
Cubic SVM	53.20%	50.90%	48.10%	50.70%	54.10%	52.50%	55.00%	56.40%	54.40%	56.80%
Fine Gaussian SVM	52.90%	50.70%	48.10%	50.20%	50.00%	51.50%	50.90%	53.40%	48.90%	53.50%
Medium Gaussian SVM	52.80%	52.20%	53.20%	52.00%	54.60%	57.00%	56.20%	55.90%	56.10%	58.40%
Coarse Gaussian SVM	54.40%	53.20%	51.90%	53.80%	52.60%	54.90%	54.20%	55.10%	52.40%	54.10%
Fine KNN	54.10%	53.50%	53.60%	52.90%	54.90%	51.10%	49.80%	52.20%	51.40%	54.90%
Medium KNN	52.40%	54.40%	50.60%	50.00%	52.10%	53.10%	55.20%	53.40%	51.70%	55.80%
Ensemble Boosted Trees	52.80%	54.00%	52.50%	52.60%	55.10%	53.00%	55.50%	58.90%	56.10%	57.50%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	91	92	93	94	95	96	97	98	99	100
Fine Tree	54.50%	54.40%	56.50%	49.80%	51.70%	52.60%	53.90%	54.60%	51.10%	50.20%
Logistic Regression	51.90%	52.50%	52.60%	49.40%	53.60%	53.90%	52.40%	53.00%	50.60%	51.60%
Linear SVM	58.50%	57.80%	56.80%	59.10%	59.80%	56.90%	57.20%	59.10%	60.60%	58.10%
Quadratic SVM	57.20%	55.80%	54.90%	54.90%	57.10%	57.80%	53.00%	54.10%	56.50%	56.40%
Cubic SVM	56.10%	57.10%	56.60%	55.20%	57.10%	55.60%	53.80%	55.20%	53.90%	57.60%
Fine Gaussian SVM	52.50%	53.80%	54.20%	52.60%	52.80%	51.60%	51.60%	53.40%	51.40%	50.40%
Medium Gaussian SVM	59.40%	60.10%	59.00%	58.00%	60.60%	58.50%	58.20%	61.30%	61.10%	59.80%
Coarse Gaussian SVM	57.40%	55.60%	53.20%	56.60%	56.40%	56.60%	56.10%	58.60%	57.80%	56.40%
Fine KNN	55.40%	58.10%	55.00%	56.60%	53.00%	56.90%	55.60%	57.40%	55.00%	54.10%
Medium KNN	57.10%	56.00%	57.60%	57.00%	55.60%	58.50%	54.10%	56.60%	53.10%	53.60%
Ensemble Boosted Trees	57.60%	60.80%	57.40%	59.50%	58.60%	56.50%	55.00%	57.60%	56.50%	57.10%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	101	102	103	104	105	106	107	108	109	110
Fine Tree	54.20%	53.80%	51.20%	54.10%	53.20%	54.50%	54.10%	54.90%	53.10%	58.60%
Logistic Regression	53.90%	51.90%	53.90%	50.60%	49.10%	55.20%	53.50%	52.60%	51.70%	50.70%
Linear SVM	60.20%	59.20%	60.50%	56.80%	57.40%	59.80%	59.20%	57.80%	59.10%	56.00%
Quadratic SVM	57.20%	58.50%	57.80%	57.60%	60.60%	60.90%	64.20%	60.20%	59.50%	56.10%
Cubic SVM	57.90%	57.80%	55.60%	57.80%	60.00%	62.50%	63.50%	57.00%	60.40%	56.80%
Fine Gaussian SVM	50.50%	53.40%	53.00%	52.40%	52.50%	53.80%	55.40%	51.20%	55.10%	54.10%
Medium Gaussian SVM	61.50%	61.80%	61.40%	62.30%	61.40%	62.40%	63.00%	60.40%	62.60%	59.40%
Coarse Gaussian SVM	58.20%	57.90%	57.80%	57.20%	55.80%	57.40%	56.80%	55.10%	55.60%	54.00%
Fine KNN	54.20%	57.20%	54.40%	54.90%	55.20%	56.80%	57.60%	54.90%	56.00%	56.80%
Medium KNN	56.50%	56.20%	56.20%	54.20%	54.90%	59.00%	58.10%	56.20%	56.90%	53.90%
Ensemble Boosted Trees	61.10%	58.20%	59.20%	57.50%	57.40%	57.90%	62.00%	58.10%	58.80%	56.90%

800 images (400 AD + 400 CN)										
Slice number	Accuracy									
	111	112	113	114	115	116	117	118	119	120
Fine Tree	57.50%	54.10%	55.60%	54.20%	52.60%	53.60%	54.50%	53.20%	51.00%	49.50%
Logistic Regression	51.50%	52.80%	46.90%	52.60%	52.10%	53.90%	54.20%	51.90%	51.90%	54.00%
Linear SVM	58.20%	57.40%	58.80%	58.50%	58.60%	59.90%	57.60%	58.00%	55.90%	58.60%
Quadratic SVM	57.60%	57.60%	61.10%	59.50%	56.50%	59.50%	58.90%	56.40%	56.10%	59.20%
Cubic SVM	61.10%	57.50%	58.10%	60.10%	59.60%	60.40%	59.10%	55.50%	56.60%	59.20%
Fine Gaussian SVM	53.60%	52.00%	57.20%	53.60%	53.20%	57.00%	54.10%	52.80%	54.50%	53.40%
Medium Gaussian SVM	62.90%	61.30%	62.00%	62.90%	61.00%	61.60%	60.40%	60.10%	56.40%	58.20%
Coarse Gaussian SVM	55.00%	56.40%	56.50%	57.80%	57.00%	55.20%	53.50%	54.20%	55.90%	56.00%
Fine KNN	57.20%	56.00%	57.00%	56.60%	55.40%	58.40%	56.00%	55.50%	53.50%	54.60%
Medium KNN	57.00%	57.10%	57.00%	58.90%	56.40%	60.10%	56.90%	55.80%	54.90%	56.80%
Ensemble Boosted Trees	61.00%	59.60%	59.00%	60.10%	58.20%	61.10%	61.90%	57.40%	57.10%	58.50%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	121	122	123	124	125	126	127	128	129	130
Fine Tree	56.40%	52.60%	52.50%	51.90%	52.10%	51.20%	52.20%	51.70%	48.20%	49.60%
Logistic Regression	54.00%	54.00%	52.00%	54.00%	49.10%	48.10%	52.20%	52.10%	52.90%	47.90%
Linear SVM	59.50%	58.10%	55.50%	58.50%	57.00%	57.80%	59.10%	56.10%	58.80%	56.50%
Quadratic SVM	58.50%	55.20%	55.00%	57.60%	58.40%	57.10%	57.90%	54.10%	57.10%	53.10%
Cubic SVM	58.20%	55.60%	54.80%	57.50%	59.00%	58.00%	57.20%	54.60%	56.50%	53.20%
Fine Gaussian SVM	52.60%	51.10%	53.50%	53.20%	55.40%	52.40%	53.80%	53.00%	53.80%	52.20%
Medium Gaussian SVM	58.40%	57.10%	57.90%	59.60%	57.80%	61.10%	58.90%	54.90%	59.40%	59.10%
Coarse Gaussian SVM	55.10%	54.80%	54.20%	56.10%	56.20%	55.50%	55.60%	55.40%	56.60%	55.80%
Fine KNN	52.90%	50.90%	54.40%	55.40%	55.40%	55.20%	56.90%	54.40%	58.00%	56.00%
Medium KNN	53.10%	54.20%	54.80%	56.90%	55.80%	55.50%	56.20%	56.50%	58.80%	57.60%
Ensemble Boosted Trees	56.10%	58.00%	56.20%	55.60%	53.60%	57.00%	59.80%	55.20%	54.00%	56.10%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	131	132	133	134	135	136	137	138	139	140
Fine Tree	52.80%	54.40%	50.90%	51.70%	56.80%	53.00%	52.90%	53.40%	49.80%	53.40%
Logistic Regression	47.00%	50.40%	50.20%	51.50%	52.20%	49.20%	53.80%	50.60%	50.10%	49.60%
Linear SVM	54.80%	51.40%	52.60%	54.90%	52.20%	52.80%	51.70%	51.00%	49.00%	53.50%
Quadratic SVM	56.10%	49.50%	53.90%	56.50%	55.50%	54.00%	54.40%	53.50%	50.00%	53.80%
Cubic SVM	56.10%	52.10%	54.40%	57.80%	57.60%	54.80%	54.90%	54.60%	50.50%	54.80%
Fine Gaussian SVM	54.00%	54.60%	51.40%	53.80%	52.40%	49.80%	53.10%	51.60%	53.40%	53.80%
Medium Gaussian SVM	57.80%	58.00%	57.60%	56.20%	55.90%	54.40%	55.60%	52.50%	50.10%	54.80%
Coarse Gaussian SVM	55.10%	56.10%	55.00%	52.40%	54.00%	53.90%	53.10%	49.00%	47.90%	51.90%
Fine KNN	57.50%	57.80%	58.20%	54.80%	57.50%	50.70%	56.40%	53.50%	55.10%	54.40%
Medium KNN	56.80%	60.90%	57.60%	54.00%	54.60%	53.40%	54.50%	51.70%	53.60%	57.00%
Ensemble Boosted Trees	56.40%	58.50%	55.90%	51.60%	54.20%	52.10%	55.50%	56.20%	53.00%	54.50%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	141	142	143	144	145	146	147	148	149	150
Fine Tree	50.90%	53.90%	51.40%	50.00%	53.60%	49.40%	50.10%	51.40%	49.50%	51.00%
Logistic Regression	51.40%	52.50%	45.00%	49.90%	51.90%	47.60%	49.20%	52.60%	46.60%	50.70%
Linear SVM	53.40%	50.90%	52.00%	51.20%	50.20%	51.60%	50.50%	54.40%	51.20%	49.10%
Quadratic SVM	52.10%	53.10%	50.40%	50.70%	54.80%	49.20%	52.40%	53.00%	49.80%	50.90%
Cubic SVM	54.50%	53.10%	53.40%	54.60%	52.10%	54.40%	52.50%	53.40%	49.60%	50.20%
Fine Gaussian SVM	56.90%	53.40%	54.50%	53.60%	52.60%	54.00%	52.60%	51.70%	51.10%	53.00%
Medium Gaussian SVM	53.20%	53.90%	54.00%	54.00%	53.10%	53.90%	51.60%	53.00%	53.80%	55.10%
Coarse Gaussian SVM	52.40%	50.20%	52.00%	51.40%	51.90%	51.60%	52.60%	53.60%	52.40%	50.00%
Fine KNN	56.10%	55.10%	57.00%	55.00%	53.90%	53.20%	52.20%	52.00%	51.60%	48.80%
Medium KNN	54.90%	57.10%	55.60%	56.60%	51.90%	55.50%	48.60%	52.40%	53.90%	52.20%
Ensemble Boosted Trees	54.20%	55.00%	54.00%	53.60%	54.50%	49.20%	50.50%	50.20%	51.90%	52.80%

800 images (400 AD + 400 CN)										
Accuracy										
Slice number	151	152	153	154	155	156	157	158	159	160
Fine Tree	53.00%	54.10%	52.00%	52.10%	49.20%	51.20%	51.50%	49.40%	53.20%	47.90%
Logistic Regression	48.90%	47.20%	50.20%	51.70%	50.70%	47.00%	47.80%	48.90%	49.00%	44.60%
Linear SVM	53.80%	49.20%	51.00%	53.00%	49.60%	51.90%	50.00%	48.80%	52.00%	52.00%
Quadratic SVM	50.20%	52.00%	56.50%	50.90%	49.40%	51.70%	50.90%	50.20%	50.50%	47.80%
Cubic SVM	51.10%	52.00%	53.00%	48.50%	48.80%	50.20%	49.50%	46.90%	49.10%	46.40%
Fine Gaussian SVM	49.50%	52.20%	55.40%	53.10%	51.60%	51.00%	52.80%	49.20%	50.40%	48.90%
Medium Gaussian SVM	54.20%	53.00%	52.90%	54.40%	50.60%	53.20%	51.90%	51.00%	51.50%	50.20%
Coarse Gaussian SVM	51.40%	49.00%	50.00%	52.40%	54.50%	54.10%	54.40%	52.20%	52.50%	51.90%
Fine KNN	53.20%	53.50%	53.60%	50.60%	49.10%	49.50%	48.40%	47.10%	51.40%	48.60%
Medium KNN	53.00%	54.10%	53.10%	52.90%	49.40%	54.00%	50.20%	49.50%	51.00%	49.60%
Ensemble Boosted Trees	54.50%	51.10%	52.60%	53.90%	51.60%	52.00%	50.50%	51.40%	51.10%	49.60%

7.3 Appendix C: Slices 1 - 160 accuracy from trained model

Full table of accuracy of slices 1 - 160 using histogram for testing slices on trained model from slice 36 and 37

Slice 36		Slice 37		Slice 36		Slice 37	
Slice number	Medium Gaussian SVM (Accuracy%)	Slice number	Medium Gaussian SVM (Accuracy%)	Slice number	Medium Gaussian SVM (Accuracy%)	Slice number	Medium Gaussian SVM (Accuracy%)
1	50.5	1	50.75	81	51	81	51.125
2	50	2	52	82	52.25	82	52.75
3	46.125	3	48.625	83	53	83	53.375
4	48.5	4	48.375	84	54.5	84	55.75
5	49	5	51.5	85	54.5	85	54.25
6	50.875	6	51.75	86	53.375	86	53
7	50.75	7	50.75	87	53.375	87	53.375
8	50.75	8	49.125	88	53.25	88	54.5
9	52	9	52	89	55.25	89	54.875
10	53	10	51.125	90	53.5	90	55.125
11	53.125	11	54	91	53.375	91	53.875
12	52.625	12	52.75	92	53.875	92	55.375
13	53.375	13	55.25	93	53	93	54.25
14	52	14	53	94	54	94	55
15	53.125	15	53	95	53.75	95	53.75
16	50.125	16	50.625	96	54	96	52.75
17	51.125	17	52	97	54.25	97	54.25
18	52.375	18	53.5	98	54.875	98	54.5
19	51.5	19	50.625	99	55.5	99	55
20	50.5	20	52	100	53.5	100	53.5
21	49.375	21	49.25	101	53.75	101	54.625
22	50.75	22	49.5	102	53.875	102	54.875
23	48.375	23	47.5	103	54.125	103	54.375
24	50.625	24	49.625	104	54	104	53
25	52.625	25	52.25	105	55	105	55.5
26	53.375	26	53.625	106	54.625	106	55.75
27	54.375	27	51.75	107	54.25	107	55.125
28	53.375	28	51.75	108	55.625	108	55.125
29	56.25	29	55.375	109	55.875	109	57
30	58.375	30	54.875	110	56	110	55
31	60.5	31	58.125	111	56.25	111	56
32	62.125	32	61.625	112	56.75	112	57.125
33	65.5	33	63.25	113	57.125	113	57.75
34	68.375	34	65.125	114	59.625	114	58
35	70.75	35	67.5	115	57.75	115	58.875
36	80.125	36	70.875	116	59.625	116	59.125
37	69.25	37	80	117	56.875	117	57.875
38	69	38	69.75	118	58	118	58.875
39	67.75	39	68.75	119	58.125	119	58.375
40	65.75	40	68.125	120	57.125	120	59.25
41	65.875	41	67.125	121	60.125	121	60
42	63	42	64.375	122	59	122	61
43	63	43	64	123	59.375	123	59.25
44	61.125	44	63.875	124	62.875	124	62.75
45	59.375	45	60.625	125	61	125	62.75
46	60.25	46	60.625	126	61.75	126	61.375
47	62	47	60.375	127	60.25	127	59.125
48	59.875	48	61.25	128	60.5	128	59.125
49	60	49	60.25	129	59	129	58
50	56.5	50	58.375	130	58.75	130	56.625
51	56.875	51	58	131	56.625	131	56.625
52	57.625	52	58.875	132	56.625	132	53.625
53	54.5	53	56.375	133	53.75	133	52.625
54	56.625	54	57.125	134	54.625	134	52.75
55	55.125	55	57.75	135	54.125	135	53.75
56	56.75	56	56.75	136	51.375	136	52.25
57	58.5	57	57.75	137	54	137	52.5
58	57	58	56.875	138	52.5	138	51.5
59	57.375	59	56.5	139	50	139	51.625
60	56.875	60	57	140	51.25	140	51.375
61	55.375	61	54.375	141	51	141	50.25
62	55.25	62	55.25	142	48	142	49.5
63	53.5	63	54.5	143	49.25	143	49.875
64	54.375	64	54.375	144	50.625	144	50.375
65	54.75	65	53.625	145	52.75	145	52.75
66	56	66	54.5	146	56.25	146	55.375
67	54.875	67	53.75	147	55.75	147	55.125
68	53	68	53.125	148	56	148	55.5
69	54.625	69	53.75	149	53.25	149	55.125
70	53.625	70	54	150	53.25	150	52.5
71	54.125	71	53.875	151	52.75	151	49.875
72	54.75	72	55.5	152	52.125	152	51.125
73	52.75	73	53.375	153	51.75	153	51.25
74	51.875	74	53.125	154	50.25	154	48.875
75	52.25	75	52.75	155	48.5	155	50
76	49.625	76	52.875	156	50.375	156	50.625
77	51.5	77	52.375	157	49.875	157	50
78	51.5	78	51.625	158	49.25	158	50.25
79	50.75	79	51.25	159	52.25	159	52.875
80	50.125	80	50	160	53.625	160	53.375

Non-exclusive license to reproduce thesis and make thesis public

I, Heba Elshatoury,

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to reproduce, for the purpose of preservation, including for adding to the DSpace digital archives until the expiry of the term of copyright,

Classification of Alzheimer's Disease From MRI Images

supervised by Prof. Gholamreza Anbarjafari and Egils Avots.

2. I grant the University of Tartu a permit to make the work specified in p. 1 available to the public via the web environment of the University of Tartu, including via the DSpace digital archives, under the Creative Commons licence CC BY NC ND 3.0, which allows, by giving appropriate credit to the author, to reproduce, distribute the work and communicate it to the public, and prohibits the creation of derivative works and any commercial use of the work until the expiry of the term of copyright.
3. I am aware of the fact that the author retains the rights specified in p. 1 and 2.
4. I certify that granting the non-exclusive licence does not infringe other persons intellectual property rights or rights arising from the personal data protection legislation.

Heba Elshatoury **20.05.2019**