

APPLICATION OF MACHINE LEARNING TECHNIQUES FOR THE CLASSIFICATION OF LOWER BACK PAIN IN HUMAN BODY

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Shubham Sharma, a candidate for the degree of Master of Applied Science in Industrial Systems Engineering, has presented a Thesis titled, **Application of Machine Learning Techniques for the classification of Lower Back Pain in a human body**, in an oral examination held on November, 2019. The following committee members have found the Thesis acceptable and apt in form and content and that the candidate demonstrated satisfactory knowledge of the subject material.

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Abstract

Advancement of technology in the field of medical science is providing promising results in this modern era. Intelligent systems designed especially for this sector not only help doctors to solve complex situations but also take comparatively lesser computational time which can be a really important factor as longer time in critical cases may lead to death of a patient. These days, everyone experiences long waiting time to see a doctor. It would be really desirable if an Intelligent System makes the work easy for a doctor by giving accurate decisions after processing patient's data, reducing examination time for the current patient and hence reducing waiting sessions for other patients.

Currently, "Lower back pain is one of the biggest problems being faced by more than 80% of the population at least once during their lifetime" [1]. Its diagnosis at early stages is necessary in order to find a proper cure. Along with Conventional Medical Diagnostic Systems, Various Non-Conventional techniques are used for the successful classification of Lower Back Pain symptoms categorised as normal and abnormal. Naïve Bayes, Artificial Neural Networks, Logistic Regression, Deep Learning, Fast Large Margin, Random Forest, Gradient Boosted Trees, Multi-Layer Perceptron, K-Nearest Neighbour, Decision Tree and Support Vector Machine methods are most suitable machine learning techniques which can classify given dataset with good accuracy.

The aim of this research is the application of several machine learning techniques to correctly classify Spine Dataset and finding best technique among those in terms of Accuracy, Precision, Sensitivity, Specificity, and F-measure [2]. Original dataset is taken from website named Kaggle (<https://www.kaggle.com/>). This dataset is normalized first and then an Automatic Feature Engineering technique has been implemented on the dataset to extract the most important features to do the correct classification. Training of each model is performed

using featured data and after training, each algorithm is tested and hence performance is calculated and compared.

After analysing results, it is found that for the problem considered the Logistic Regression algorithm is the best classifier in terms of Accuracy giving 90.91% accurate results on test data followed by an Artificial Neural Network algorithm whose accuracy is 88.64%. In terms of Precision calculation, the Logistic Regression is best and the ANN Classifier is second best algorithm. Taking Sensitivity into Consideration, the Fast-Large Margin is best. ANN Classifier is best in terms of Specificity. Logistic Regression provides best results in terms of AUC (Area under Curve).

Keywords: Non-Conventional Techniques, Machine Learning Techniques, Lower Back Pain (LBP), Fast Large Margin (FLM), LBP data classification

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List of Abbreviations

ML –Machine Learning

AI – Artificial Intelligence

ROM - Range of Motion

LBP – Lower back pain

PI – Pelvic Incidence

LLA- Lumbar lordosis angle

PR – Pelvic Radius

MLP - Multilayer Perceptron

SRM - Structural Risk Minimization

SVM - Support Vector Machine

ANN - Artificial Neural Networks

KNN - K-Nearest Neighbours

FLM – Fast Large Margin

FIS - Fuzzy Inference Systems

Chapter-1 Introduction

1.1. Research background:

These days, Modern life has become very hectic. Everyone is chasing out for different reasons like success or money and this chase is one of the major reasons of occurrence of physical and mental problems being faced by people in every day's life. Some of the injuries and illnesses are short term and can be detected and diagnosed within a short period of time. There are many of them on which we don't pay attention when they are in their initial stages. We are always ignorant towards these kind of problems because of our busy schedule and giving them less priority. But as life goes on and people grow older, these problems increase their impact in time, and these can be so severe which can even generate disabilities in human body.

One of the biggest health problems of this kind is ***Lower Back Pain***. It is the most common problem being faced by more than half of the population in the world at some stage in their life [3]. This health issue is present in all age groups and affecting old aged people severely. Keeping in mind the severity and amount of population getting affected by this problem, there is a huge demand of chiropractors who diagnose this issue and provide solutions to get rid of this back issue.

Due to the fact that ratio of number of affected people to the number of chiropractors is quite large, people usually face a long waiting time to get the appointment. One of the reasons for long waiting time is in order to diagnose any specific pain, a chiropractor must perform certain tests which include physical examination, analysing X-ray results and other reports. Combining all the valuable facts given by these different reports makes them able to detect pain symptoms and advising affected patients to mitigate its effects. Especially in the detection of type of Lower Back Pain, symptoms are so similar that it is hard to decide

whether it is abnormal or normal back pain and this process usually takes long time. In order to reduce this long and cumbersome process, a study has been done to classify LBP in which different Non-conventional techniques have been implemented to get most accurate LBP classifier by using available dataset which will not only give results accurately but also take less computational time to give the decision. The LBP, the most accurate classifier, can be used as Clinical Decision Support system to assist chiropractors while examining the pain symptoms of a patient. The Normal and Abnormal types of back pain have different symptoms; for example, abnormal back pain is usually caused due to some disease. The Non-conventional binary classifiers can play an important role here as once diagnosis of the type of lower back pain is done; the doctor only has to think about that specific type of lower back pain which has been identified and treat the patient according to that specific type of lower back pain.

1.2 Intelligent Systems:

Intelligent Systems are special devices that can “learn” from the past experiences. These systems interact with environment to extract data, process that data and give some output which can be distributed to other connected systems automatically with minimal human intervention. These devices consist of “intelligent” components which are connected to do a specific task. These systems are trained by the available data and based on this training, generate the output. The output of an intelligent can be searching, pattern recognition, optimization, prediction, classification, regression, speech or image recognition and many more.

Intelligent Systems have got a great success in different sectors such as transportation, automation, medical science, hospitality and management, E-commerce, Banking and manufacturing. These days, Intelligent Systems are being designed using latest “smart”

technologies like deep neural networks that allows these systems to emulate some thinking process of human beings.

There are some really great examples of intelligent systems which are in common use like Siri, which is a pseudo intelligent digital personal assistant [4]. It is voice activated computer system which can understand our natural language and process it as input and gives road directions, music, help in sending messages and many more as output. It uses Machine Learning algorithms to “learn” some patterns and be “smart” to predict future behaviours.

1.3 Machine Learning:

Machine learning is a branch of Artificial Intelligence which deals with training a machine/computer. It tells a machine how to learn from available dataset and after analysing the data, predicting patterns and giving valuable decisions without human intervention. Machine learning performs the data analysis and hence contributes towards the automation of modelling of analytic systems. The accuracy of ML based models can be checked by imposing new data set on the model and calculating the deviations of model output from the actual output.

Machine learning is not a recent technology. Even in the past, it was common in pattern recognition but recently it has become trendy by providing fast and accurate results even with bigger datasets. Computers can “learn” from the patterns in the data and give predictions based on similar patterns. Machine Learning plays a vital role in those processes especially when there is not available a mathematical formula to model that process. In these cases, it is possible to gain knowledge from the previous computations to produce reliable results.

Currently, Machine Learning is being used in many industries for various applications. In banks, Machine Learning helps in getting insights of data and helpful in fraud detection. In medical science, Machine Learning is used to detect a disease and its diagnosis, classify the symptoms of an injury for normal and abnormal cases, keeping health records of patients smartly and medical imaging diagnosis such as for Tuberculosis or Cancer. Machine learning algorithms are being used by most of the companies in the e-commerce sector. Through ML, customers get suggestions to buy the stuff on the website or mobile applications depending upon their previous search or purchase.

Machine Learning techniques used in this thesis to classify the symptoms of Lower Back Pain are explained in much detail in Chapter 4.

1.4 Artificial Intelligence:

Artificial Intelligence is a discipline focusing on the development of methodologies that try to emulate the human thinking process and human brain functions. These days, devices, computer and machines, are being designed to emulate the human brain functions to give decisions like human beings on some problems. It is now one of the most widespread and fastest growing technology on this sphere. Presently, it has made its place into several fields and subfields be it public or customized [5]. It is one of the most appealing and extensive approaches of computer science which tends to have a wide outlook in coming millennium. The basic idea of AI is to design a device with the capability to make some decisions as a human being. The design process involves feeding the system in the form of information and rules which contributes towards the “learning” of that intelligent system. After acquiring the data, the Intelligent System approximates the results and corrects its accuracy after each instance which makes it “smart”.

Primary objective of AI is to develop devices and machines which can perform the following functions:

- Simulation of some functions of the human thinking process
- Deal with problems which demand high knowledge
- Build up a smart relation between presumption and execution
- Construct a model which uses some rudimentary “intelligence” [5].

Artificial Intelligence can be categorised into three types explained as below:

- i) Analytical Artificial Intelligence: This is the type of AI which typically depicts “cognitive intelligence”. Systems “learn” from the data provided or past experiences and predict future instances based on that learning. Quality of data is critical in this case as decisions are purely based on how system learns [6].
- ii) Human Inspired Artificial Intelligence (HIAI) [6]: This type of AI possesses “emotional intelligence” along with “cognitive intelligence” to make HIAI “smart”. These systems use the intelligence acquired through analytical learning as well as human emotion factor to predict output which is more accurate than Analytical Artificial Intelligent Systems [6].
- iii) Humanized Artificial Intelligence (HAI) [6]: These systems are competent in every aspect. They possess “cognitive behaviour”, “emotional intelligence” as well as “social intelligence” [6].

Artificial Intelligence techniques are being adopted worldwide by different sectors for different applications. Whether the task is selecting relevant stories on Facebook for different users or translating the text from one language to another language on google, is done by Artificial Intelligence. This research is focused on analytical artificial intelligence for training the proposed models.

1.5 Fuzzy Inference Systems:

Fuzzy Logic Control is one of the most important categories of Intelligent Systems which can be used for smart applications. Fuzzy inference system is the primary component in the fuzzy logic system. Its elementary function is to perform the decision-making process by deriving the calculation using the provided input to obtain the output. This drafting draws a ground base with respect to which the decisions were derived, and patterns were determined. It considers the pre-specified 'If... Then' rules and formulates the given input in order to procure the output. The input and output values are all real valued in contrast to the internal processing, i.e. they follow fuzzy rules and fuzzy arithmetic. Fuzzy logic controllers are used in a lot of appliances which we use in our day to day life like Air Conditioners, Washing Machines, and Televisions and in other switching applications.

1.6 Using Machine learning techniques to classify LBP symptoms in human body:

Industries have aligned their interest towards using Non-Conventional techniques to unravel their analytical complications. These techniques have emerged as a powerful tool for not only giving smart decisions like humans but also substituting hard labour work with automation. Methods which use Machine Learning, Artificial Intelligence, or Fuzzy Logic for the classification or prediction of any physical phenomenon can be commonly termed as Non-Conventional methods. Machine Learning is termed as “Non-Conventional” when the frame of reference is diagnosis of Lower Back Pain; however, this technique comprises of both conventional and unconventional methods which can be used to diagnose lbp.

Conventional Programming basically refers to the process where a computer is given a set of instructions by human to do some specific task. Then computer follows those instructions and gives us an output. But in non-conventional techniques, computer is given a bunch of data

and computer is asked to get patterns from data and give output using algorithms designed to do those specific tasks. The output can be Classification, Regression, Forecasting, or any other type of data analytics.

In this Thesis, 11 ML techniques are applied to classify lower back pain dataset which is publicly available on Kaggle website. These 11 techniques are implemented in current research as these techniques are most frequently used in classification problems and constitute a good blend of old and new techniques. Following algorithms have been used to classify LBP symptoms which are named as follows:

- Naïve Bayes Classifier
- Logistic Regression
- Deep Learning
- Random Forest
- Support Vector Machines
- Gradient Boosted Trees
- Decision Trees
- Artificial Neural Networks
- Multilayer Perceptron (MLP)
- KNN Classifier
- Fast Large Margin

It may be worth mentioning that several Machine Learning techniques used in this research for classification are traditional conventional techniques while some others are comparatively recent. Naïve Bayes Classifier is an “old” technique firstly introduced by the text retrieval community in 1961, [7]. Logistic Regression is also an “old” technique which was developed

by Joseph Berkson [8]. Decision trees is also a traditional technique which was firstly used in 1959 by William Belson [9]. KNN is a traditional technique and the algorithm was written in 1967. The ANN and MLP can be categorized as “old” techniques as well. One neural network model was developed in 1957 by Frank Rosenblatt and named it as perceptron [10]. On the other hand, Deep Learning is considered as recent technique; however, the term was firstly introduced by Rina Dechter in 1986 to the Machine Learning community, and by Igor Aizenberg to the Artificial Intelligence family in 2000 [11], [12]. It became trendy in 2012 when it was used to detect biomolecular target of one drug [13]. Random forests and Support vector machines are also considered as recent technologies which were introduced in 1995 [14][15][16]. Fast Large Margin (FLM), is a recent technique which is pretty much similar to Support Vector Machine (SVM), but it can be able to process any number of variables and data points, [17].

RapidMiner software (<https://rapidminer.com/>) platform is used to construct and analyse all classifiers. The dataset used for constructing the classifier is taken from Kaggle website which is an open source platform for gathering datasets for machine learning. The dataset is having a total 310 data points, contains 13 different columns out of which 12 columns are pelvic parameters or Range of Motion (ROM) attributes which are explained well in chapter 3 and 13th columns tell if those parameters show Abnormal or normal symptoms of lower back pain. Automatic Feature Engineering method is used to extract features from the available dataset which have more correlation with the output. These generated features are then loaded to the above-mentioned machine learning algorithms to train and test different classification models whose implementation procedures are explained in chapter 5. The classifiers’ performances are compared, and results generated for each algorithm are displayed in chapter 6.

1.7 Summary:

This chapter provide the general information on terms like Intelligent Systems, Machine Learning, Artificial Intelligence, and Fuzzy Inference Systems. This chapter also outlines the research aim and gives an idea of implementation of proposed Machine Learning techniques to find a “best” classifier which can successfully classify Lower Back Pain symptoms and hence, can act as Clinical Decision Support System.

Chapter-2 Literature Review

As discussed in previous chapter, Lower Back Pain is a serious problem and should be cured before leading to chronic stage. In order to get proper treatment, it is mandatory to know about the type of LBP, a person is suffering from and for this purpose, a good diagnostic model can really help a chiropractor or a physician by acting as clinical decision support system. Many studies have been done in this field i.e., Lower Back Pain diagnosis and its treatment. This chapter gives information about important researches that have already been done in this field. Some of the classical researches are summarized in the below section.

2.1 Related Work:

This section gives detailed summary of the key researches done in this field.

Lin L. et al [2006], conducted a study and prepared a paper on “A Decision Support System for lower back pain diagnosis: uncertainty management and clinical evaluations”. A web-based decision support system is designed, implemented and evaluated which builds a quite feasible framework for obtaining details about patient and relatively prefer diagnosis. This system brings out the challenging characteristics of LBP diagnosis. Systematic evaluation, knowledge-based verification and system validation were done using a Turing test and a clinical efficacy assessment which was conducted upon 5 clinicians and 180 true cases from different clinics. The evaluation done is thorough and the proposed system is up to the mark for clinical upliftment. This research possessed clinical support for LBP diagnosis and laid a helping hand in decision support system research [18].

Nijs j. et al, [2015] presented “A comprehensive review on the guidelines for the clinical classification of lower back pain”, which was itself based upon certain content of actual

original research papers and expert opinion of 18 experts from 7 various countries. This review threw light on the assumptions, using which clinicians can differentiate between the three classifications namely neuropathic, nociceptive and central sensitization pain in LBP patients. It discussed about the clinical methods being employed for classifying the central sensitization pain, neuropathic and nociceptive pain. Classification algorithm was being considered to evaluate the LBP population. Initially it tested for the existence of any neuropathic lower back pain and then the clinical algorithm was implied for the differential analysis between prevailing nociceptive and central sensitization pain. Although it had certain limitations [19].

Bishop J.B. et al [1997], designed an artificial neural network based predictive model for classification of LBP which was dependent on kinematic data. This data was obtained by testing it on 183 subjects adjoined with different training and test groups using a triaxial goniometer and was termed as dynamic motion data. It was basically designed in order to determine certain traits of trunk linked with various types of spinal disorders. It was also used to check if it could help in deciding the effectiveness of neural work analysis system in differentiating patterns. The data obtained from 183 subjects were sent to a two-stage neural network classifier which worked on a radial basis function architecture. Its output was then compared with Quebec Task Force pain classifications. In short with the help of motion characteristics also the lower back pain could be determined by the system [20].

Fourney D. et al [2011], presented a review of clinical pathways for lower back pain and case study of the Saskatchewan Spine Pathway. Its main motto is to figure out the differences between clinical pathways and clinical guidelines, its example and testing of its success and about SSP. Following the guidelines for LBP can help in fetching wonderful outcomes and increase the credibility by cutting down unwanted imaging, ineffective treatment and inappropriate surgical referrals. The “translation gap” between the clinical guidelines and real

practice is attempted to conquer by a clinical pathway. The motto of finding of the difference between the guidelines and pathways was achieved by performing a qualitative review which conclude that proofs of clinical pathways are basically obtained from guidelines whereas pathways are separately defined by coordination of multidisciplinary care, facilitation of communication among care providers with the primary focus on patient's eyes. The example portion was carried out by conducting a systematic review for the articles published in March 2011. The final portion is about the case study of SSP which has many unique characteristics [21].

Kafri1 A. et al [2018], presented a research paper on Segmentation of Lumbar Spine MRI Images for Stenosis Detection using Patch-based Pixel Classification Neural Network which threw light on the central problem of automatic segmentation of lumbar spine Magnetic Resonance Imaging (MRI) images to delineate boundaries between the anterior arch and posterior arch of the lumbar spine. It is important to identify the occurrence of lumbar spinal stenosis as one of the major reasons of chronic lower back pain. The pixels of MRI images were classified and labelled by implementing a patch-based classification neural network comprising of convolutional and completely connected layers. This classifier is then processed through overlapping patches of size 25x25 pixels taken from a set of cropped axial-view T2- weighted MRI images of the bottom three intervertebral discs. The classification network was tested for the segregation of images when the discs were either all or individually used, by performing a set of experiments. It was conferred that this approach brings out better segmentation results as compared to eleven other pixel classifiers, with the help of performance metrics of pixel accuracy, mean accuracy, mean Intersection over Union and frequency weighted IoU. It also emphasized on the fact that by using this approach more accurate delineation of all-important boundaries could be achieved making it best suited for the subsequent stage of lumbar spinal stenosis detection [22].

Sandag1 G. et al [2018], published a paper on the Classification of Lower Back Pain Using K-Nearest Neighbour's Algorithm in this paper they described about the study they conducted on normal or abnormal lower back pain based on 12 Range of Motion (ROM) with the proposed methodology of K-Nearest Neighbour algorithm. They implied machine learning algorithms of KNN, Logistic Regression, Naïve Bayes, Random Forest, Decision Tree, and CART for classification of LBP which improve the accuracy level up to 15.96%. The interesting fact about this research was that author used K-fold cross validation method to test the data. This research paper claims to measure accuracy of classification model 91.94% which comes at K=36, meaning out of 310 samples, not even 8 samples are used for testing which is certainly not the appropriate way to predict the accuracy. Hence the results predicted by this research are questionable [23].

Jenkins H. [2002], presented a paper in which he mentioned about the classification of lower back pain. To distinguish between lower back pain responsive to chiropractic treatment and one due to pathological causes this algorithm was being developed. This helps the practitioner to avoid the assumptions and decide for the treatment only after proper confirmation through diagnosis [24].

Hayashi Y. [2004], reviewed and submitted a revised English version on “Classification, diagnosis and treatment of lower back pain”. This paper basically addresses about the different types of lower back pains with their classification, its diagnosis and respectively related treatments for such types, as such issues affect the life of elderly living people to much extent [25].

Coupe V. et al [2017], presented a paper on “Decision Support tools in lower back pain” which throws light on the development, presentation; and prepares for extended validation, implementation and updating of Nijmegen Decision Tool for Chronic Lower back Pain

(NDT-LBP). It basically throws light upon all the possible ways of treatment, toes of patients, pros and cons and presentation as a feasible toolkit [26].

Summers A. [2010], presented about “Diagnosis and treatment of Meralgia Paresthetica” in his paper. It is explained about dealing with a gentle kind of lower back pain experienced by men who wear belts too tight. It is a quite uncertain and benign sort of painful condition firstly brought into light in 1940. Meralgia Paresthetica occurs in about one in every 2300 patients. Its symptoms, causes and relative conservative treatments are discussed here which enforces medical practitioners to keep into eye about this pain [27].

Gaonkar A. et al [2017], published a paper on “Classification of Lower Back Pain Disorder Using Multiple Machine Learning Techniques and Identifying Degree of Importance of Each Parameter” in International Journal of Advanced Science and Technology. It is explained here about the research priorities of primary care medical practitioners of lower back pain. Physical Spine data of 381 patients with 12 parameters were collected in order to test for the person is normal or abnormal. This study also focusses on the level of importance of every parameter considered in this classification and then the parameters are arranged sequentially accordingly by assigning ranks to them. Authors used KNN, Random Forest, J48 Decision Trees and Support Vector Machines algorithms to design the classification models and J48 Decision tree was most accurate of them having accuracy of 90.29% on test data [28].

Hoy D. et al [2010], from different universities of Australia came together and presented this study on the epidemiology of Lower back Pain. Concluding from different studies lower back pain ranges are discussed at 1year incidence and remission. It throws the light on more importance to be paid to the lower back pain problems prevailing with the help of figures. Various factors for the cause of LBP are mentioned [29].

Some of the work shown above describes some conventional approaches to detect lower back pain. Along with conventional methods, Machine Learning approaches have also been introduced in this field [20] [23] [24] [28].

S. No.	Author(s)	Machine learning Methods used	Features	Accuracy
1	Sandag1 G. et al [2018]	KNN, Logistic Regression, Naïve Bayes, Random Forest, Decision Tree, and CART	Col1, Col2, Col3, Col4, Col5, Col6	91.94%
2	Gaonkar A. et al [2017]	KNN, Random Forest, J48 Decision Trees and Support Vector Machines	Col1, Col2, Col3, Col4, Col5, Col6	90.29%

Table 2.1 comparison of previous work done to diagnose Lower Back Pain

2.2 Summary:

This chapter depicts the research work that has already been done in this sector. Present research is benefitting the target research sector by giving an accurate and reliable diagnostic model which can be used as clinicians when they examine the patients and support their decisions. Several Machine learning approaches have also been introduced to detect LBP in a human body but the results obtained cannot be considered satisfactory.

Chapter-3 Lower Back Pain

3.1 Human Spine:

This section explains about human spine and its various sections.

3.1.1 Introduction:

The Spinal Cord is considered as the pillar of human anatomy. It is housed in a cavity known as the spinal canal or vertebral foramen. The Spinal cord is a long and tubular structure that is made up of the nervous tissue which extends from the medulla below the brain up to the level of first or second lumbar vertebrae [30]. The various segments or parts of the spinal column are known as vertebrae. The spinal cord encloses the central canal of the spine which contains the cerebrospinal fluid.

Through the nerves of the spine, the signals to and from the brain can travel and a protective shield in the cord increases the nerve efficiency. There are 31 spinal nerve segments in the human spinal cord [30].

3.1.2 Sections of Spine:

A human spine can be bifurcated into five vertebral sections. Each section has several spinal nerves running through the numerous vertebral pieces.

- Cervical Spinal cord: The Cervical sections runs from the top of the spine having seven vertebrae and these sections are typically named as C1-C7 vertebrae (C=Cervical). There are bundle of nerves running through the section and there are 8 cervical nerves in total [31].

- Thoracic Spinal cord: The Thoracic spinal section starts beneath the cervical spinal section and has total of twelve number of vertebrae. These vertebrae are typically named as T1 – T12 Vertebrae. (T=Thoracic) [31].
- Lumbar Spinal cord: The Lumbar or Lower spinal section has large vertebrae among all other spinal sections. It is near to spinal end / spinal base. There are in total five lumbar vertebrae and they are named as L1-L5 (L=Lumbar). The end of the spinal cord is at L2 Lumbar vertebrae. After L2, there are only nerve roots rather than the spinal cord expanding up to the base of the spinal column [31].
- Sacral Spinal cord: The Sacral Spinal vertebrae has five vertebrae like lumbar vertebrae, but they are fused together. Due to such fusing, they lack flexibility like other spinal column sections. They are named as S1- S5 Sacral Vertebrae (S= Sacral/Sacrum) [31].
- Coccygeal Spinal cord: Coccygeal spine section has only two vertebrae. And, they have only one spinal nerve bundle between them. Also, these vertebrae are generally fused in adults [31].

Current research mainly focuses on injuries and pain in the Spinal Column. The Spinal cord injuries can be due to problems such as traumas, excessive pressure, stretching, laceration, etc. The vertebral bones can shatter, leading the spinal column to be ruptured by a sharp fragment of bones.

Usually, the victim of such complexity suffers loss of feeling in certain parts of body, sometimes may suffer damage to the hand or foot functioning and may suffer from paraplegia – partial paralysis and full body paralysis.

Spinal shock or neurogenic shock can be the worst consequences of the spinal injury. These things can be temporary but damage the muscle tone of the body.

The most commonly injured parts of the spinal column are Cervical spinal section and the Lumbar spinal section. The Spinal injury can also be non-traumatic and due to some diseases. Proper care should be taken to avoid these kinds of problems.

3.2 An Overview of Lower Back Pain:

3.2.1 Definition:

The Spinal column is the strength of the human body and no organ can function steadily without its stability. Sometimes, the stability goes into an unstable situation resulting into an unbearable condition termed as **Lower Back Pain** [32].

Lower back pain is the physical discomfort or physical adversity occurring in lower part of the spine or back part, may be low, mild or severe and lead to a disable condition.

The major causes of such casualty are excessive workout, heavy lifting, prolonged sitting, standing or doing an activity periodically for a longer time, lying down, wearing an uncomfortable outfit, sleeping or resting in an uncomfortable posture/situation etc. leads to such postural and spinal deformity or pain in the lower spine [32].



Fig. 3.1 Lower Back of human being [33]

3.2.2 Functions of Lower Back:

Functions of a Human Lower back are as follows:

- Structural support, movement and protection of some parts.
- Supporting weight of the body.
- Protecting soft nerves and tissues of the nervous system.
- Protection of certain organs in pelvic and abdominal area and their proper alignments [32].

3.2.3 Symptoms of the Lower Back Pain:

Following are the symptoms that are likely to occur to a person encountering lower back pain:

- Feeling intense or constant pain.
- Weakness in body, especially in one or both legs.
- Experience swelling, unintentional weight loss.
- Develop pain that extends up to thighs/legs.
- One can't work properly, sleep or perform his/her daily chores.
- Sometimes one may feel like high fever.
- Facing trouble in excretion.

3.2.4 Causes of Lower Back Pain:

Lower Back Pain is one of the biggest problems being faced by current population, yet no one pays much attention to this issue until it becomes prominent. It can even generate disabilities or severe chronic disorders which resists people from doing daily activities as well as engaging in professional work. The occurrence of severity caused by lower back pain has increased by 54% from 1990 to 2014 according to a study [34]. More than half of the population of working-class Americans revealed feeling back pain symptoms periodically

throughout the life [35]. Most of the back-pain symptoms are short termed and people usually get relief after a good bed rest. This type of back pain is usually referred as Sub-acute pain and vanishes typically after 4-12 weeks. These kinds of back pain symptoms are categorized as normal back-pain symptoms. There are less chances of chronic stages in this category. Sometimes, Lower Back Pain occurs due to some disease, injury, disorders or mechanical causes. It persists more than 12 weeks in a human body and proper treatment is required to cure this type of back pain. Symptoms felt during this type of pain are categorized as Abnormal back pain symptoms. Following factors can generate LBP in a human body:

- **Sprains and Strains:** Usually these mechanical causes generate acute back pain. Sprain occurs due to over stretch in ligaments and strain happens due to tear in tendons or muscles. These occur due to improper lifting or heavy lifting and can cause serious damage to back muscles as well, by generating spasms in the muscles.
- **Irregularity in Skeleton:** An abnormal curvature in the spinal cord results to this unbearable condition. This irregularity alters the shape of arch or curve of lower back which is essential for standing and sitting purposes.
- **Spondylolisthesis:** In this condition, the lower vertebrae shifts forward over the other bone and the nerves come out from the spinal column.
- **Sciatica:** The compression of the sciatic nerve, which extends from the buttocks to the back end of the leg causes this extreme pain. Due to interruption in nerve signals, the muscles of the leg suffer weakness and temporary sensations in the body.
- **Spinal Stenosis:** The narrowing of the spinal column affects the spinal cord and the spinal nerve, which are very essential messengers sending signals to and fro, resulting numbness in leg muscles and loss in senses.

- **A deep Injury:** A deep injury or trauma because of an accident, sport activity, regressive or wrong way stretching, a fall/slide leading to injury in muscles, ligaments and even tendons are affected causing the lower back pain.
- **Radiculopathy:** An inflammation, compression or injury in the spinal nerve root rises this pelvic condition. It results into a severe pain, sensations in the nerves that leads to pain in other parts of the body connected by that spinal nerve.
- **Slipped disc:** One can have a slip in their disc around any part of the spine either neck or lower back or any section of the spine.
- **Cervical Dysplasia:** The cells in the cervical section of the spine undergo abnormal changes [36].

Some Indirect causes of lower back pain are shown in Table 3.1.

3.2.5 Treatment of Lower back pain:

The medical treatments are meant for reducing pain but unfortunately these treatments don't cure the source of pain completely. Also, physical therapy is prescribed along with treatment.

Different types of surgical and non-surgical treatments are described in following section.

Causes of the Back Pain	How they affect the spinal system
Infections	Pain in the vertebrae and joints connecting the lower spine to the pelvis.
Tumours	Often pains in the back, due to cancer in some other part of the body.
Abdominal Aneurysm or Enlargement	The blood vessel supplying blood to the pelvis, abdomen, legs enlarges.
Kidney stones	Sharp pain in the lower back on either side.
Endometriosis	Uterine tissue build-up outside the uterus.
Osteoporosis	Decrease in the bone density causes the fracture in the vertebrae.
Fibromyalgia	A chronic muscle pain and fatigue.
Joint Diseases	An inflamed vertebrae, arthritis, rheumatoid arthritis, spondylitis causes lower back pain.
Threatened Abortion	A threatened miscarriage or abortion leads to bleeding in the female organ.
Dissection of the Aorta	The blood has entered the walls of artery between the inner and middle layers.
Whiplash	The Head moves in forward and backward direction with a great force causing cervical pain.

Table 3.1 Indirect Causes of Lower Back Pain [36]

3.2.5.1 Non-surgical treatments:

There are some ways to reduce lower back pain which don't require surgery which are discussed below.

- **Narcotic pain medicines:** The narcotic medications or the famous “painkillers”, lessens the effect of pain by weakening the signals sent to the brain [37]. These are most often used for treating a short-term pain, to feel relief from the pain for a shorter span, to treat pain after the operation. But these are not used or rarely used for long term pain as they have side effects and may become addictive [37].
- **Back braces:** A back brace can help in comfort, keeping a good posture of body and reducing the pain up to some extent. It can be worn daily along with ongoing physiotherapy exercises.
- **Steroid injections:** This treatment involves direct injection of steroid in the outer part of the Dural sac – which surrounds the spinal column. For this process, a live X-ray called Fluoroscopy is used to guide the needle to the exact area to be operated. Such injections relieve the pain temporarily and reducing the inflammation around the operated spinal nerve [37].

3.2.5.2 Surgical treatments:

Surgery is the last resort for the treatment of lower back pain.

- Surgery can be opted for severe back pain. It is only considered after the lesser effects of non-surgical treatments and if it doesn't get better.
- Surgeries are only recommended when the patient has limitations in performing daily activities and can-do limited work only.
- Back surgery is not to be initiated or thought for, if cause of pain is not detectable through imaging tests.
- Decompression surgeries remove the part of layer of the bone or a soft tissue that is compressing a nerve or more nerve roots.

And, most of the surgeries are a day surgery or are overnight surgery. Hence, the Lower back pain can be cured, and the good spine column will impart a comfort to live on further, if detected and operated within time.

3.3 Range of Motion (ROM) Attributes or Pelvic Parameters:

Pelvic area or Pelvis is the lower part of the torso – located between the abdomen and the thighs/legs. At such a critical location in our body, it has lot to do with the nervous system-a controller of the whole-body structure and brain.

The major cause of the Lower back pain or its initiation is from the pelvic congestion and this congestion can further lead to pelvic pain, adversity knocks when it pains the human's backbone and even makes one nervous – affecting human behavior and his daily life.

Spinal deformity is a disorder affecting mostly half of the aging population. There are mainly 12 Range of Motion (ROM) attributes which effect lower back pain. These Attributes can be measured from the radiographic images using a virtual goniometer which measures angles on digital images using Microsoft PowerPoint [38]. Each one of them is explained below as follows:

3.3.1 Pelvic Incidence:

Pelvic incidence is defined as the angle between the perpendicular to the sacral plate at its midpoint and the line connecting this point to the femoral heads.[39]

The Normal value of Pelvic Incidence or PI is **50°**.

The pelvic incidence appears to be the main axis of the sagittal balance of the spinal cord [39]. It controls spinal curves in accordance with the adaptability of the other parameters.

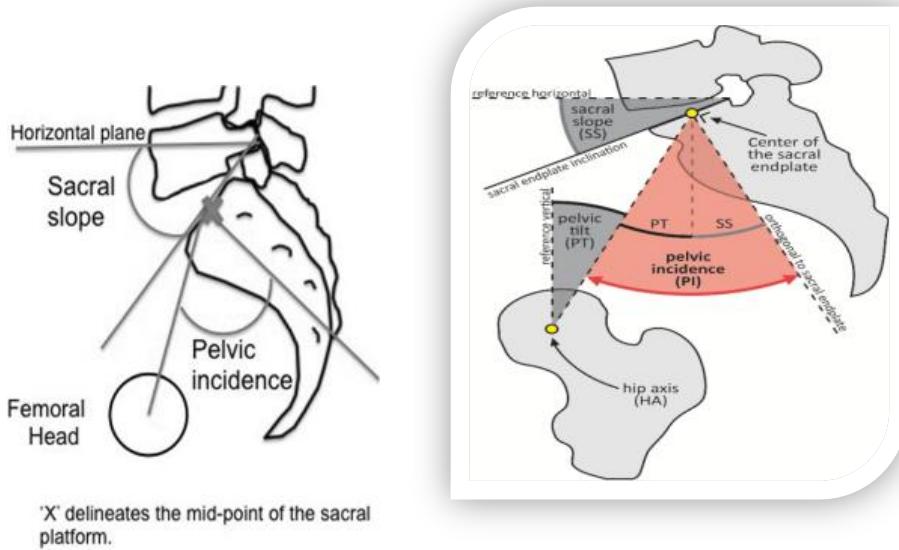


Fig. 3.2 Pelvic Incidence (line diagram) and Pelvic Incidence Angle [39]

Now, Sagittal balance is the imbalance in the spine and Lordosis is the inward curve of the lower or lumbar spine.

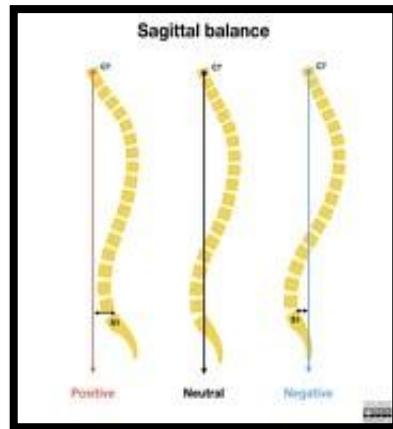


Fig. 3.3 Sagittal Balance [40]

The patients with smaller pelvic incidence (PI) tend to be restored higher and those with a larger pelvic incidence were more likely to be restored at lower pace. For patients with normal sagittal balance, the surgical outcomes in the treatment of low-grade lumbar (lower spine) degenerative spondylolisthesis with spinal fusion are not correlated with restoration of the lumbar lordosis (LL) [38].

Also, the PI changes significantly during whole life span. It increases during childhood as the spine adapts to changing physiological needs and stabilizes after adulthood, shows wide variation in normality. The PI dictates ideal sacral orientation and therefore, ideal lumbar lordosis (LL): higher PI means greater ideal LL & lower PI equals lesser ideal LL.

3.3.2 Pelvic Tilt:

Pelvic tilt is the orientation of the pelvis in respect to the thigh bones and the rest of the human body.

The pelvis can tilt towards the front, back or either side of the body structure. And there are two common abnormalities with regards to the orientation/posture of the pelvis – Anterior pelvic tilt and Posterior pelvic tilt. Usually, Pelvic Tilt is normal and not a worthy thing to be worried about. If pelvic tilt becomes problematic, then it offers only a poor posture and one can get rid from it easily.

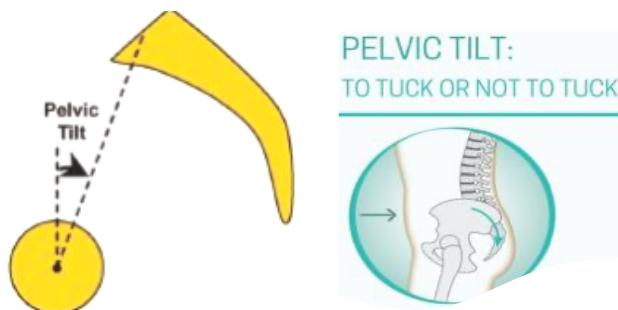


Fig. 3.4 Pelvic Tilt [41]

Symptoms of the pelvic tilt are such that it gives **poor posture** and a curvature in one's spine.

It may follow as –

- A curving in lower spine.
- Tight muscles in the thigh area.
- Weak stomach muscles and projecting/extended stomach.

- Weaken gluteus maximus (hip area), which is the main extensor muscle responsible for movement of thighs.

The inactivity of any kind, sitting over longer periods and a posture alignment easily lead to the pelvic tilt.

3.3.3 Lumbar Lordosis Angle:

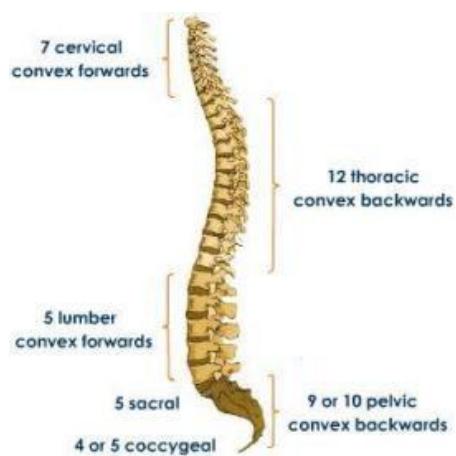


Fig. 3.5 Spinal structure showing 5 vertebral parts [42]

Lordosis is the normal inward curvature of the **lumbar** (lower) and cervical regions of the human spinal cord [43]. The normal outward curve (convex curvature) in the thoracic and sacral region is termed as kyphosis. Generally, the term lordosis means to bend backward.

The Lumbar Lordosis is a key element of body-posture. It is measured as an angle (LLA).

LLA stands for Lumbar Lordosis Angle which is an ideal parameter for the evaluation of LL.

According to spine specialists and researchers, there is no accurate or standard measurement, but it ranges from 39 to 53 degrees and this lumbar lordosis angles vary between people up to a greater extent [43].

It is measured with the help of radiographs of the spine.

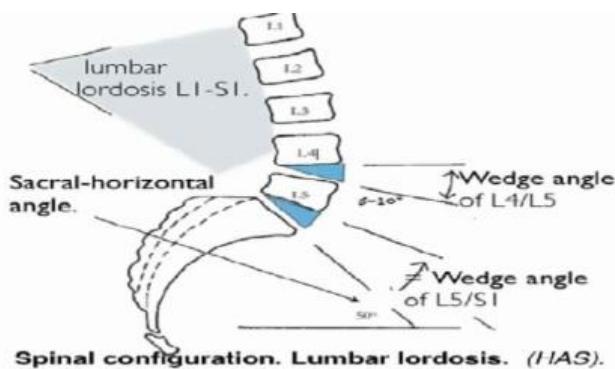


Fig. 3.6 Lumbar Lordosis (LL) Angle [Lower back] [44]

Symptoms of the lumbar curve tilt:

- Weakness in the lower back spine.
- Back pain and discomfort.
- Numbness leading to lumbar nerve compression.
- Cramping or sudden muscle contraction in lumbar area.
- The hip area getting more pronounced.
- Problem in moving in certain directions.
- Large inward arch in the lower back vertebrae.

3.3.4 Sacral slope:

The **Sacral slope**, also **Sacral inclination** is the angle between the vertical plane and the tangential line to the sacral vertebrae [45].

In the patients with lower back pain, the position of the pelvis is often a focus of manual therapy [46]. The primary method to determine sacral inclination is by radiograph but methods to measure sacral inclination externally with an inclinometer have also been introduced.

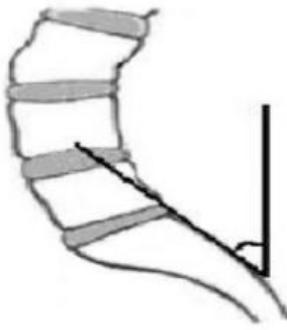


Fig. 3.7 The Sacral Inclination (Slope) [47]

Measurements of curve of the lumbar spine are useful in the investigations of lower back pain. It is incalculable whether the degree of lumbar lordosis, sacral inclination (slope) and lumbo-sacral angulation are the same for all normal adults.

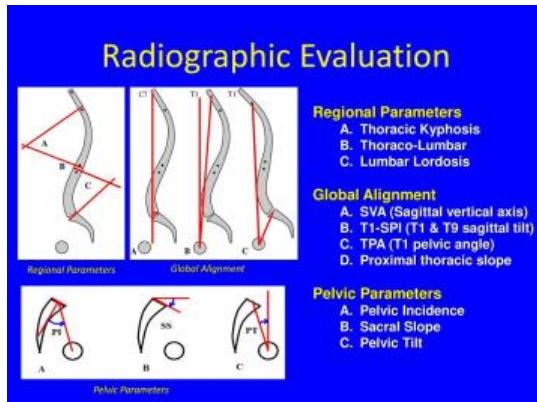


Fig. 3.8 Radiographic (X-Ray) Evaluation depicting 3 main Spinal parameters [48]

Sacral slope is one of the most important parameters in the measurement of Lumber Lordosis (LL) which is explained in the summary of research mentioned below.

Radiographic studies were carried out on the lumbar spines of subjects aged 10-60 years. In Radiographic evaluation of 50 consecutive patients with LBP, radiographs of 41 patients were useful for the required measurements on the radiograph [49]. Result of study showed that the mean difference between the radiographic evaluation and inclinometer method was 23.12 degrees. The measurement error was about 8.25 degrees [49]. It can be concluded that all three parameters varied steadily with age. The pattern of changes differed in males and females. Females had greater angles than males. The method used to measure sacral slope

with an inclinometer proved to be an invalid one. Sacral slope appears to be a much more important determinant of the degree of lumbar lordosis (LL).

3.3.5 Pelvic Radius:

Pelvic Radius or Pelvic Radius angle is a requisite parameter for sagittal alignment and movement of the spine [50].

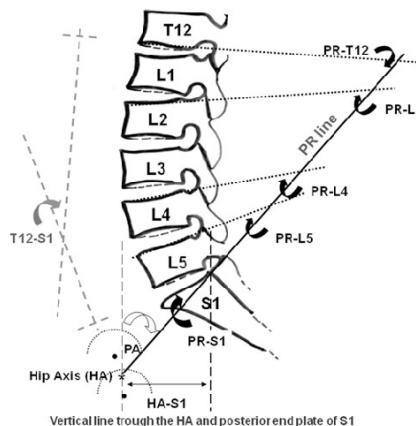


Fig. 3.9 Pelvic Radius Angle [51]

As Observed from the above figure, Pelvic Radius can be measured as the distance between PR line to the horizontal [50]. PR Line is the line connecting HA and the post exterior line S1.

Line drawing shows black dashed lines, vertical line trough HA and posterior superior corner of S1, gray lines, T12-S1 measurement. Arrows indicate angles of representation.

3.3.6 Degree Spondylolisthesis:

The Spondylolisthesis can be evaluated by its degree of spinal slip or spinal deformity. The Spondylolisthesis is measured in different level of grades. These grades determine the degree of slip in the spinal column. It is very important to know this degree in determination and diagnosis of spinal complexity and much helpful in the pelvic treatment.

The Grade of Spondylolisthesis counts from low advanced level to higher advanced level grade. The Slip shows the vertebrae i.e. a part or section of the spinal column going forward beneath the other body part. This spinal slip drastically ruptures the spinal structure.

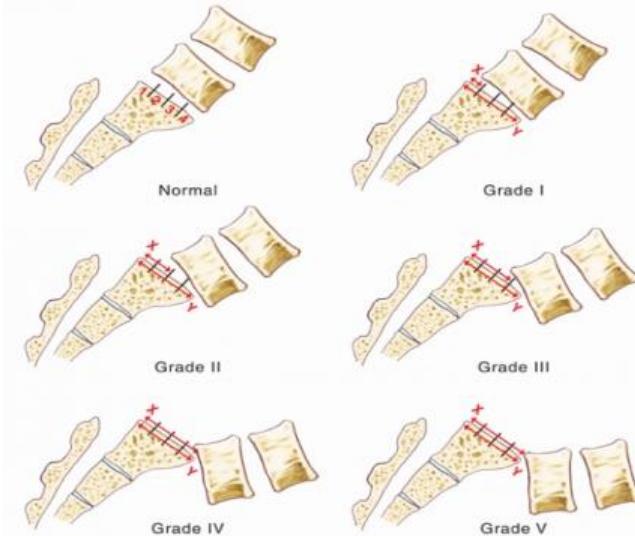


Fig. 3.10 Various Grades of Spondylolisthesis [52]

The Above diagram shows the normal spinal part and the various grades of spinal shift (Spondylolisthesis). It can be observed that with the increase in the Grade of Spondylolisthesis, more complex situations are getting generated in human's back.

The various Spondylolisthesis Grades of slip can be constituted as below –

<u>Level of Grade:</u>	<u>Percentage of Slip severity:</u>
Grade 1	25% [Least advanced grade]
Grade 2	50%
Grade 3	75%
Grade 4	100%
Grade 5	Complete fall of spinal part/vertebrae [Most advanced grade]

Table 3.2 Spondylolisthesis grades of Vertebrae Slip [53]

3.3.6.1 Occurrence of Spondylolisthesis in Human body:

- The **Spondylolisthesis** is found only in very meagre percentage of population, almost 3 to 5% of population.
- Generally, males are affected much by it than females. The reason being more physical activeness of males than that of females.
- Any person who is engrossed in more physical acts, sports especially weightlifting, football, gymnastics, running etc. Task involving much higher body movement and force application by body or on body.
- It is astonishing that children below 5 years may get this disease either prematurely or may have undetected Spondylolisthesis. But such cases are rare.

3.3.6.2 Types of Spondylolisthesis:

Spondylolisthesis are of two categories –

3.3.6.2.1 Developmental Spondylolisthesis:

This type may exist at birth, develop during childhood but generally is not noticed even in adulthood [53].

3.3.6.2.2 Acquired Spondylolisthesis:

Now, acquired one can be caused in two different ways –

- First, due to the impact of daily stress on spine because of carrying heavy items, regular sports, etc, the spine may get distorted. As the connections between the vertebrae weakens, it will lead to Spondylolisthesis.

- Second, due to a single or a force applied on repeated basis can cause Spondylolisthesis. For example, impact of falling off a ladder and landing onto feet, by regularly enduring offensive linemen playing football [53].

3.3.6.3 Symptoms:

- Sudden pain in the lower back, especially after physical exercise.
- Weakness and pain in one or both the legs and thighs.
- Reduced ability to control bowel and bladder functions [53].
- Increase in the lordotic (inner) curvature of the spine.
- The style of posture and way of standing and walking may change. This leads the abdomen to protrude and muscles spasms may occur in lower back.

3.3.7 Pelvic Slope:

The **Pelvic slope /Pelvic Inclination** is the angle between the horizontal plane and the plane of pelvic – inlet [54].

The Pelvic slope is the anteroposterior movement of the pelvis around an imaginary axis in the pelvic plane.

Key information regarding pelvic slope:

- Pelvic slope is measured by using anteroposterior radiographs of the hip.
- The Average measurement of pelvic slope in the females is **55°** [54].
- X-ray and inclinometer are the primary methods to measure pelvic slope / inclination.
- The postural variations and the application of pressure are also considered.

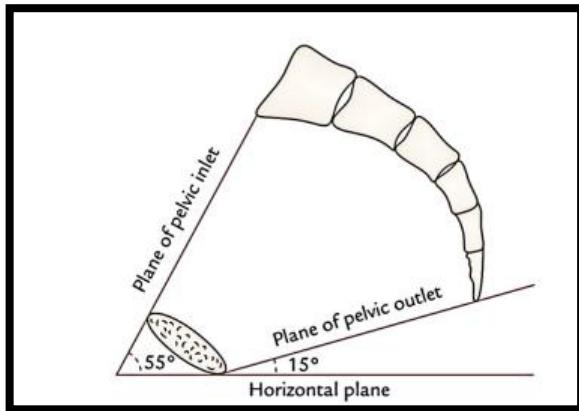


Fig. 3.11 Pelvic Inclination Angle [55]

3.3.7.1 Pelvic slope angle:

Now, to assess the pelvic slope angle from radiographs, a formula was determined by a trigonometric function. A significant correlation between the angle calculated by formula and the measured angle on lateral radiographs was confirmed.

The calculated angle (θ_1) was obtained from two measured values: the pelvic foramen height (H) on radiographs and the pelvic distance (D) on lateral radiographs [56].

The formula used was $\sin \theta = [\frac{H}{D}]$.

Also, the calculated angle (θ_2) was obtained from the pelvic foramen height on radiograph, because the pelvic foramen distance on lateral radiographs [56] substituted for the average of the pelvic foramen distance investigated.

The formula was $\sin \theta = (\frac{H}{\text{average}})$ [56].

Hence, it can be concluded that both the calculated angles are significant in their values and the pelvic slope can be inferred by measuring the height of pelvic with accordance to above formula.

3.3.8 Direct tilt:

Direct Tilt is a position-based parameter termed as the angle made by a line running from the sacral end plate midpoint to the center of the bifemoral heads (thigh muscle at back) and the vertical axis [57].

It is an upward and backward rotation of the pelvis bone. While exercising or standing, the chronic position of pelvis crucial for alignment of spine and lower back health. When a person stays in a tilt position of pelvic area for a prolonged time, it develops pain in knees, back, hips and feet.

The direct tilt changes the posture as the front of the pelvic rotates forward and the back rises. To avoid bad postures and such vulnerable pain, one needs to focus on stretching the body, to develop much core strength in body by physical exercises of plank etc. The direct tilt causes to reduce one's height functionally. Slouching posture is one such where the upper back is rounded forward and the pelvis is tucked underside (posterior pelvic tilt) [57].

Symptoms of direct tilt:

- Bad posture and spinal alignment.
- Severe pain in knees, back, hips and feet.
- Stiffness of the joint.
- No steadiness while standing and running.

3.3.9 Thoracic Slope:

Thoracic Slope is the angle between a plumb line of cord and a straight line from the first thoracic vertebra (T1) to the first sacral vertebra (S1) [59].

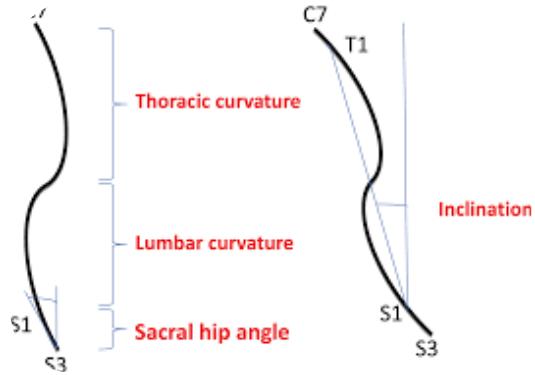


Fig. 3.12 Inclination graph for 3 sections of spine – (See) Thoracic curve [58]

From the above diagram, the difference between curvature and its inclination can be easily understood, especially of Thoracic curvature of the spinal column.

The Thoracic spine is that part of the vertebrae that enters the formation of thorax. The thoracic spine contains twelve vertebrae and they are labelled as T-1 to T-12. It supports the ribs structure. Each number corresponds with the nerves in the spinal column. These nerves and muscles help control the rib cage, lungs, the diaphragm and the muscles that assist in breathing. T-6 to T-12 thoracic vertebrae's controls or affects the abdominal and the back muscles [59].

T1 - first Thoracic vertebrae makes up the largest and central vertebrae of the spinal cord which is between the lumbar vertebrae and the cervical vertebrae (neck area) of the spine [60].

Now, a greater thoracic spine slope / inclination imposes a forward one, a stooped posture (leaning posture) which articulates as poor sagittal balance. A stooped posture has one's body or especially head moved in forward and downward kind of structure.

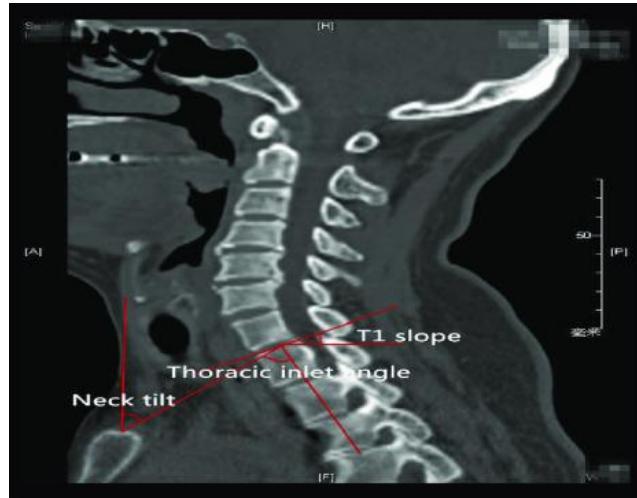


Fig. 3.13 The Neck area tilt and slope (X-ray Image) [61]

The thoracic nerves and spinal thoracic vertebrae communicate with the central section (T1-T8) of the human body.

The thoracic controls and regulates various parts as below:

THE THORACIC VERTEBRAE	REGULATION OF THE BODY PART
T 1 VERTEBRAE	The side of the forearm and wrist [61].
T 2 VERTEBRAE	The posterior aspect of the upper arms.
T 3 VERTEBRAE	The pectoral area in the chest.
T4 T5 T6 T7 T8 VERTEBRAE	The other muscles in the chest and the trunk of the human body [61].
T9 T10 T11 T12 VERTEBRAE	They form the Base of the thoracic vertebrae [62].

Table 3.3 Different parts controlled by Thoracic vertebrae [61][62]

3.3.9.1 Thoracic Spine Injuries:

The Injuries in the thoracic part of the spinal column are rare due to the ribcage protecting the spine. But, still the causes of injuries in the spine are due to such reasons – Birth defects, Infection, Vehicle accidents, Trauma and Tumours.

3.3.9.2 Symptoms of Thoracic Slope:

- Lack of function in legs which results into paraplegia (i.e. Partial paralysis).
- Lack of bowel / bladder function [62].
- Lack of dexterity in fingers and hand.
- Reduced ability to handle the abdominal and trunk part of the body.

3.3.10 Cervical Tilt:

The neck region of the spinal column is known as the Cervical vertebrae. It consists of seven bones namely C1 to C7 vertebrae.

The Cervical disorder or Cervical tilt is an ill effect to the cervical spine that starts from below the skull and ends by the shoulder segment [63]. The cervical spine contains main anatomic compositions as muscles, ligaments, bones and joints. All these anatomic structures have nerve endings that can detect pain when and where it occurs.

The Cervical tilt disorder results into a neck pain or a stiff neck. When one or more nerves around cervical spine goes under compression, then one may suffer from pain, numbness, weakness in the shoulders, arm and the hand and thus majorly affecting physical activity.

Symptoms of cervical tilt:

- A nerve may get damage by sudden pitching or receiving no signal – i.e. Numbness.
- Weakness due to cervical nerve compression [63].
- Headache, Neck-ache or neck pain, the cervical region muscles got tighten.

- The arms and shoulders feel pain.
- Major suffering is difficulty in walking, balancing and in posturing of backbone.
- Inability to move or use arms, arms may feel heavy [63].
- Neck may tilt from side to side.

A term called Cervical kyphosis may occur as the vertebral nerve compression fracture which can lead to collapse in spine shape as of a wedge [63]. This again leads the spine area to tilt forward and this imbalance inculcates the loss of normal curvature of the cervical section (neck).

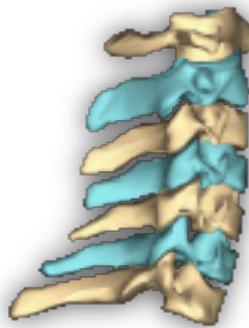


Fig. 3.14 The Cervical Vertebrae. (Neck) [64]

3.3.11 Sacrum Angle:

The Sacrum in the human anatomy is a larger and triangular bone located in the lower back of the spine formed from fused sacral vertebrae and situated between the two hip bones of the pelvis [65]. It forms the solid base of the spinal cord where it intersects with the hip bones to form the pelvis. It is a very strong and stiff bone that supports the weight of the upper body as it spans across the pelvis and the legs [65]. It consists of five segments which are named as S1 to S5 and are fused together.

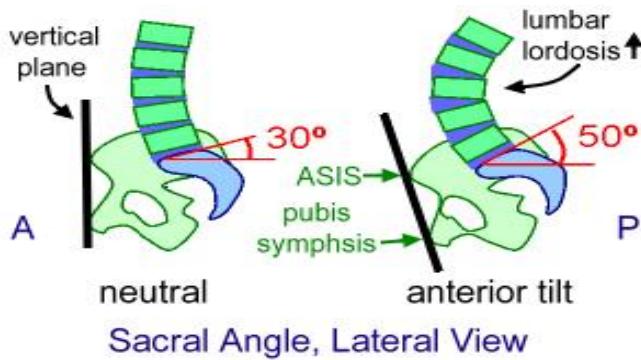


Fig. 3.15 Sacral Slope Angle [66]

The **Sacrum Angle** is the angle formed by the true conjugate with the two pieces of the sacrum.

In normal conditions, the value of sacrum angle is generally more than 40° [67]. A sacral (sacrum) angle of lesser degree suggests the funnelling of the pelvis. Even, it plays a vital role in judging for Spondylolisthesis and various pains related to lower back. The extremes of the sacral angle are one of the reasons for the lower back pain.

Particularly in some parts of our human anatomy, due to any extreme complexity, cancer may rise its head. The **Sacral Cancer** can be associated by following reasons –

- Lower back pain which the root of all causes.
- Numbness (weakness) in the legs [66].
- Loss of bladder and bowel control.
- A mass on the lower back that is tender to the touch [66].

3.3.12 Scoliosis slope:

Scoliosis represents a severe condition in which the spine shows a lateral shift and forms a sideway curvature. The curve of the spine is generally C- or S- shaped [67]. It is the most vulnerable spinal deformities one can be diagnosed with.

Scoliosis is an asymmetry in the posture of the spinal. The scoliosis slope can be generally known through **postural observation** by parents or any clinician or nurse. The patient will be said to bend forward to the waist in order to see the rib cage alignment. If the rib cage has shifted or elevated on one side, then this uneven ribcage suggests that the spinal cord may be twisting as well as curving. The scoliosis slope of the rib cage is measured with the help of a device called Scoliometer. The Scoliometer measurements can be useful for screening tools but need to be supplemented in order to guide the treatment decisions.

Scoliosis or scoliosis slope is generally measured in terms of degrees. The measurements of the spinal curvature are made on an X-ray by identifying the upper (top) and the lower vertebrae of a curve and then measuring the slope angle between these two points of the curve.

The Spinal curve may be described as having a “Cobb Angle” because the measurement method for the spinal deformation was named after an Orthopaedic surgeon, John Cobb. Very accurate and precise assessments of the Cobb Angles are crucial because treatment strategies vary considerably based on the severity of the spinal curvature and on the evidence that curve may be of progressing/ protruding tendency [68].

Most Scoliosis have twisting or rotational element in the spinal curve. The rotation of the curve is stated as in grade 1 to grade 4 and that depends on the severity of the spine curvature.

Surgery is generally advised and reserved for those who have curves exceeding 45° [69]. This magnitude of the curve can cause crowding of the organs and the functions of the heart and the lungs may be compromised.

If the Scoliosis remains untreated or not looked upon then it can lead to a severe deformity of the spine – painful and can lead to such conditions that one may not be able to work or walk

as usual [69]. It can cause problem in breathing, can incur death or may lead to heart and lung damage.

3.4 Summary:

This chapter explains the most important factors which affects lower back pain. Background knowledge of each factor is provided in this chapter and features which are used for actual analysis are explained specifically in detailed manner. Explanation is provided about Human spine and its different sections. Here, a detailed introduction of Lower Back Pain has been described with its causes, conventional diagnosis techniques and treatments. Important pelvic parameters have been explained in a detail manner in last section.

Chapter 4 Machine Learning Techniques used for Classification of LBP symptoms

The huge advancement in the technology in today's era is the consequence of the development of great devices having compact dimensions, faster speed and effortless by humans. Amongst all the trending technologies, some of them are Artificial Intelligence, Machine Learning and Fuzzy Inference Systems. Methods which are designed using any of the above-mentioned technologies for the tasks like classification, regression, forecasting, image recognition, pattern recognition can be commonly termed as the Non-Conventional techniques. Here, 11 Machine Learning techniques have been used in this Thesis for classification which are named as follows:

- Naïve Bayes Classification
- Logistic Regression
- Deep Learning
- Random Forest
- Support Vector Machines
- Gradient Boosted Trees
- Decision Trees
- Artificial Neural Networks
- Multilayer Perceptron (MLP)
- KNN Classifier
- Fast Large Margin

Working principle of each of the above-mentioned Machine Learning based Classification techniques is briefly explained below:

4.1 Naïve Bayes Classification:

Naive Bayes is one of the simplest techniques used for the construction of classifiers. Classifiers are those models which allocates class labels to the problem samples which are illustrated as array of every measurable feature. Here, the tags of the class are fetched from a bounded set. To perform the classification task, Naïve Bayes classification accounts for one of the most candid and powerful algorithms. Naïve Bayes approach provides a feasible environment even while undertaking a data set with millions of records with some characteristics. There exists a family of algorithms for training such classifiers hinged on similar principles. Although this classification has unsophisticated design and hypothetical inferences, many times it proved its credibility prudently in complicated practical world cases [70].

The Naive Bayes classifier draws the input from the provisional probability of each one characteristic A_i provided the class tag C . Every single attribute A_i is hypothetically independent, the class C counts being provided. After accessing data, classification is further processed by implementing Bayes rule for calculating the probability of C class provided every solitary occurrence of A_1, \dots, A_n , followed by presuming the class of the maximum succeeding probability. By drawing a strong independent assumption, this calculation can be rendered feasible (the attributes A_i considered are hypothetically independent provided the class C counts). [71]

Provided, at any instance, considering all probable counts for A, B, C ;

$$PR(A|B, C) = PR(A|C) \text{ with the condition that } PR(C) > 0 \text{ [72].}$$

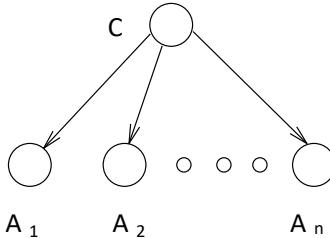


Fig. 4.1 Key network of Naive Bayes Classifier [73]

The random variables in the graph are represented by vertex and the edges represent the direct correlation between variables.[74] One vertex to one variable. The network presented above showcases the basic assumption behind the naïve Bayes classification, i.e., Every Attribute (leaf) is independent of the other attributes, provided the class variable (root).[75]

4.2 Logistic Regression:

In order to deal with classification problems, a development in linear model was compassed which turned out to be identified as Logistic Regression. This is one of the vital contributions of the statistics to the field of machine learning. It portrays the probabilities for classification problems by two viable results. In this method of examining the dataset, the outcome is determined by one or more independent variables (dualistic variables). Provided the group of independent variables, binary results can be predicted. Pseudo variables are used for illustrating the binary outcome.

Just like other regression analyses, logistic regression is also prognostic in nature. It defines the data and illustrates the dependency of a binary variable on one or more formal, numeral, halt or ratio level individual variable [76].

4.2.1 Logistic Function:

The logistic function is an s-shaped curve. It counts any real valued number and sketches it into the interval between 0 and 1, although those margins are never touched.

Logistic Function can be mathematically represented as:

$$\text{Logistic Function} = \frac{1}{(1+e^{-\text{value}})}$$

Where,

e= base of natural algorithms

value= the mathematical value to be transformed [77].

Using logistic function, a graph of numbers between -5 and 5 transformed to the range of 0 and 1 is plotted in the figure below [77].



4.2.2 Assumptions made in Logistic Regression:

- Binary Output Variable: The logistic regression function presumes the probability of any occurrence being associated to the original class and which can be decoded into the classification of 0 or 1.

- Noise elimination: Any oddity or indeterminate occurrences are abandoned from the original flowing data as the output variable in logistic regression is pretended to be errorless.
- Gaussian Distribution: It embraces a linear connection of the input values with the output [78].

4.3 Deep Neural Networks (Deep learning):

Deep learning is a phrase used to explain the concept of some neural networks and their algorithms which accept very original input data [79]. This data is processed through multiple layers of non-linear transformations and the final expected output is calculated.

Deep learning is one of the arms of the cluster of techniques identified as future learning or representation learning. Feature extraction is accounted to determine the features to be paid attention to. Deep learning has been implied favourably in a lot of applications of AI techniques are counts for one of its best and appropriate. These algorithms are used for learning problems categorised as supervised, unsupervised and semi-supervised [79].

Every layer of nodes training depends on the special types of features which are depending on the former layer's output. With the advancement in the network there arise more complicated features which the nodes can identify as they balance and combine the with former layer's features

Conversely these algorithms depend on optimal model election and development via model coordination. It is most feasible for solving problems where early knowledge of features is not so expected or unnecessary, and where tagged information is absent or is inessential for primary step. With the help of artificial neurons, the input data is passed through each layer of deep learning neural network. When the data is passed, it gets transformed and this

transformation which over the process from input to output is called as credit assignment path. [80] This can be termed as feature hierarchy which is an increasing complexities and consideration. It magnifies the capability of deep learning networks to manage large and high dimensional data batch with excess parameters passing via nonlinear functions [80].

While processing untagged data, every nodal stage of deep network recognizes the features on itself because of frequent tries of recreation of input from which the samples are obtained, trying to decrease the variation in between the network's presumptions and probability distribution of the input received. During the whole training, the neural networks become versed to determine the interrelation of some concerned features and their gilt-edge results, and derive the linkage between them, either it be a complete transformation or along with labelled data [80].

Deep-learning networks finally finish at the output layer where relatability to every outcome is allotted by a logic classifier. The final data from the network can be practiced on unorganized data which allows it to take input machine learning designs. This is the formula for better and greater functioning, i.e., to tend near to the accuracy more and more data to be processed on [79] [80][81].

4.4 Random Forests:

Random forests are a collection of learning methods for classification, regression and other tasks. These methods work based on establishing an assemblage of decision trees at training time and presenting the output which is mode of the classes, i.e., classification or average presumption, i.e., regression for every unique tree [82].

4.4.1 Algorithm:

In Random Forest classification, Multitude of decision trees is constructed during the training time and from all the classes generated, output class is ‘mode’ of classes if it is a classification problem and ‘mean’ of classes for a regression problem of individual trees. The tree learning in decision trees are nearest for fulfilling the conditions for acting as an off-shell procedure [81]. Under Scaling and different types of conversions of feature variables, the decision trees become invariant. It’s sturdy for involving unconcerned features and then providing outcomes as inspectable models.

4.4.2 Bagging:

The ordinary method of bootstrap aggregating or bagging is used in the training algorithm for random forest trees [82].

Training set $X = x_1, \dots, x_n$

Responses $Y = y_1, \dots, y_n$,

Bagging chooses any random value while replacing it with the training set and tones trees to these samples [82].

For $b = 1, \dots, B$:

Examine, along with restoration, n training examples from X, Y ; be it X_b, Y_b .

Develop a classification tree f_b on X_b, Y_b [82].

Next to training, presumptions of obscure samples x' can be found by averaging the presumptions from every singular regression tree on x' :

$$f = \frac{1}{B} \sum_{b=0}^B f_b(x)$$

Or by putting up the maximum vote in case of classification trees [82].

4.5 Support Vector Machines:

In the past few years, Support Vector Machine classification technique has been much accentuated amongst other machine learning techniques. Its principal fundamental is the concept of structural risk minimization (SRM). Support vector machines are those controlled training models coupled with learning algorithms which analysis data being considered for classification and regression [83][84]. Along with the linear classifications, non-linear classifications can also be executed using the Kernel method. In the kernel method, the input values are basically been aligned into a higher dimensional element sphere. A collection of training values associated with either of the two categories makes it a non-probabilistic linear classifier [84].

By outlining the largest margin hyperplane which isolates the data from variable conditions or sets the SVM shots a layout from it. This hyperplane is determined by data of admitted labels, and process is called as training. To detect the data with unknown labels, SVM considers the hyperplane concluded during the process of training. This is considered for determining if it is possessed by a patient or some control. The points (value) placed in the higher dimensional space are considered as patients. The figure given below indicates the abstract of algorithm in visionary 2d space. The two different imaging scan data noted from two groups or conditions are represented separately by dots and crosses [85].

It's tough or almost impossible to detach the two groups just with the data provided for one dimension. But if two-dimensional data is provided, its union can provide perfect separation.

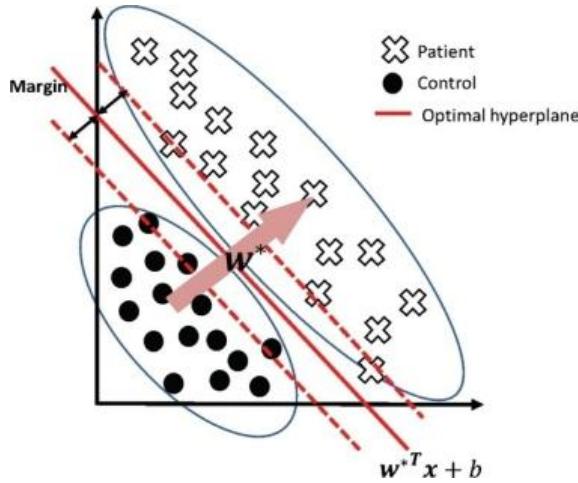


Fig. 4.3 SVM plot in 2D [86]

It illustrates the fact that an individual anatomical region cannot cater the minimum mandatory discriminative power required between the groups, which can be achieved by determining the concerned hyperplane by the multivariate SVM [86] [88] [89].

4.6 Gradient boosted trees:

For building predictive models for regression and classification problems in machine learning technique, one of the most powerful techniques counted today is Gradient boosted trees. It creates a presumption model as a group of weak prediction models such as decision trees. The model is constructed in a stage wise manner [90].

The concept of boosting can be illustrated as an expansion algorithm in the vicinity of a proper cost function, the idea of gradient boosting clicked to Leo Breiman [90].

Gradient boosting involves three elements:

- Loss function for optimizing it.
- Weak learner for giving predictions.
- For addition of weak learners in order to reduce the loss function, an additive layout [91].

4.6.1 Loss Function:

Depending on the type of problem to be answered, the loss function is selected. Gradient boosting does not actually derive a new boosting algorithm for every loss function to be used [91].

4.6.2 Weak Learner:

Gradient boosting considers decision trees as the weak learner elements [91].

4.6.3 Additive Model:

Without making any changes in the existing trees new trees are added. To reduce

the damage caused while adding trees a gradient descent procedure is followed [91].

The outcome of the new tree is summed up with the existing tree to improvise the concluding model output.

4.7 DECISION TREES:

Decision trees are one of the ways of supervised machine learning. It provides the explanation of the input and its corresponding output present in the running data. Based on a specific criterion, the data is breached. Based on two primary elements, i.e., node, branch and leaf, this tree is analysed. Here a node stands for an attribute, branch represents a declaration and leaf is the element which represents the absolute value [92]. The data is split while going from every node to leaf via branch. Hence nodes can also be labelled as decision nodes. In short, the main idea of decision tree algorithm is to set up a tree in which the complete data will be processed, and the outcome will be obtained at every leaf accordingly [92].

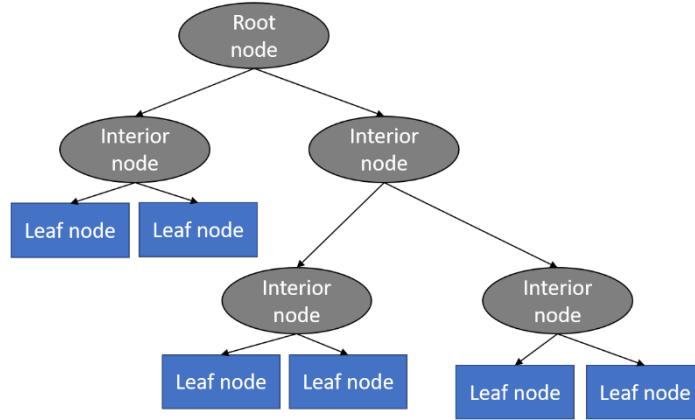


Fig. 4.4 Basic decision tree structure [93]

The decision trees can be mainly classified into two major types: Categorizing trees and Regression trees. Each type of decision trees is explained below:

4.7.1 Categorization of Decision Trees:

Decision Trees can be categorized into two sections namely:

4.7.1.1 Categorizing trees (yes or no):

An example of categorizing trees can be seen in the figure shown below where it is predicted

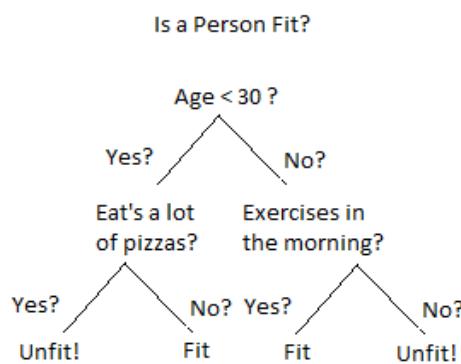


Fig. 4.5 Categorizing trees example [92]

whether the person is fit or not based on the information provided. Here the result was a variant as “fit” or “unfit”. It can be considered as a yes or no sort of problem [94].

4.7.1.2 Regression trees (continuous):

As the name suggests the resultant variable here is endless, i.e., continuous.

4.7.2 Terminology for Decision Trees:

For a better understanding of the decision tree algorithm we need to elucidate certain terms related with it. Most important of them are:

4.7.2.1 Impurity:

Whenever there can be chances of cast of one class's division in to the other, there arises a condition which is termed as impurity. It can occur due to the two main reasons;

- a. When the features available for class division are bygone.
- b. When small percentages of impurity are tolerated for active execution [95] [96].

4.7.2.2 Entropy:

This property tells the degree of randomness for the data provided. It can also be termed as measure of impurity. It is also identified as Shannon Entropy [95] [96].

4.7.2.3 Information Gain:

It quantifies the relevant changes in entropy corresponding to the independent variables.

$$\text{Information Gain (n)} = \text{Entropy}(x) - (\text{[Weighted Mean]} * \text{Entropy}) \quad [95] \quad [96]$$

4.8 Artificial Neural Networks:

In today's growing arena of scientific research and application, Artificial Neural Networks are one of the most effective data processing models. It is basically a lateral data execution system which works on the concept of biological neuron model. ANN can deliver up to the

mark results even if there is any loophole in the information provided as well can be used to crack realistic problems because of highly brisk processing. Artificial neurons in large amount are connected in ANNs. An output signal is obtained by sending weighted input signals to the artificial neuron casted together and transcended via an activation function(f) [97].

Evaluation of an artificial neuron can be represented as:

$$O = f \left(\sum_{j=1}^N w_i * x_j + w_0 \right)$$

Where,

x_j = input

O = output

w_i = weight

w_0 = bias of artificial neuron

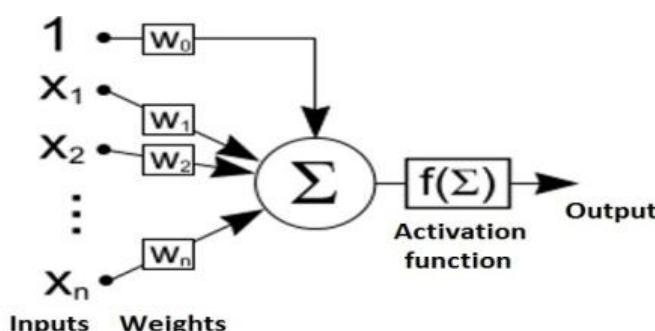


Fig. 4.6 Simplified format of artificial neuron [97]

An exemplary model of ANN comprises of 3 levels; Input, Hidden and Output layers. An additional neuron with a sustained output 1 is combined to each neuron for working of hidden and output layers. Input layer receives the input signal, transmits it through the hidden layer and finally reaches the output layer. Neurons and Activation functions in varied quantity are present in this layer [97].

Connectivity weights combine all the neurons with the neurons of the successive layer. Insights are obtained by ANN while taking up the learning process during which the expected output is obtained by dealing with the connectivity weights.

Modes of learning: Supervised and Unsupervised. Supervised learning is undertaken by providing an input vector at input layer and output vector at output layers for training samples. While unsupervised learning accounts for only input vector at input layer. The most suitable algorithm for multi-layer feed forward network is Back-propagation (BP). It is because of its mathematical form of complex non-linear linkage. The performance index of BP algorithm is the Least Mean Square Error which is evaluated by calculating the difference between the target output and the network output [97]. It is a supervised learning where expected network behaviour is given along with the learning rule.

$$\{p_1, t_1\}, \{p_2, t_2\}, \dots, \{p_q, t_q\}$$

p_q = input to the neural network's input

t_q = correlated target output.

With the application of every input to the network, its output is compared with the target [97].

4.9 Multilayer Perceptron (MLP):

Multi-Layer Perceptron can be considered as a family of feed forward ANNs. The MLP normally is just a feedforward model; while a general ANN model can be recurrent or feedforward [98]. Hence, MLP can be considered as a particular type of Artificial Neural Network. Basically, MLP has three layers and they are namely Input layer, Hidden or intermediate layer, and the final output layer. The input layer catches the signal and the output layer provides the presumption about the input received. The intermediate hidden layers are considered as the main functional part of an MLP. Here, every node count for a

nonlinear activation function other than the input node. For an MLP with a single layer, its proximity for any continuous function increases [99].

For training, MLP undergoes a supervised method named back propagation, and hence are often interacted with supervised learning problems. The training progresses on sets of input-output pairs simultaneously deriving the interrelation amongst the inputs and outputs. During training parameters are monitored and set accordingly in order to reduce the error. To make the relevant changes with respect to error, back propagation is practiced so that error is measured by various methods.

4.9.1 Activation function:

For all neurons, if one linear function measures input to the output of each neuron, then according to linear algebra, a linear model of two-layer (input-output) can be derived from any number of layers. Also, some neurons account for nonlinear activation function which are frequently witnessed in the measuring of frequency of action potentials, firing of biological neurons. These two activation functions are sigmoid [100].

4.9.2 Layers:

As discussed earlier, MLP basically comprise of three layers namely input, output and hidden (uncertain number). These layers posses' non-linearly activating nodes. MLPs are entirely interconnected networks and so are the nodes in them of one layer of specific weights ω_{ij} connected with every node in the successive layer [100].

4.9.3 Learning:

Learning is that outcome which happens when the associated weights are altered after the data of every portion is being processed, depending upon the measure of error obtained while

computing output with respect to desired outcome. MLP is one of the illustrations of supervised learning using back propagation [100].

4.9.4 MLP Algorithm:

The fundamental MLP algorithm is listed down.

1. Boot the network, while adjusting the weights between -1 and +1 inconstantly.
2. Demonstrate the most prior training pattern to derive the output.
3. Analyse the obtained network output with the desired output.
4. Error is to be proliferated backwards.
5. The error is to be computed by deriving the mean difference between the practical and desired output [100].

4.10 K-Nearest Neighbours:

KNN is one the most basic and simple yet essential algorithms implied in Machine Learning. It is usually implemented for classification and regression problems. It accords into the supervised learning class where it is extensively used for pattern recognition, data mining and intrusion detection [101].

The maximum poll for its neighbours works for classification. The neighbour with maximum vote is allotted the data. With the increase in number of neighbours the precision also increases, i.e., k's value [102].

For practicing any techniques, one has to fore look into 3 very important aspects of it.

a. Simple output interpretation.

b. Calculation time

c. Predictive Power [103]

4.10.1 KNN algorithm:

KNN model can be brought into action by implying below mentioned steps:

1. Stack the data
2. Boot up the value of k
3. For getting the predicted class, repeat 1 to the final number of processing data points.
 1. The space between the data to be tested and the current row of training data is to be computed using Euclidean distance as the distance measurement. Now the distances computed are arranged in ascending order depending on the distance values.
 2. Obtain the foremost k rows for the arranged array.
 3. From these rows obtain the most persistent class.
 4. And finally report the presumed class [103].

4.11 Fast Large Margin:

Fast large Margin is an operator which is a learning technique of large margin development. Based on linear support vector study presented by R.E. Fan, K.W. Chang, C.J. Hsieh, X.R. Wang, and C.J. Lin an apprentice of fast large margin is implied by the operator. SVM or logistic regression outcomes are very close to the fast-large margin outcomes but still FLM

classifier has the capacity to deal with data set comprising of a million numbers of examples and attributes.

This operator can also be understood a peer insight into SVM's functions and outcomes. SVM is a non-probabilistic binary linear classifier which receives input, makes predictions compares classes for them. SVM model features examples as points and divides the classes making a cleft. More examples are then drawn into that space and then presumptions are carried out as to which side will it be inclined of the cleft. The generalization error of the classifier is minimised in order to enlarge the margin.

The key components of this operator are:

- **Input:**

The input here is expected an example set. As it fails to deal with nominal attributes, it is provided with numeric attributes. Prior to operating with it Nominal to numerical operator is to be implied most often.

- **Output:**

The expected result that is the classification model is obtained from here which is now ready to work with unseen datasets.

The data set passed as input to the input port is obtained from this output port without any alteration. Commonly it is practiced in order to reuse the same set for upcoming operators or for viewing it in Results Workspace [104].

4.12 Summary:

This review provides an outlook on the theoretical aspect of Machine Learning techniques considered in this Thesis research. The practical implementation of above described techniques is explained in Chapter 5.

Chapter 5 Methodology

5.1 Introduction:

This chapter describes the pre-processing of the original dataset, extracting the important features and then constructing classification models using non-conventional techniques used in this research.

Machine Learning classification models can act as clinical decision support systems and can be crucial in complex situations when it's hard to predict using conventional methods. In this study, 11 Machine Learning techniques classification models are considered. Machine learning classifiers are implemented and analysed in RapidMiner Software (<http://www.rapidminer.com/>). RapidMiner software is developed on an open core model and is extensively used for data preparation, machine learning, deep learning, text mining, and predictive analytics. This software gives innovative analytical solutions using template-based framework which eliminates the needs of hard coding. RapidMiner provides a GUI to design and execute the workflows. A workflow is known as a "Process" in this software and consists of sequence of operators functioning together to provide desired solution. Every operator performs its own unique task and out of one operator is input of other operator.

5.2 Dataset:

The dataset used to frame classification model is taken from website named Kaggle (<https://www.kaggle.com/>) which is an online community of data scientists and machine learning experts owned by Google LLC [101]. Dataset consists of 311 rows or datapoints from which 187 datapoints are used to train the models and 124 datapoints are used for testing (60% of dataset is used for training and 40% is used for testing). 60:40 ratio is selected so that testing can be done on a large amount of data. Once the trained model gets a

wide variety of data for testing, and in case model is over fitted or under fitted, it can be detected by give wide variety and big number of test data. Data set contains 13 columns out of which 12 columns named col1 to col12 are pelvic parameters or Range of Motion (ROM) attributes and 13th column gives us information if 12 pelvic parameters show abnormal symptoms or normal symptoms of Lower back pain [105]. These Parameters are usually extracted from X-rays or Radiographs with extraction techniques like gray level histograms [106].

Name of col1 to col12 Attributes (Numeric Values) are mentioned below:

- Col1 = pelvic incidence
- Col2 = pelvic tilt
- Col3 = lumbar lordosis angle
- Col4 = sacral slope
- Col5 = pelvic radius
- Col6 = degree spondylolisthesis
- Col7 = pelvic slope
- Col8 = direct tilt
- Col9 = thoracic slope
- Col10 = cervical tilt
- Col11 = sacrum angle
- Col12 = scoliosis slope

This raw data is firstly normalized and then reordered using Waikato Environment [106].

After getting normalized and reordered data, The Automatic Feature Extraction method is used for the process of data reduction. This method uses a multi-objective evolutionary algorithm to find the most features sets from a given dataset. Each features set is pareto-

optimal with respect to complexity vs model error. Complexity is calculated based on the feature set where every single feature has complexity one. The first output is the best feature set from the Pareto set according to the balancing parameter. The second output is the complete final population of the optimization run, i.e. the full Pareto-front of all optimal trade-offs between complexity and accuracy. Finally, the log data of best performance, smallest feature set, and largest feature set size for all generations are also delivered for plotting purposes. The data reduction process is implemented to get those features which only are having a high correlation with the output; and therefore removing those features which are not contributing much towards classification [107].

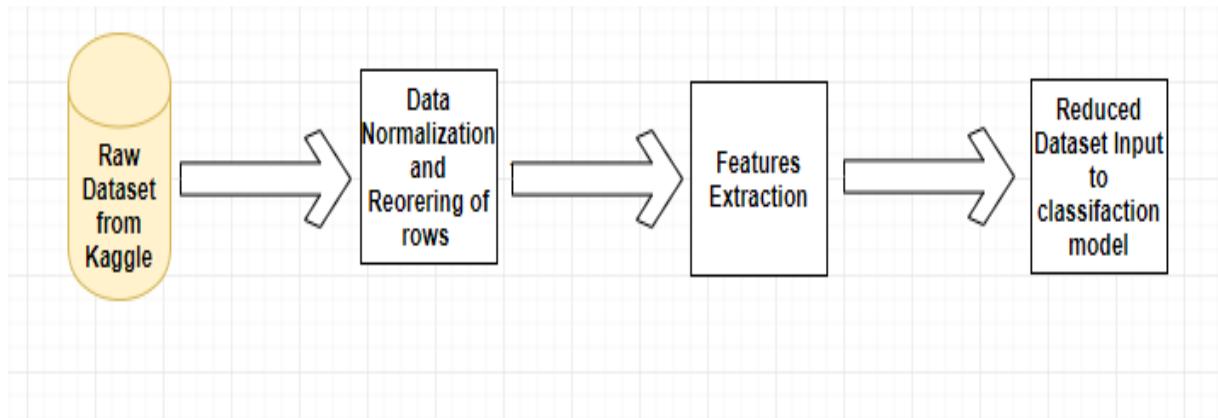


Fig 5.1 Data Collection and Pre-processing

The Figure 5.1 represents the schematic flow starting with collection of data from open source platform named Kaggle and ending with reduced dataset containing only those features which have high correlation with output class.

Attributes used in this research to classify this dataset are pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, degree spondylolisthesis and cervical tilt with model inputs as col1, col2, (col5/col10), col3, col4, col5, col6, sqrt(col5/col10).

The Fig. 5.2 represents the sample of the dataset containing features which are having high correlation with output to classify if the symptoms are abnormal or normal.

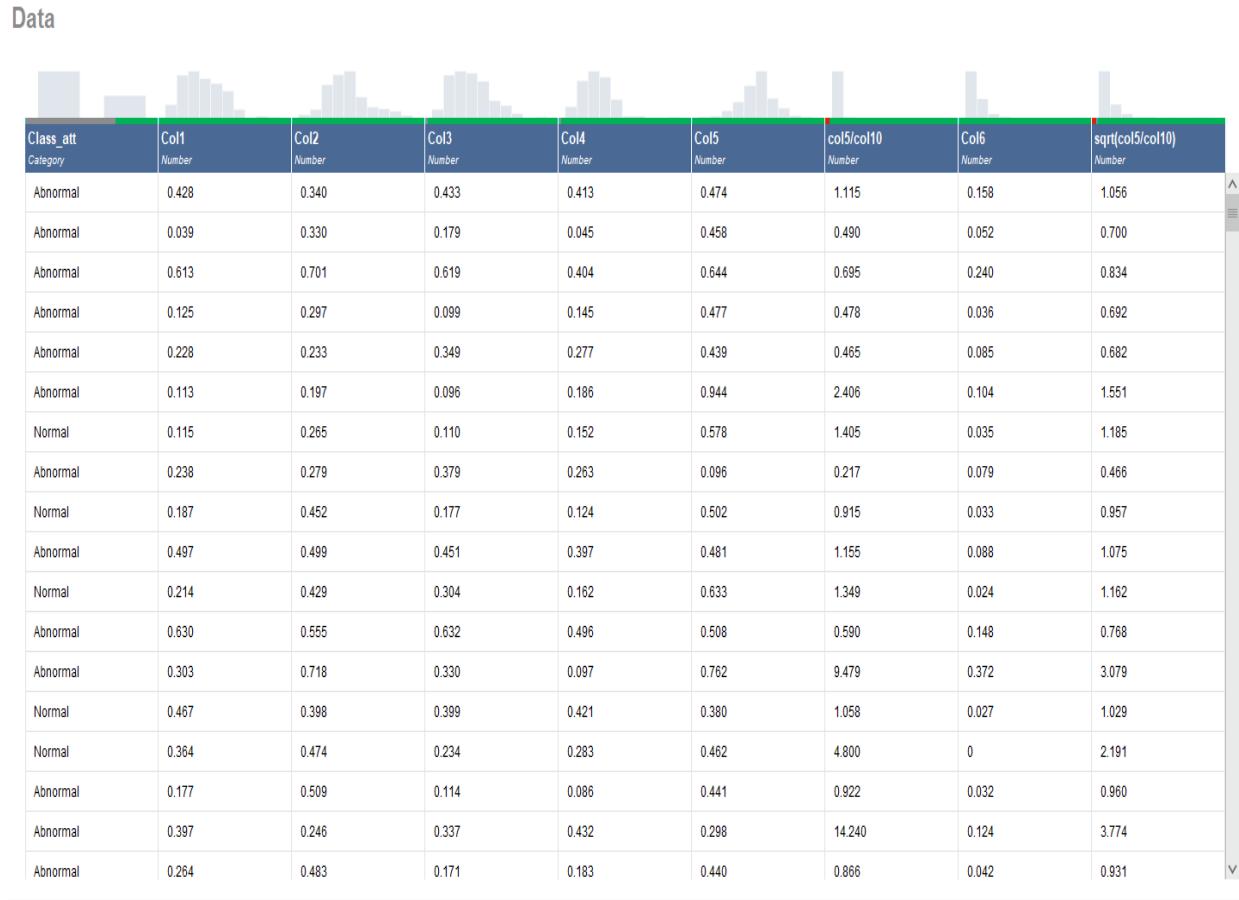


Fig. 5.2 Sample dataset used in the classification

This reduced dataset will be used to train and test the classification models based on the machine learning algorithm describe below.

5.3 Proposed Methodology:

Lower back pain symptoms are classified as Normal or Abnormal based on different Machine Learning techniques used in this research. This section explains the methodology of implementation of different Machine Learning algorithms to generate classification models.

Classifiers based on Machine Learning algorithms used in this research are designed on RapidMiner software. The following Machine Learning classifiers are designed:

- Naïve Bayes Classifier
- Logistic Regression
- Deep Learning
- Random Forest
- Support Vector Machines
- Gradient Boosted Trees
- Decision Trees
- Artificial Neural Networks
- Multilayer Perceptron (MLP)
- KNN Classifier
- Fast Large Margin

For each classifier mentioned above, Cleaned and reduced dataset is fed to the input terminal of the model. Process from loading input data into software till reaching to the model is shown in fig. 5.3.

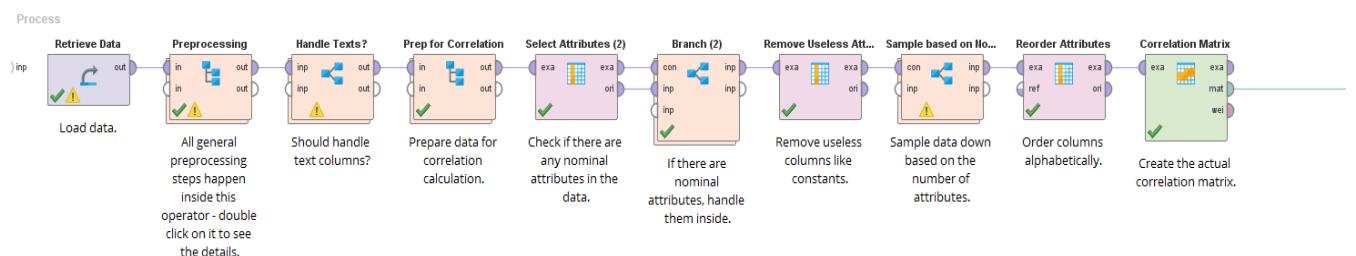


Fig. 5.3 Pre-processing of input data in RapidMiner Software

RapidMiner software provides a GUI for analytical workflows. Workflows are termed as processes in this software. Each process consists of several components called operators to do specific task. The classification models are designed in similar manner in this software. The Parameters' tuning of each of the above mentioned classifier is done to yield the best

accuracy. The Splitting of the dataset is the same for every model which is 60:40 for training and testing respectively and input is featured data for all models.

It might be worth to mention that some of the machine learning algorithms explained above require large training dataset to provide more accurate results while some of them don't require large dataset to give accurate predictions. Among all proposed methods, Deep Learning, ANN and MLP classifiers require large dataset for training. The remaining classification techniques (SVM, Logistic Regression, Random Forest , Naïve Bayes, Decision Trees, Gradient Boosted Trees, KNN, FLM) can perform really well even by less training data.

Process flow diagrams and Model Parameters for each machine learning based classification models are attached in Appendix A.1 – A.11.

Results obtained after implementation of these classification models and comparison of their performance are explained in chapter 6.

5.4 Summary:

This chapter describes the overall procedure performed in this research. Starting from gathering the data, it's cleaning, and its use as an input of the classification model is explained initially. Then design of different Classification models has been explained. Results and Observations are thoroughly discussed in Chapter 6.

Chapter 6 Results

In this research, 11 Machine Learning algorithms have been used to generate a Lower Back Pain symptoms classification model. This Chapter explains the experimental results obtained after the implementation of each model.

Parameters upon which each classifier's performance has been measured and different classifiers are compared are explained below:

- **Accuracy:** Accuracy of a classification model tells the percentage of instances classified correctly by the model with respect to number of instances given to the model as test dataset.
- **Precision:** Accuracy of a classification model tells the fraction of relevant instances with respect to number of retrieved instances given to the model as test dataset. It is also termed as positive predictive value.
- **Recall:** Recall value signifies the percentage of relevant instances which have been retrieved over total amount of relevant instances.
- **Sensitivity:** This is number of true or actual positive instances which have been identified correctly with respect to total number of instances reported to be positive instances.
- **Specificity:** This is number of true or actual negative instances which have been identified correctly with respect to total number of instances reported to be negative instances.
- **Attributes Weights:** This gives the final updated weights given to each attribute used as input to the classification model.

- **Area under Curve (AUC):** This parameter is an important tool in classification analysis to know ratio of used models which classifies the class best with respect to the total number of used models.
- **F-measure:** In the field of classification, f-measure is a measure to test the accuracy of the model. It considers both recall as well as precision value related by the formula:

$$F_1 = \left(\frac{\text{recall}^{-1} + \text{precision}^{-1}}{2} \right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Fig. 6.1 Formula to calculate F-measure

- **Lift chart:** Lift chart is the graphical aid to visualise model performance. This chart shows the effectiveness of a classification model and calculated as the ratio between the results with classification model and without classification model.
- **Optimal Parameters:** Optimal Parameters show model's performance for different parameters settings. In this research auto optimized models are created.

6.1 Naïve Bayes classifier:

Naïve Bayes classifier classifies the used dataset with an **accuracy of 81.82%** on test dataset. The Process Flow diagram and the Model Parameters of Naïve Bayes Classifier are shown in Appendix A.1. Performance parameters are shown below:

accuracy: 81.83% +/- 4.76% (micro average: 81.82%)

	true Normal	true Abnormal	class precision
pred. Normal	18	5	78.26%
pred. Abnormal	11	54	83.08%
class recall	62.07%	91.53%	

Fig. 6.2 Accuracy of Naïve Bayes Classifier

f_measure: 87.07% +/- 3.12% (micro average: 87.10%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	18	5	78.26%
pred. Abnormal	11	54	83.08%
class recall	62.07%	91.53%	

Fig. 6.3 F-measure of Naïve Bayes Classifier

sensitivity: 91.21% +/- 8.73% (micro average: 91.53%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	18	5	78.26%
pred. Abnormal	11	54	83.08%
class recall	62.07%	91.53%	

Fig. 6.4 Sensitivity of Naïve Bayes Classifier

specificity: 60.57% +/- 32.66% (micro average: 62.07%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	18	5	78.26%
pred. Abnormal	11	54	83.08%
class recall	62.07%	91.53%	

Fig. 6.5 Specificity of Naïve Bayes Classifier

precision: 84.63% +/- 10.35% (micro average: 83.08%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	18	5	78.26%
pred. Abnormal	11	54	83.08%
class recall	62.07%	91.53%	

Fig. 6.6 Precision of Naïve Bayes Classifier

AUC: 0.904 +/- 0.036 (micro average: 0.904) (positive class: Abnormal)

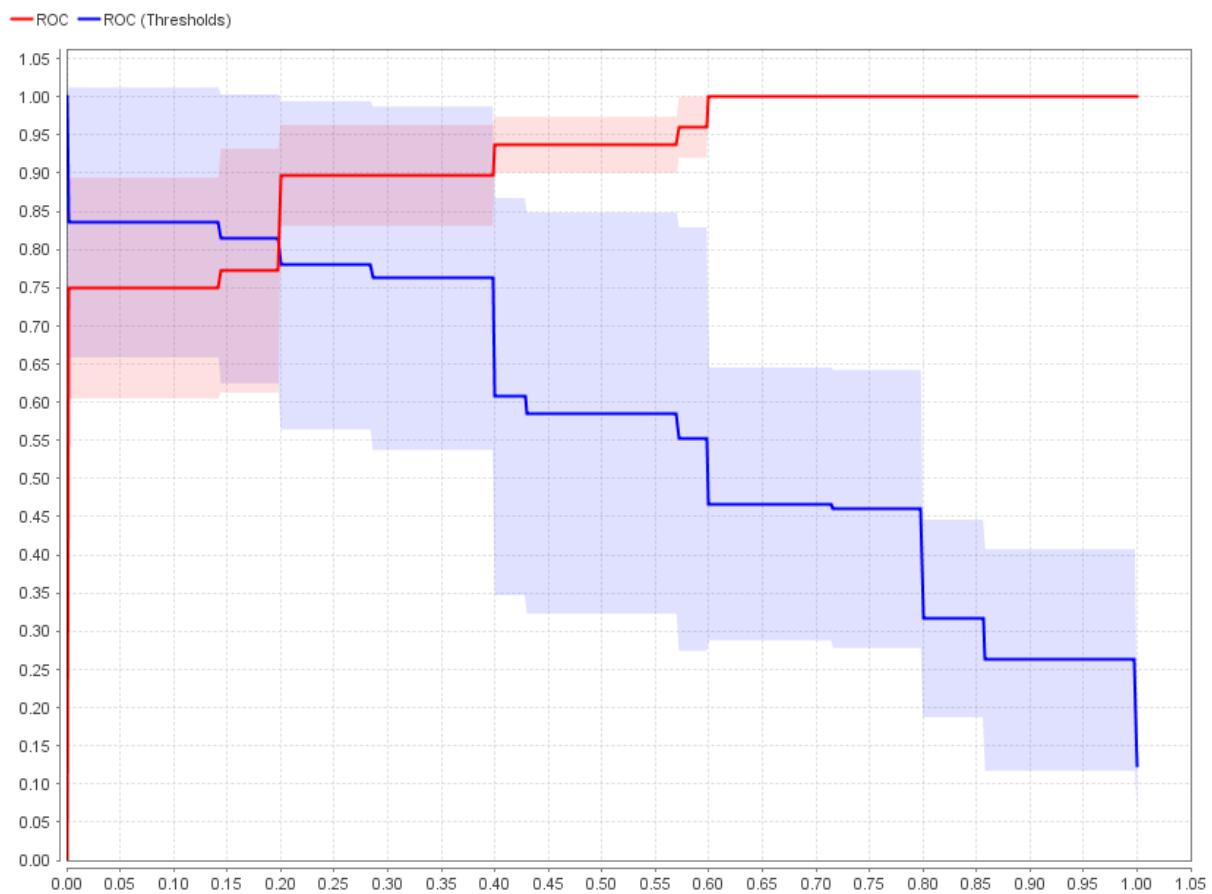


Fig. 6.7 AUC of Naïve Bayes Classifier

Naive Bayes - Weights

Attribute	Weight
Col6	0.168
Col3	0.079
Col2	0.052
Col4	0.045
Col1	0.044
col5/col10	0.044
sqrt(col5/col10)	0.033
Col5	0.007

Fig. 6.8 Weights of Attributes of Naïve Bayes Classifier

Naive Bayes - Lift Chart

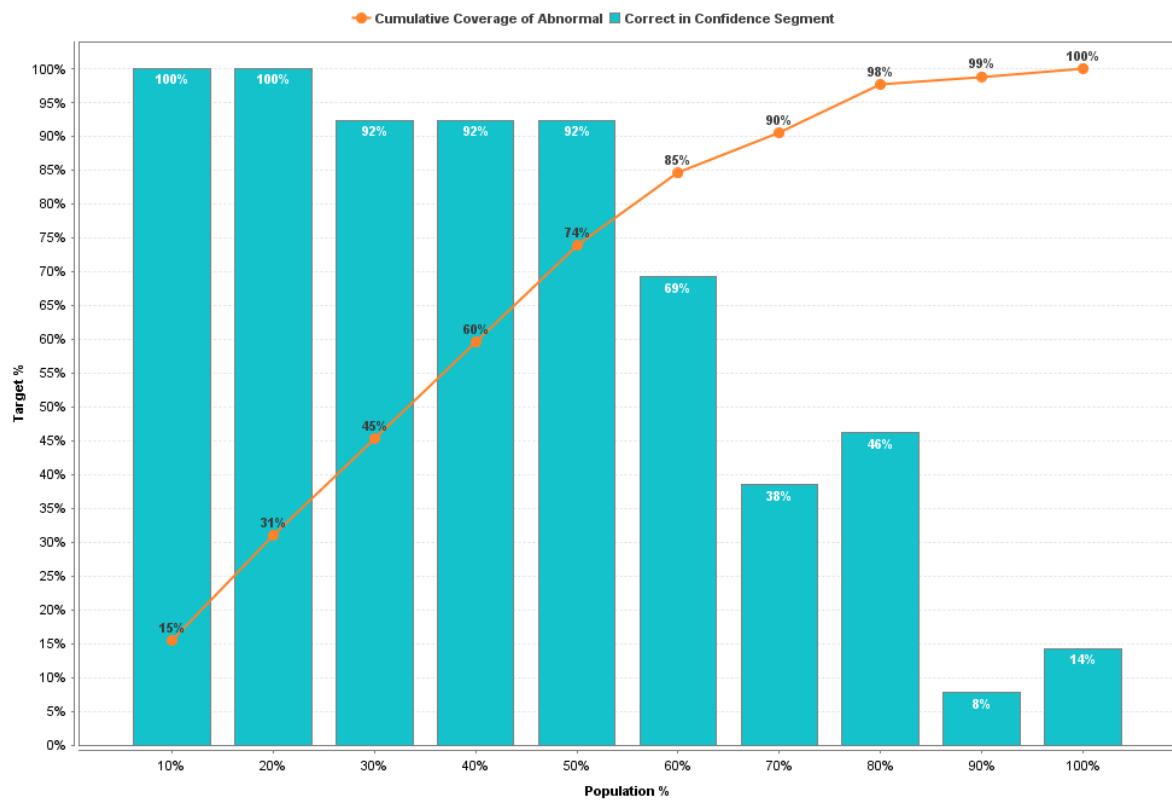


Fig. 6.9 Lift Chart of Naïve Bayes Classifier

Predictions given by the Naïve Bayes classifier on 124 datapoints is shown in appendix B.1.

6.2 Logistic Regression Classifier:

The Logistic Regression classifier classifies the used dataset with an **accuracy of 90.91%** on test dataset. The Process Flow diagram and Model Parameters of this classifier are shown in Appendix A.2. Performance parameters are shown below:

accuracy: 90.92% +/- 6.64% (micro average: 90.91%)

	true Normal	true Abnormal	class precision
pred. Normal	20	2	90.91%
pred. Abnormal	6	60	90.91%
class recall	76.92%	96.77%	

Fig. 6.10 Accuracy of Logistic Regression Classifier

precision: 91.16% +/- 6.01% (micro average: 90.91%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	2	90.91%
pred. Abnormal	6	60	90.91%
class recall	76.92%	96.77%	

Fig. 6.11 Precision of Logistic Regression Classifier

specificity: 76.67% +/- 17.00% (micro average: 76.92%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	2	90.91%
pred. Abnormal	6	60	90.91%
class recall	76.92%	96.77%	

Fig. 6.12 Specificity of Logistic Regression Classifier

f_measure: 93.76% +/- 4.58% (micro average: 93.75%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	2	90.91%
pred. Abnormal	6	60	90.91%
class recall	76.92%	96.77%	

Fig. 6.13 F_measure of Logistic Regression Classifier

sensitivity: 96.67% +/- 4.56% (micro average: 96.77%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	2	90.91%
pred. Abnormal	6	60	90.91%
class recall	76.92%	96.77%	

Fig. 6.14 Sensitivity of Logistic Regression Classifier

Logistic Regression - Weights

Attribute	Weight
Col6	0.467
Col2	0.128
col5/col10	0.107
sqrt(col5/col10)	0.070
Col1	0.043
Col4	0.042
Col5	0.029
Col3	0.022

Fig. 6.15 Weights of attributes of Logistic Regression Classifier

Logistic Regression - Lift Chart

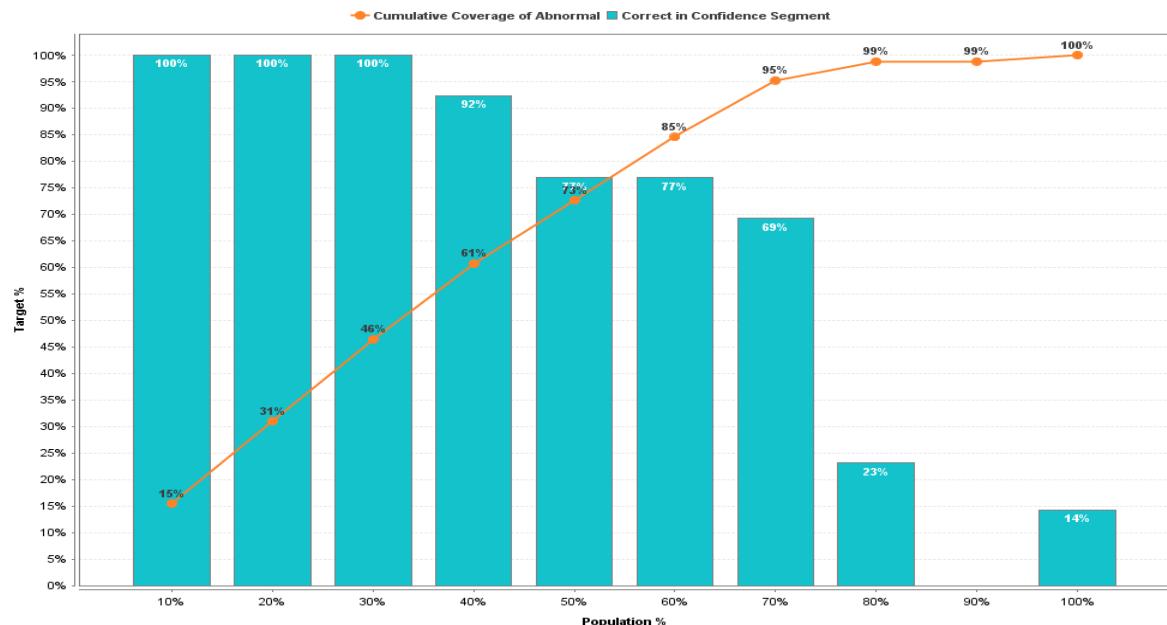


Fig. 6.16 Lift Chart of Logistic Regression Classifier

AUC: 0.964 +/- 0.024 (micro average: 0.964) (positive class: Abnormal)

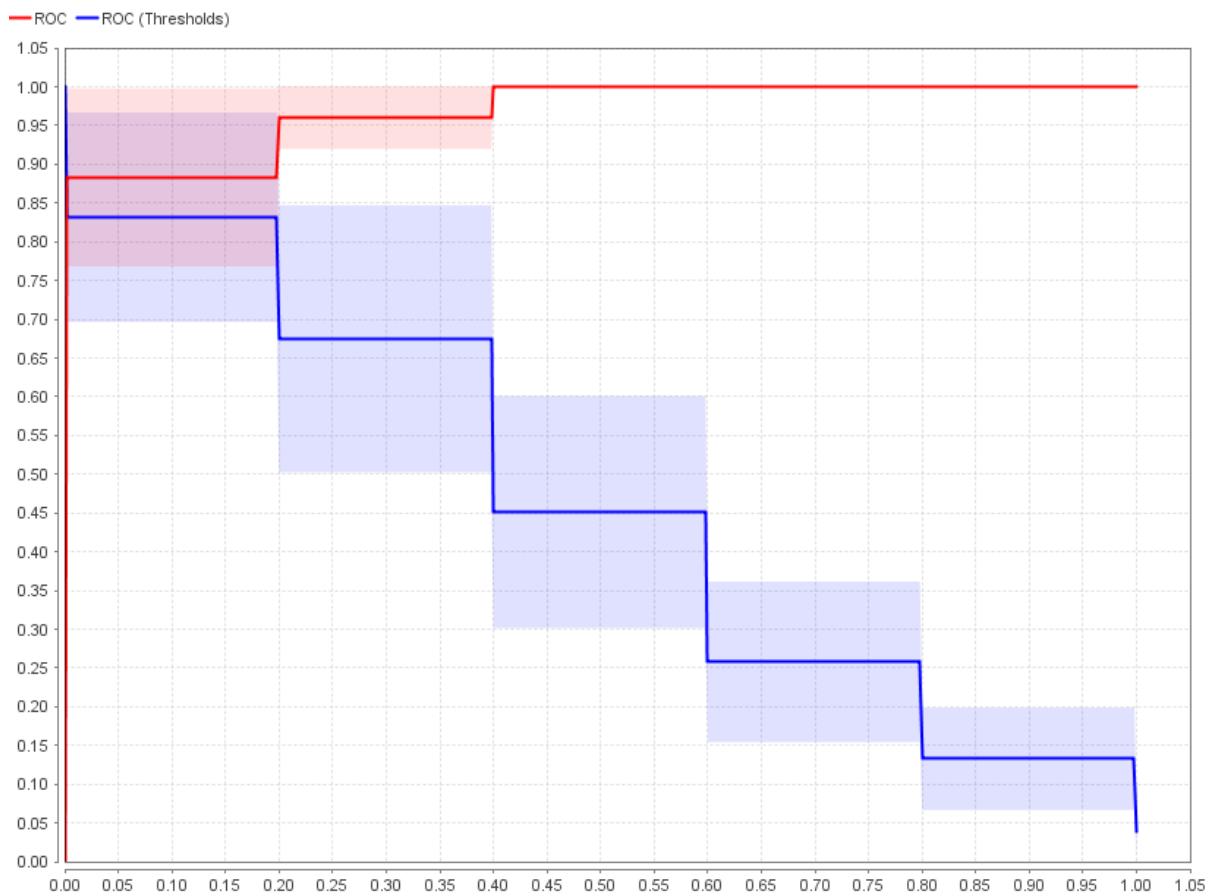


Fig. 6.17 AUC of Logistic Regression Classifier

Predictions given by the Logistic Regression classifier on 124 datapoints is shown in appendix B.2.

6.3 Deep Learning Classifier:

The Deep Learning classifier classifies the used dataset with an **accuracy of 83.87%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.3. Performance parameters are shown below:

accuracy: 83.87%

	true Abnormal	true Normal	class precision
pred. Abnormal	74	10	88.10%
pred. Normal	10	30	75.00%
class recall	88.10%	75.00%	

Fig. 6.18 Accuracy of Deep Learning Classifier

precision: 88.10% (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	30	10	75.00%
pred. Abnormal	10	74	88.10%
class recall	75.00%	88.10%	

Fig. 6.19 Precision of Deep Learning Classifier

f_measure: 88.10% (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	30	10	75.00%
pred. Abnormal	10	74	88.10%
class recall	75.00%	88.10%	

Fig. 6.20 F-measure of Deep Learning Classifier

sensitivity: 88.10% (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	30	10	75.00%
pred. Abnormal	10	74	88.10%
class recall	75.00%	88.10%	

Fig. 6.21 Sensitivity of Deep Learning Classifier

specificity: 75.00% (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	30	10	75.00%
pred. Abnormal	10	74	88.10%
class recall	75.00%	88.10%	

Fig. 6.22 Specificity of Deep Learning Classifier

AUC: 0.904 (positive class: Abnormal)

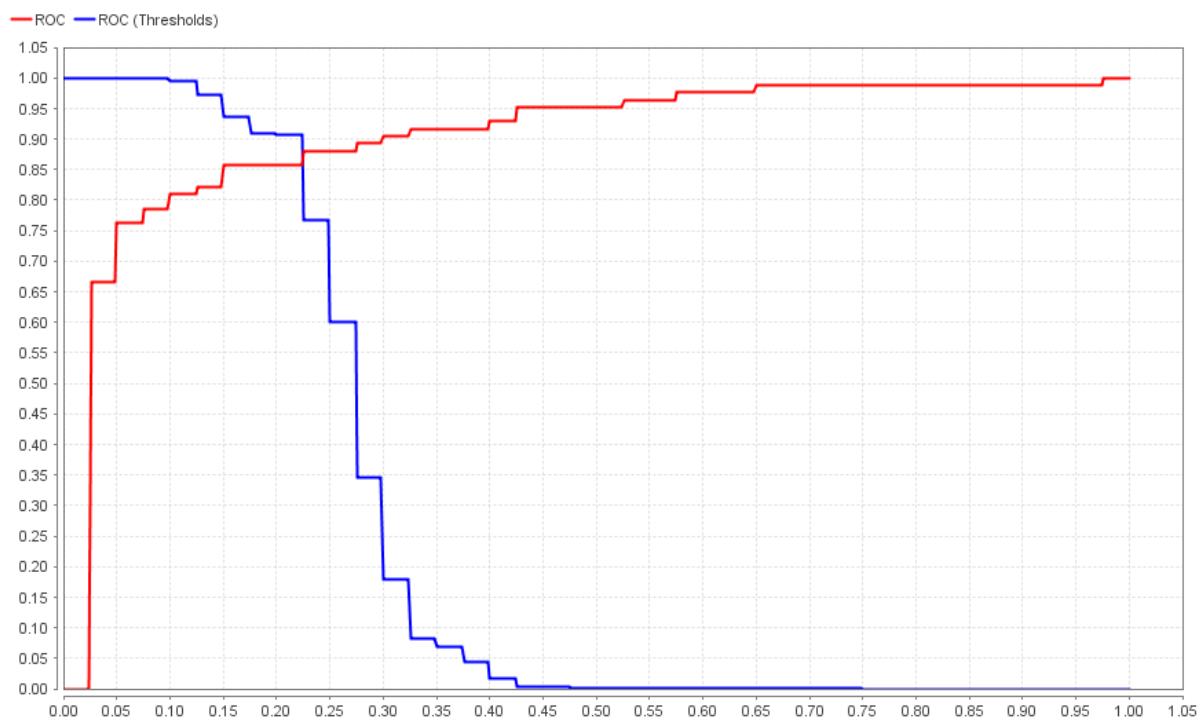


Fig. 6.23 AUC of Deep Learning Classifier

Deep Learning - Weights

Attribute	Weight
Col6	0.449
Col2	0.089
col5/col10	0.082
Col4	0.063
Col5	0.050
Col3	0.027
Col1	0.018
sqrt(col5/col10)	0.007

Fig. 6.24 Weights of attributes of Deep Learning Classifier

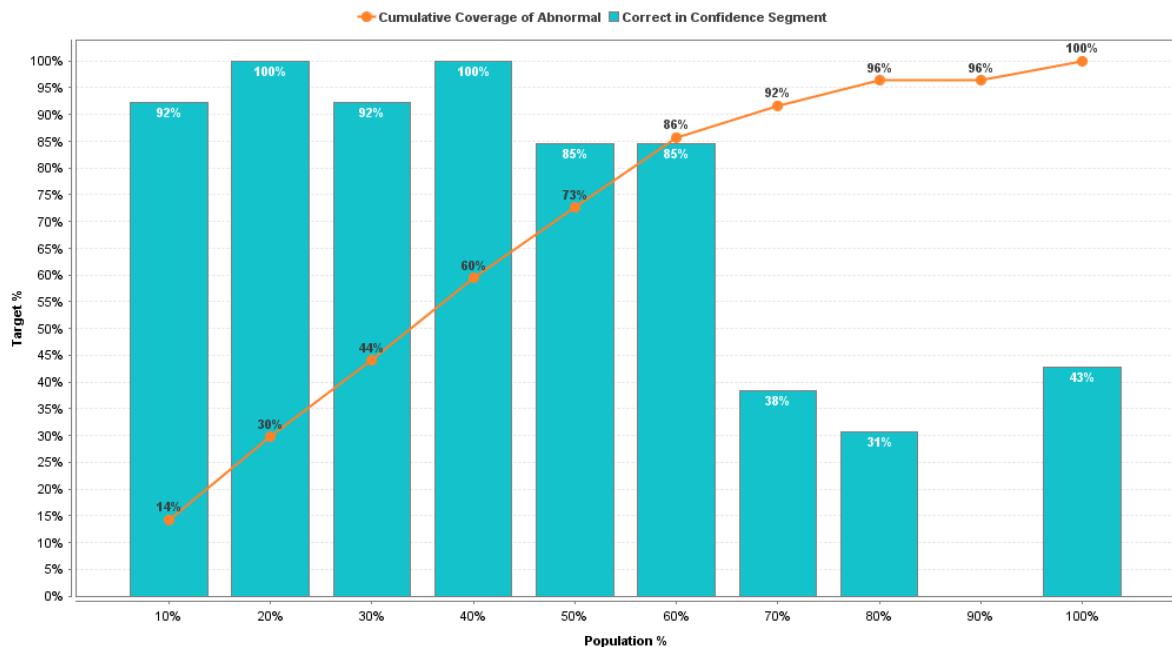


Fig. 6.25 Lift Chart of Deep Learning Classifier

Predictions given by the Deep Learning classifier on 124 datapoints is shown in appendix

B.3. Deep Learning model parameters are described more in Appendix D.

6.4 Random Forest Classifier:

The Random Forest classifier classifies the used dataset with an **accuracy of 82.95%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.4. Performance parameters are shown below:

accuracy: 82.94% +/- 0.54% (micro average: 82.95%)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	10	57	85.07%
class recall	61.54%	91.94%	

Fig. 6.26 Accuracy of Random Forest classifier

precision: 85.69% +/- 5.39% (micro average: 85.07%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	10	57	85.07%
class recall	61.54%	91.94%	

Fig. 6.27 Precision of Random Forest classifier

f_measure: 88.30% +/- 1.02% (micro average: 88.37%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	10	57	85.07%
class recall	61.54%	91.94%	

Fig. 6.28 F_measure of Random Forest classifier

sensitivity: 91.92% +/- 8.03% (micro average: 91.94%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	10	57	85.07%
class recall	61.54%	91.94%	

Fig. 6.29 Sensitivity of Random Forest classifier

specificity: 61.33% +/- 20.22% (micro average: 61.54%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	10	57	85.07%
class recall	61.54%	91.94%	

Fig. 6.30 Specificity of Random Forest classifier

Random Forest - Model

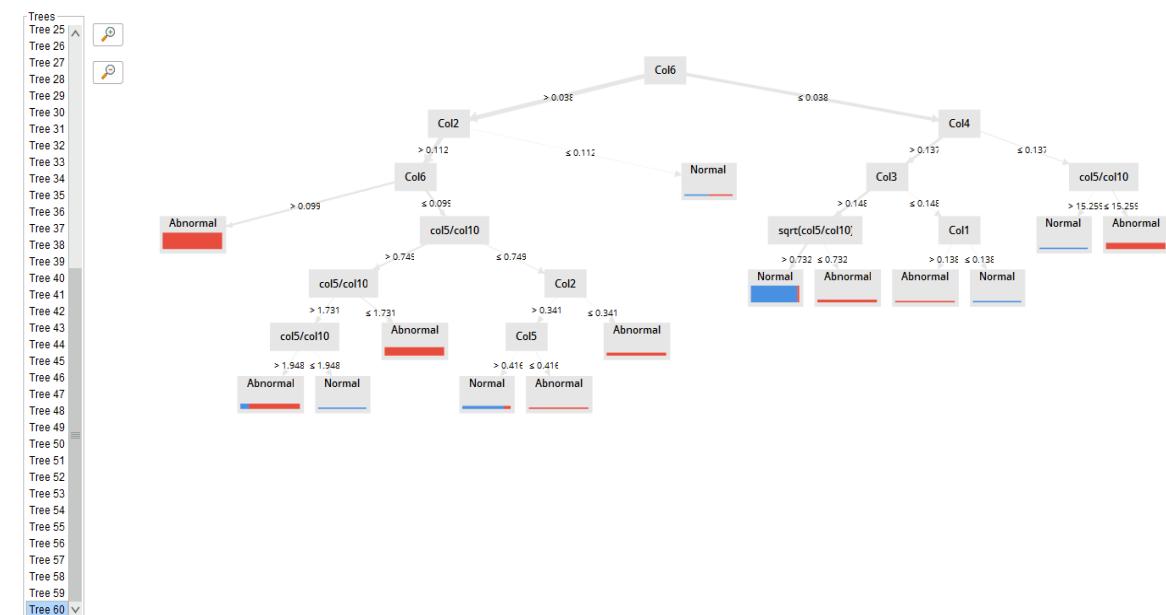


Fig. 6.31 Tree Model of Random Forest classifier

Random Forest - Weights

Attribute	Weight
Col6	0.356
col5/col10	0.134
Col2	0.123
Col1	0.047
Col3	0.044
Col5	0.041
sqrt(col5/col10)	0.035
Col4	0.030

Fig. 6.32 Attributes of Weights of Random Forest classifier

Random Forest - Optimal Parameters

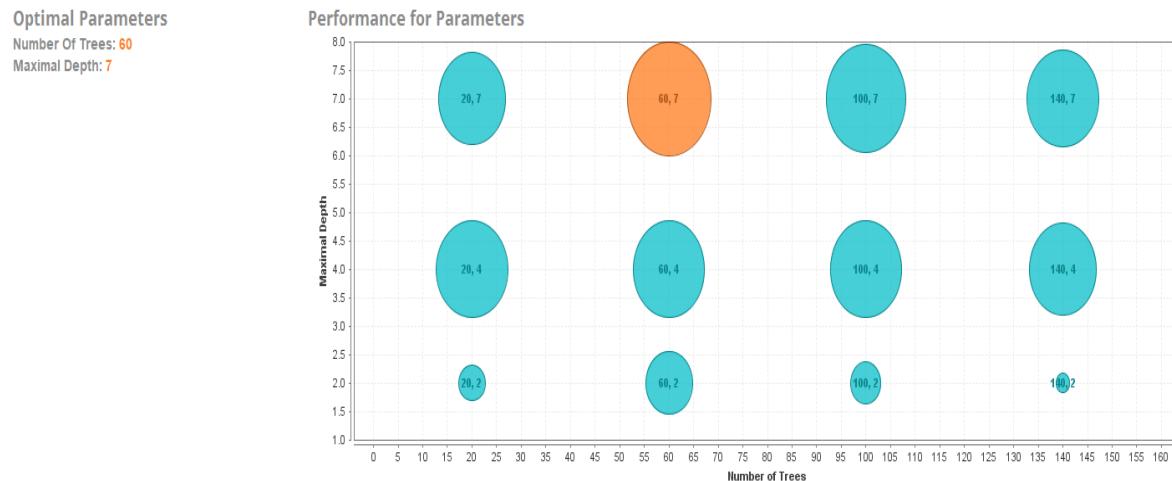


Fig. 6.33 Optimal Parameters of Random Forest classifier

Random Forest - Lift Chart

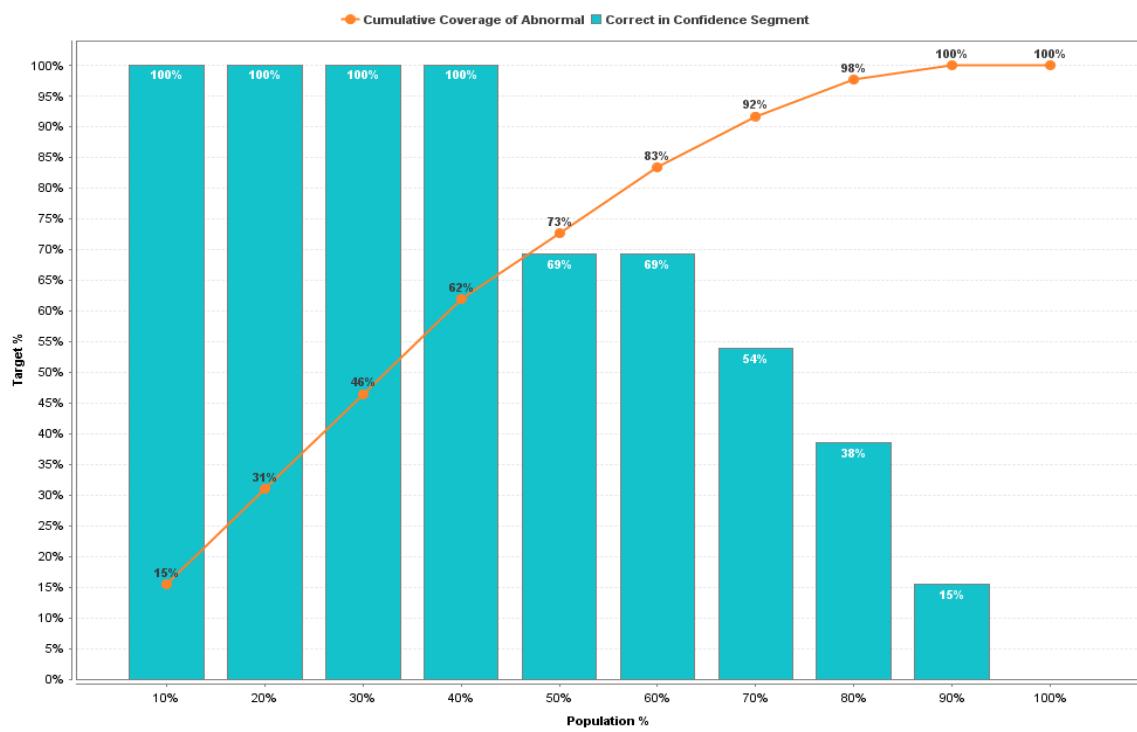


Fig. 6.34 Lift Chart of Random Forest classifier

AUC: 0.938 +/- 0.023 (micro average: 0.938) (positive class: Abnormal)

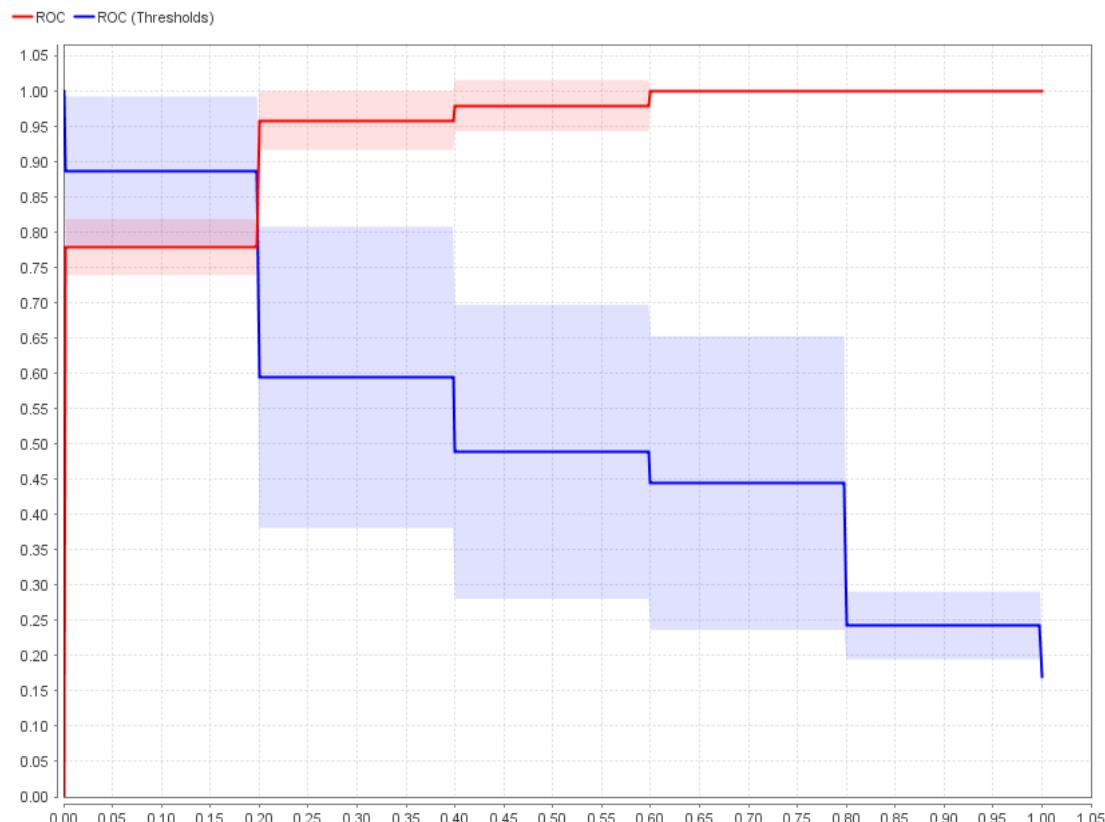


Fig. 6.35 AUC of Random Forest classifier

Predictions given by the Random Forest classifier on 124 datapoints is shown in appendix

B.4.

6.5 Support Vector Machine Classifier:

The Support Vector Machine classifier classifies the used dataset with an **accuracy of 80.68%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.5. Performance parameters are shown below:

accuracy: 80.65% +/- 6.73% (micro average: 80.68%)

	true Normal	true Abnormal	class precision
pred. Normal	20	9	68.97%
pred. Abnormal	8	51	86.44%
class recall	71.43%	85.00%	

Fig. 6.36 Accuracy of Support Vector Machine Classifier

precision: 86.88% +/- 5.52% (micro average: 86.44%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	9	68.97%
pred. Abnormal	8	51	86.44%
class recall	71.43%	85.00%	

Fig. 6.37 Precision of Support Vector Machine Classifier

f_measure: 85.66% +/- 4.81% (micro average: 85.71%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	9	68.97%
pred. Abnormal	8	51	86.44%
class recall	71.43%	85.00%	

Fig. 6.38 F-measure of Support Vector Machine Classifier

sensitivity: 84.83% +/- 7.26% (micro average: 85.00%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	9	68.97%
pred. Abnormal	8	51	86.44%
class recall	71.43%	85.00%	

Fig. 6.39 Sensitivity of Support Vector Machine Classifier

specificity: 69.81% +/- 19.52% (micro average: 71.43%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	20	9	68.97%
pred. Abnormal	8	51	86.44%
class recall	71.43%	85.00%	

Fig. 6.40 Specificity of Support Vector Machine Classifier

Support Vector Machine - Weights

Attribute	Weight
Col6	0.106
sqrt(col5/col10)	0.037
Col3	0.035
Col1	0.026
Col2	0.025
Col4	0.019
Col5	0.012
col5/col10	0.006

Fig. 6.41 Attributes of Weights of Support Vector Machine Classifier

Support Vector Machine - Model

Kernel Model

```
Total number of Support Vectors: 79
Bias (offset): -1.839

w[Col1] = 635.191
w[Col2] = 931.490
w[Col3] = 698.925
w[Col4] = 566.402
w[Col5] = 1296.312
w[col5/col10] = 5112.462
w[Col6] = 119.050
w[sqrt(col5/col10)] = 2945.698

number of classes: 2
number of support vectors for class Abnormal: 41
number of support vectors for class Normal: 38
```

Fig. 6.42 Kernel Model of SVM

Support Vector Machine - Optimal Parameters

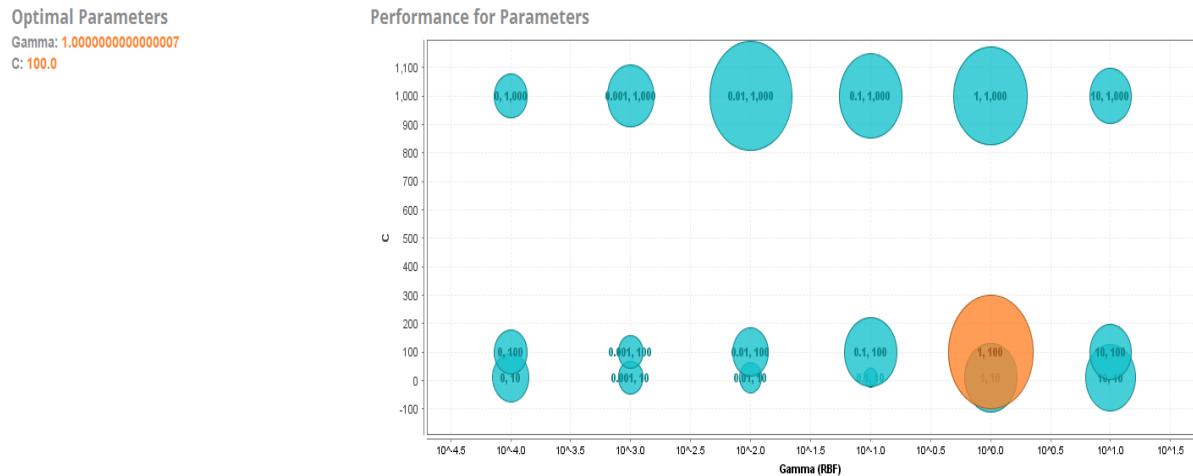


Fig 6.43 Optimal Parameters of Support Vector Machine Classifier

AUC: 0.869 +/- 0.074 (micro average: 0.869) (positive class: Abnormal)

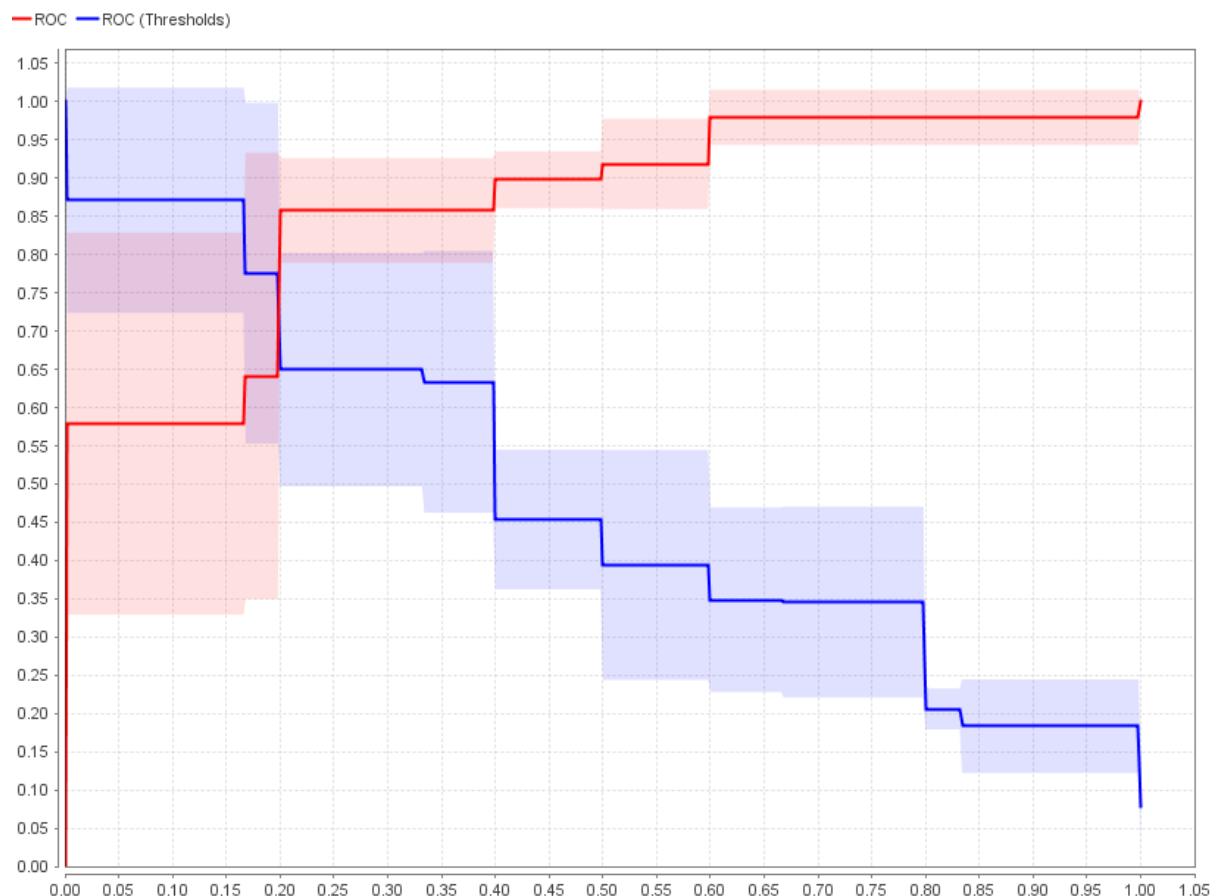


Fig 6.44 AUC of Support Vector Machine Classifier

Support Vector Machine - Lift Chart

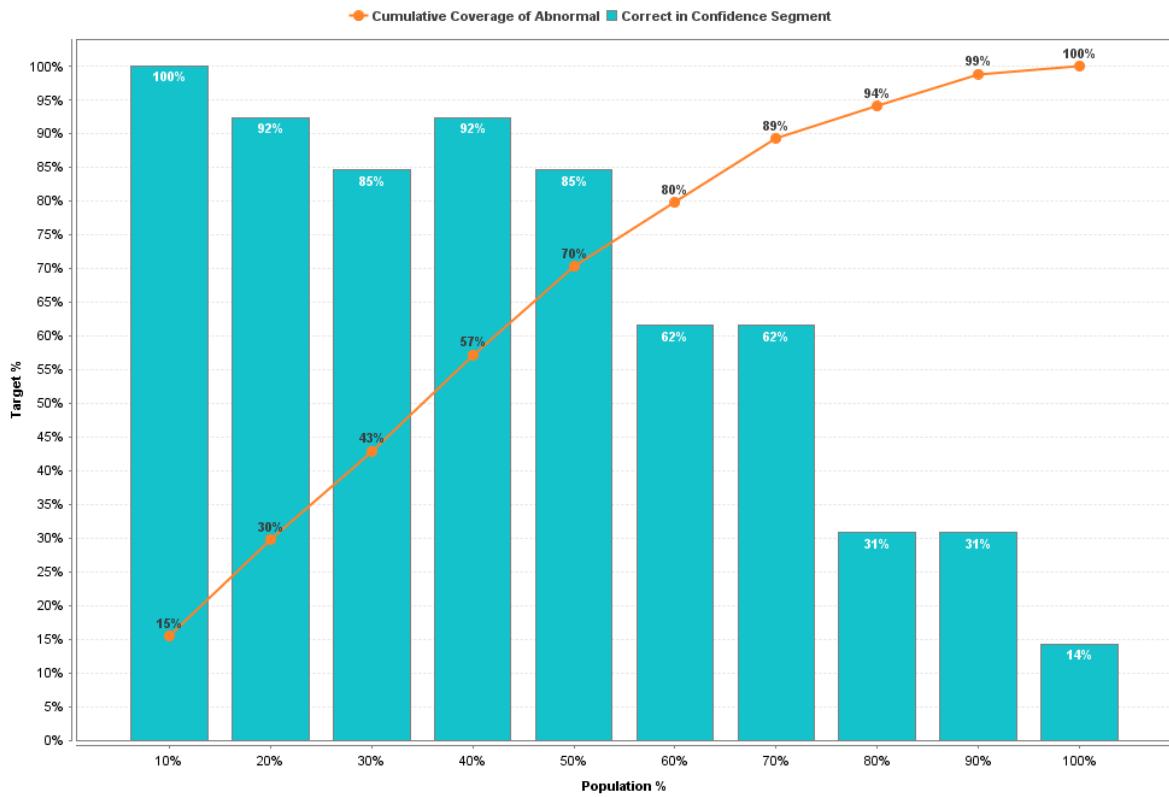


Fig 6.45 Lift chart of Support Vector Machines Classifier

Predictions given by the Support Vector Machines classifier on 124 datapoints is shown in appendix B.5.

6.6 Gradient Boosted Trees:

The Gradient Boosted Trees classifier classifies the used dataset with an **accuracy of 80.90%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.6. Performance parameters are shown below:

accuracy: 80.85% +/- 5.22% (micro average: 80.90%)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	12	56	82.35%
class recall	57.14%	91.80%	

Fig. 6.46 Accuracy of Gradient Boosted Trees

precision: 82.48% +/- 6.02% (micro average: 82.35%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	12	56	82.35%
class recall	57.14%	91.80%	

Fig. 6.47 Precision of Gradient Boosted Trees

f_measure: 86.65% +/- 4.10% (micro average: 86.82%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	12	56	82.35%
class recall	57.14%	91.80%	

Fig. 6.48 F-measure of Gradient Boosted Trees

sensitivity: 91.64% +/- 5.91% (micro average: 91.80%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	12	56	82.35%
class recall	57.14%	91.80%	

Fig. 6.49 Sensitivity of Gradient Boosted Trees

specificity: 57.43% +/- 14.79% (micro average: 57.14%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	16	5	76.19%
pred. Abnormal	12	56	82.35%
class recall	57.14%	91.80%	

Fig. 6.50 Specificity of Gradient Boosted Trees

AUC: 0.923 +/- 0.048 (micro average: 0.923) (positive class: Abnormal)

— ROC — ROC (Thresholds)

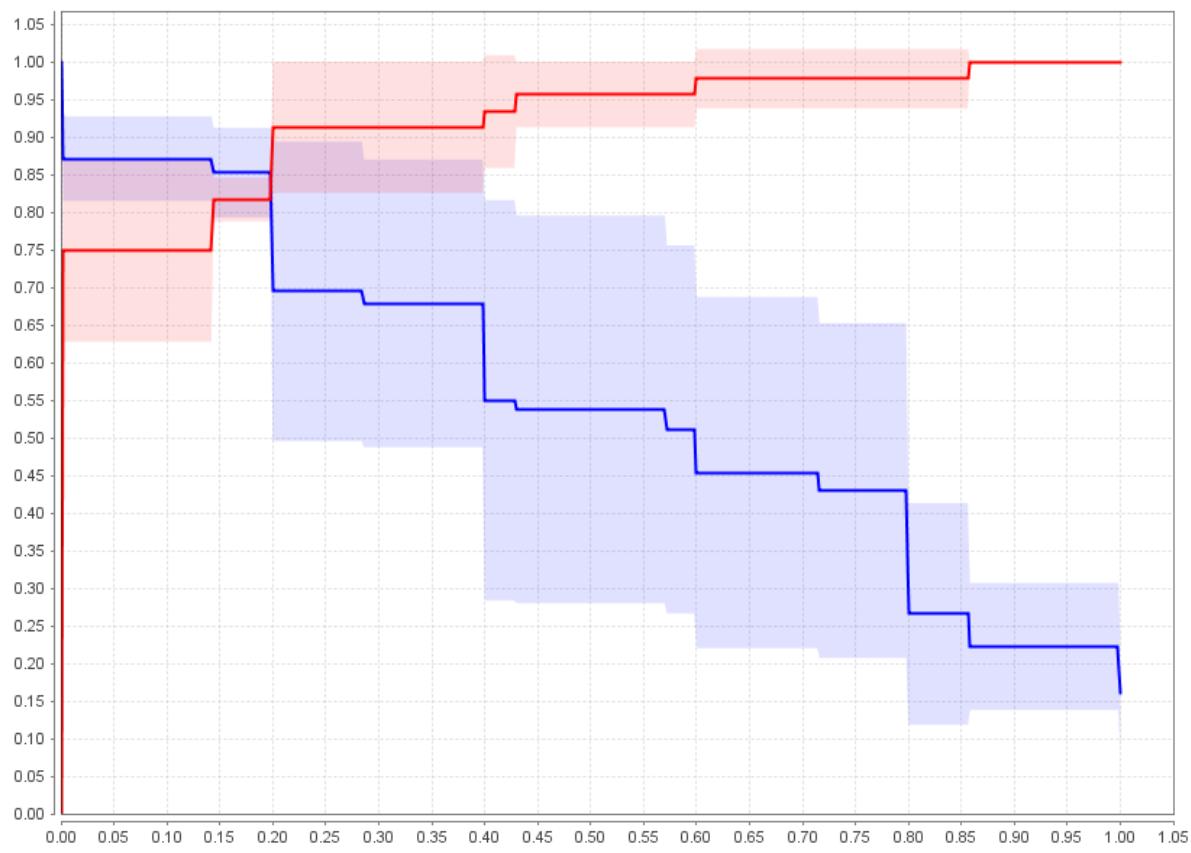


Fig. 6.51 AUC of Gradient Boosted Trees

Gradient Boosted Trees - Weights

Attribute	Weight
Col6	0.415
Col2	0.077
Col4	0.059
col5/col10	0.038
Col5	0.030
Col3	0.022
sqrt(col5/col10)	0.018
Col1	0.011

Fig. 6.52 Attributes of Weights of Gradient Boosted Trees

Gradient Boosted Trees - Model

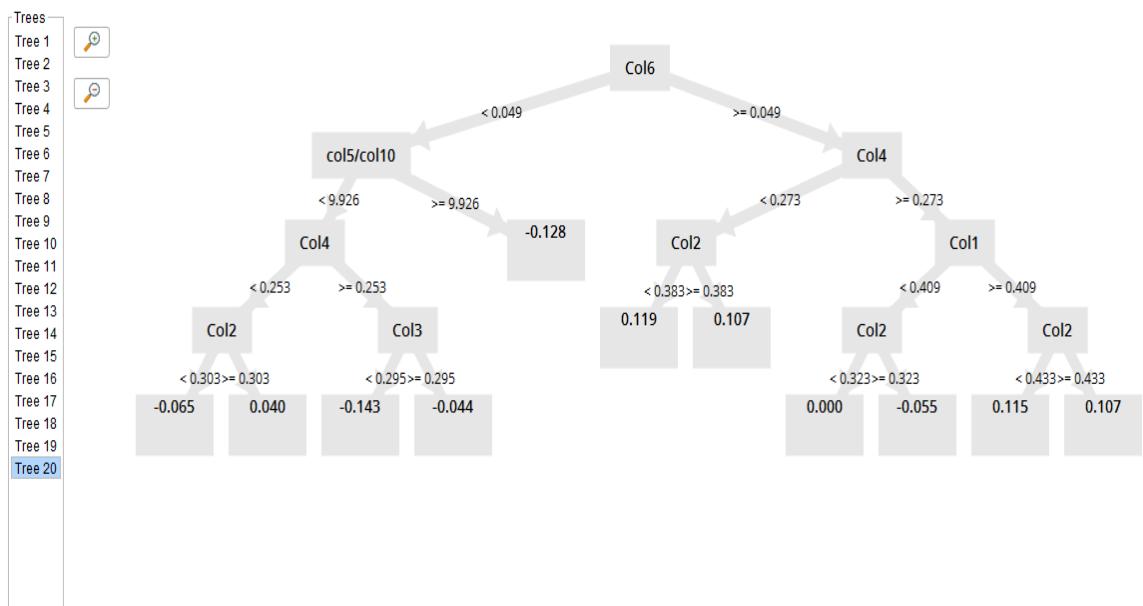


Fig. 6.53 Trees Model of Gradient Boosted Trees

Gradient Boosted Trees - Optimal Parameters

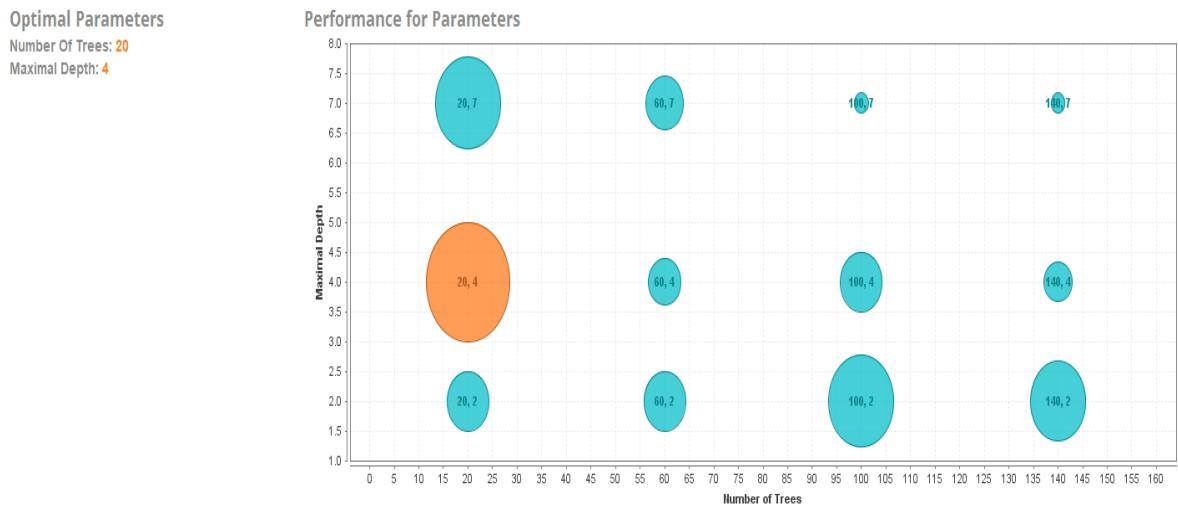


Fig. 6.54 Optimal Parameters of Gradient Boosted Trees

Gradient Boosted Trees - Lift Chart

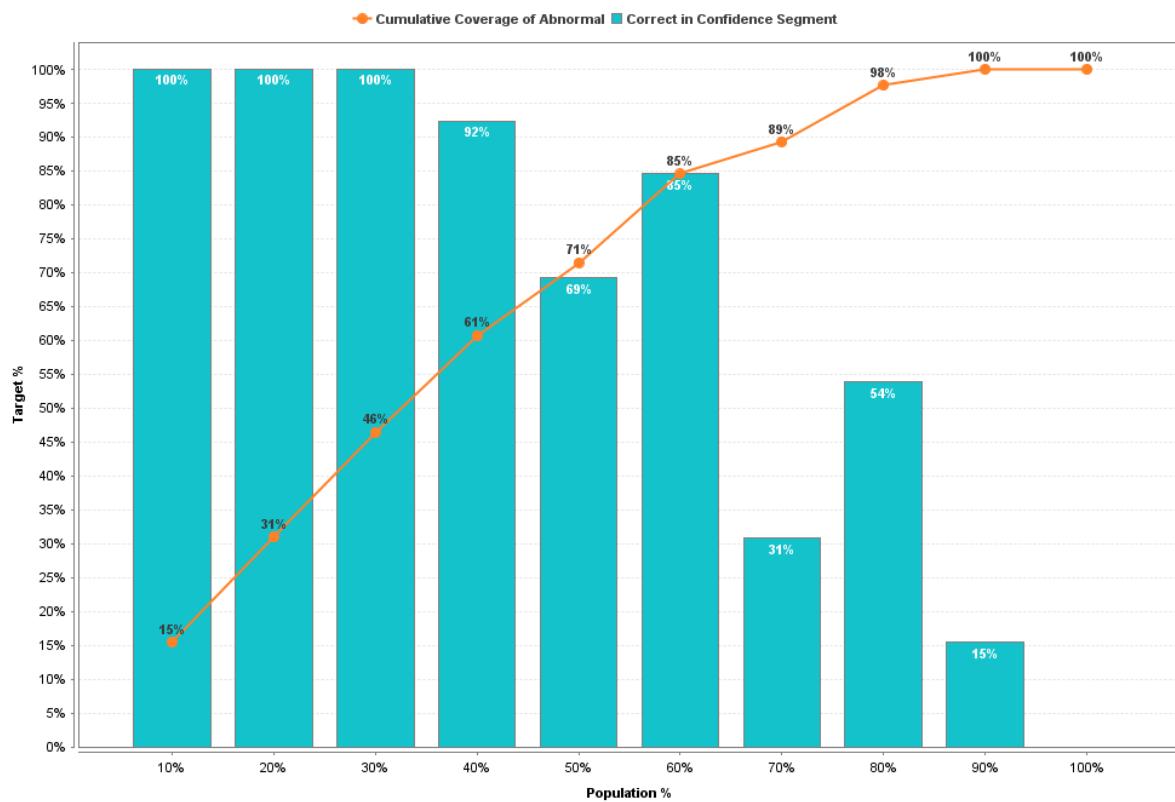


Fig.6.55 Lift Chart of Gradient Boosted Trees

Predictions given by the Gradient Boosted trees classifier on 124 datapoints is shown in appendix B.6.

6.7 Decision Trees:

The Decision Trees classifier classifies the used dataset with an **accuracy of 84.09%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.7. Performance parameters are shown below:

accuracy: 84.05% +/- 6.35% (micro average: 84.09%)

	true Normal	true Abnormal	class precision
pred. Normal	17	5	77.27%
pred. Abnormal	9	57	86.36%
class recall	65.38%	91.94%	

Fig. 6.56 Accuracy of Decision Trees Classifier

precision: 86.27% +/- 3.68% (micro average: 86.36%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	17	5	77.27%
pred. Abnormal	9	57	86.36%
class recall	65.38%	91.94%	

Fig.6.57 Precision of Decision Trees Classifier

f_measure: 88.83% +/- 5.02% (micro average: 89.06%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	17	5	77.27%
pred. Abnormal	9	57	86.36%
class recall	65.38%	91.94%	

Fig. 6.58 F-measure of Decision Trees Classifier

sensitivity: 91.79% +/- 8.34% (micro average: 91.94%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	17	5	77.27%
pred. Abnormal	9	57	86.36%
class recall	65.38%	91.94%	

Fig. 6.59 Sensitivity of Decision Trees Classifier

specificity: 65.33% +/- 8.69% (micro average: 65.38%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	17	5	77.27%
pred. Abnormal	9	57	86.36%
class recall	65.38%	91.94%	

Fig. 6.60 Specificity of Decision Trees Classifier

Decision Tree - Weights

Attribute	Weight
Col6	0.207
col5/col10	0.114
Col1	0.041
Col2	0.038
Col4	0.035
Col3	0.022
sqrt(col5/col10)	0.019
Col5	0.009

Fig. 6.61 Attributes of Weights of Decision Trees Classifier

Decision Tree - Model

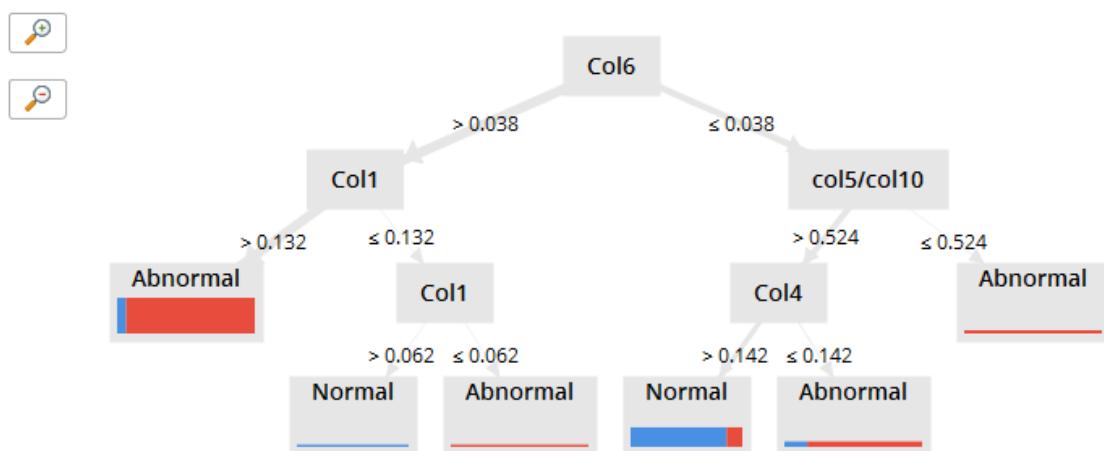


Fig. 6.62 Tree Model of Decision Trees Classifier

AUC: 0.824 +/- 0.069 (micro average: 0.824) (positive class: Abnormal)

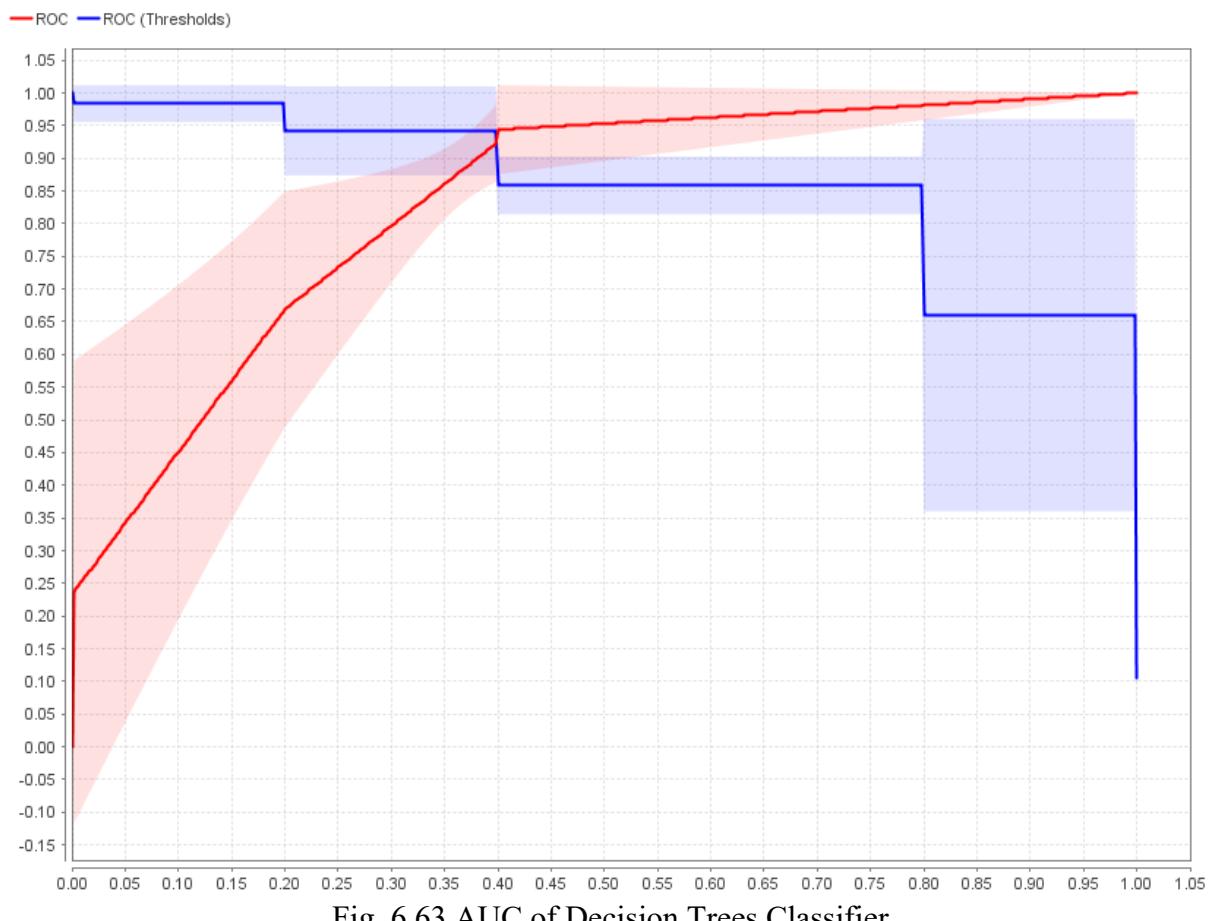


Fig. 6.63 AUC of Decision Trees Classifier

Decision Tree - Optimal Parameters

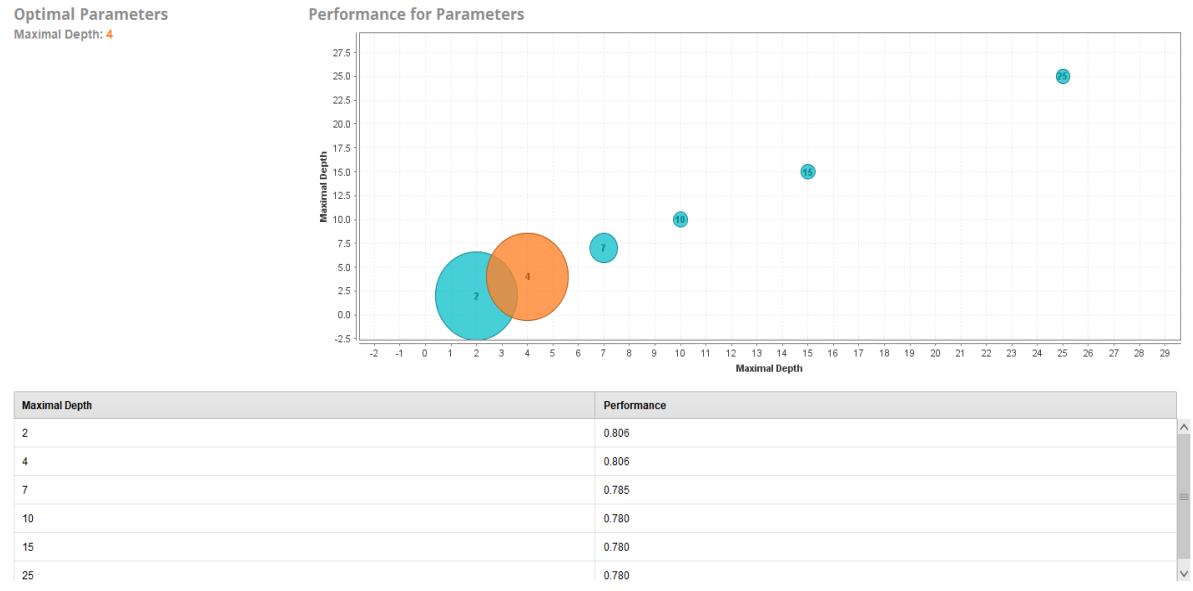


Fig. 6.64 Optimal Parameter Performance of Decision Trees Classifier

Decision Tree - Lift Chart

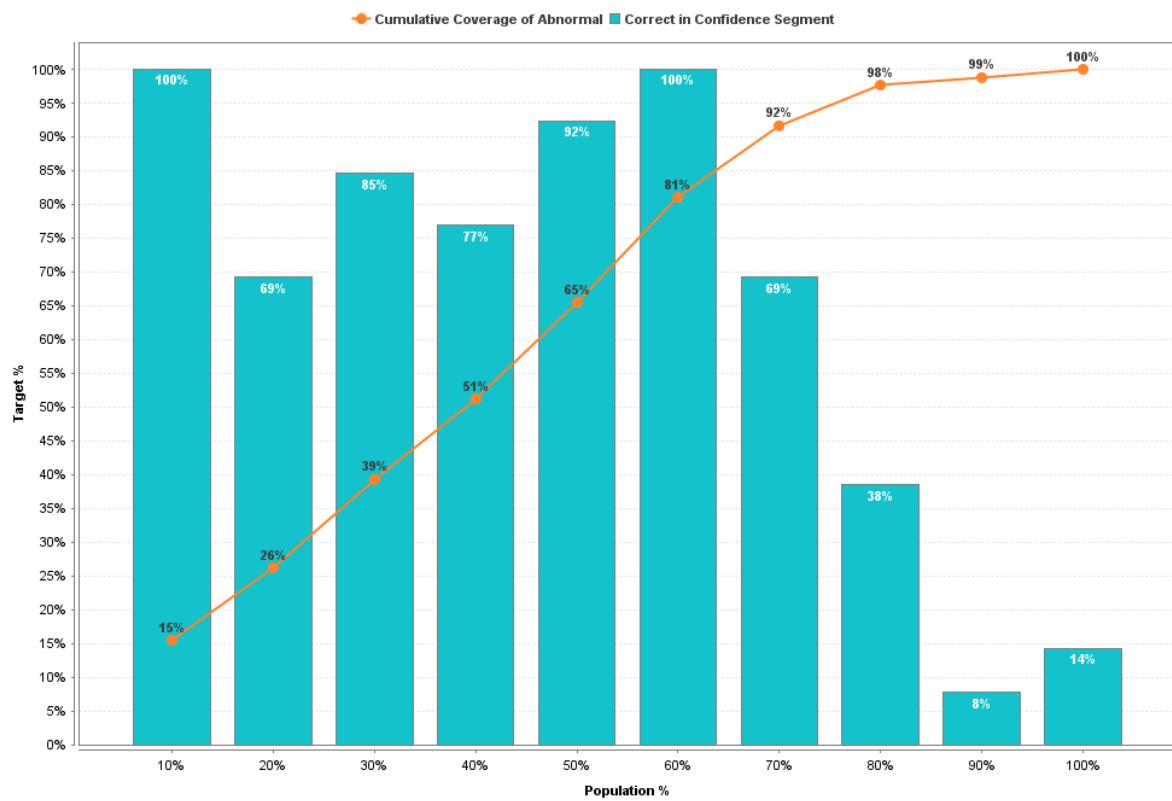


Fig. 6.65 Lift Chart of Decision Trees Classifier

Predictions given by the Decision Trees classifier on 124 datapoints is shown in appendix B.7.

6.8 Artificial Neural Networks (ANN) Classifier:

The Artificial Neural Networks (ANN) Classifier classifies the used dataset with an **accuracy of 88.64%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.8. Performance parameters are shown below:

accuracy: 88.63% +/- 0.36% (micro average: 88.64%)

	true Normal	true Abnormal	class precision
pred. Normal	22	4	84.62%
pred. Abnormal	6	56	90.32%
class recall	78.57%	93.33%	

Fig. 6.66 Accuracy of ANN Classifier

precision: 90.52% +/- 2.18% (micro average: 90.32%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	22	4	84.62%
pred. Abnormal	6	56	90.32%
class recall	78.57%	93.33%	

Fig. 6.67 Precision of ANN Classifier

f_measure: 91.75% +/- 0.70% (micro average: 91.80%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	22	4	84.62%
pred. Abnormal	6	56	90.32%
class recall	78.57%	93.33%	

Fig. 6.68 F-measure of ANN Classifier

sensitivity: 93.18% +/- 3.83% (micro average: 93.33%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	22	4	84.62%
pred. Abnormal	6	56	90.32%
class recall	78.57%	93.33%	

Fig. 6.69 Sensitivity of ANN Classifier

specificity: 77.81% +/- 10.24% (micro average: 78.57%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	22	4	84.62%
pred. Abnormal	6	56	90.32%
class recall	78.57%	93.33%	

Fig. 6.70 Specificity of ANN Classifier

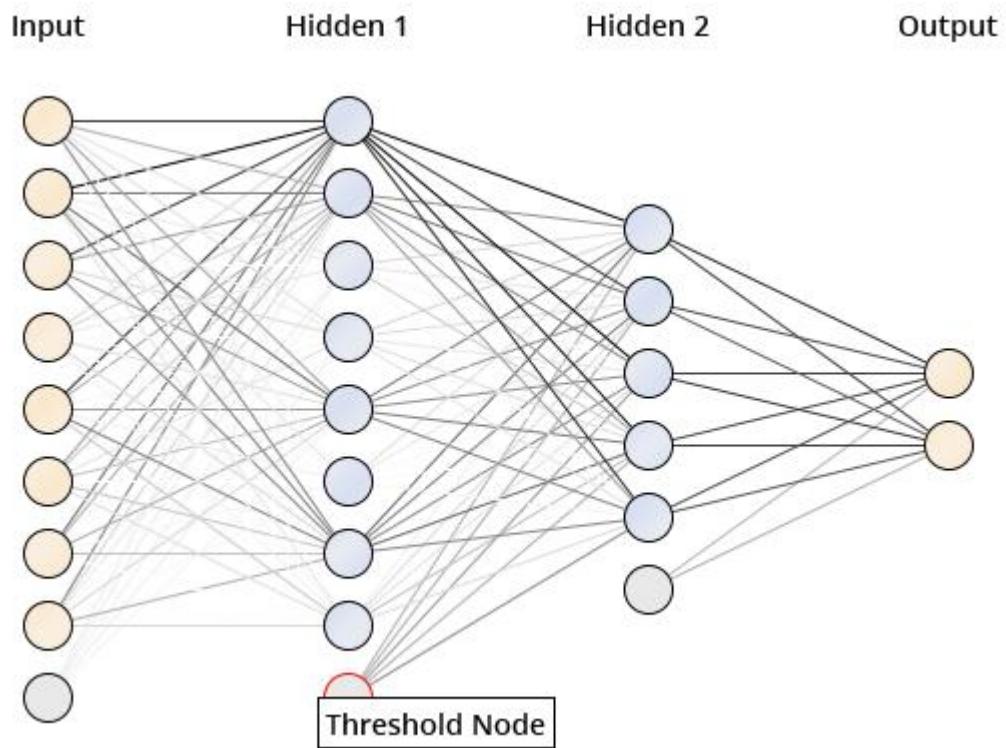


Fig. 6.71 ANN Model

attribute	weight
Col6	0.450
Col2	0.108
Col4	0.067
col5/col10	0.055
Col5	0.041
sqrt(col5...)	0.039
Col3	0.028
Col1	0.017

Table 6.1. Attributes of ANN Classifier

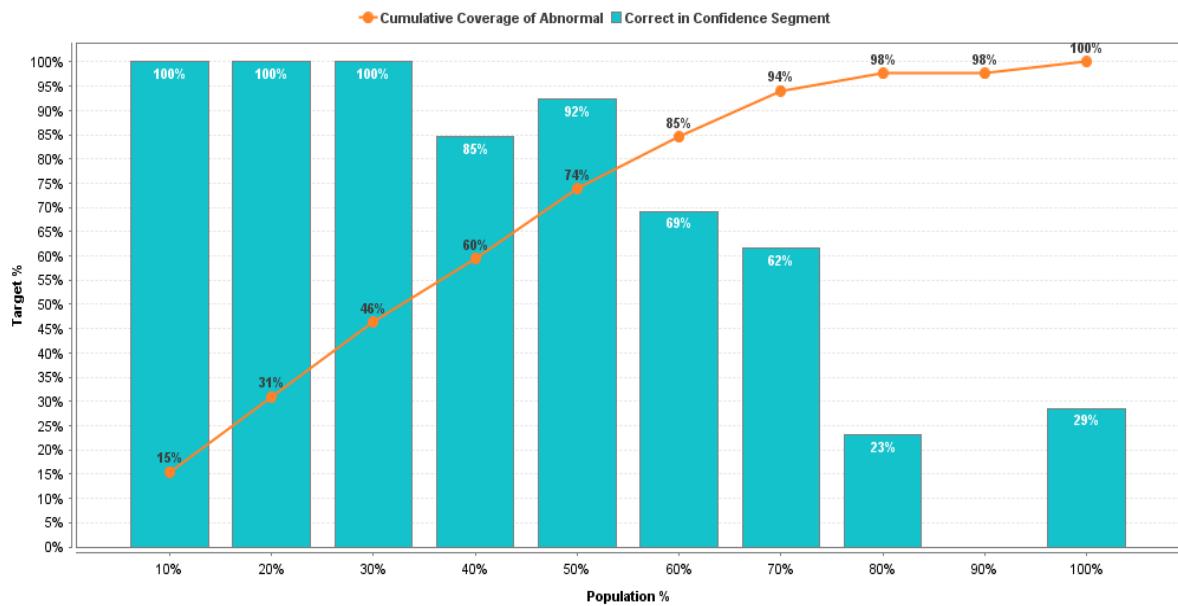


Fig.6.72 Lift Chart of ANN Classifier

AUC: 0.943 +/- 0.026 (micro average: 0.943) (positive class: Abnormal)

— ROC — ROC (Thresholds)

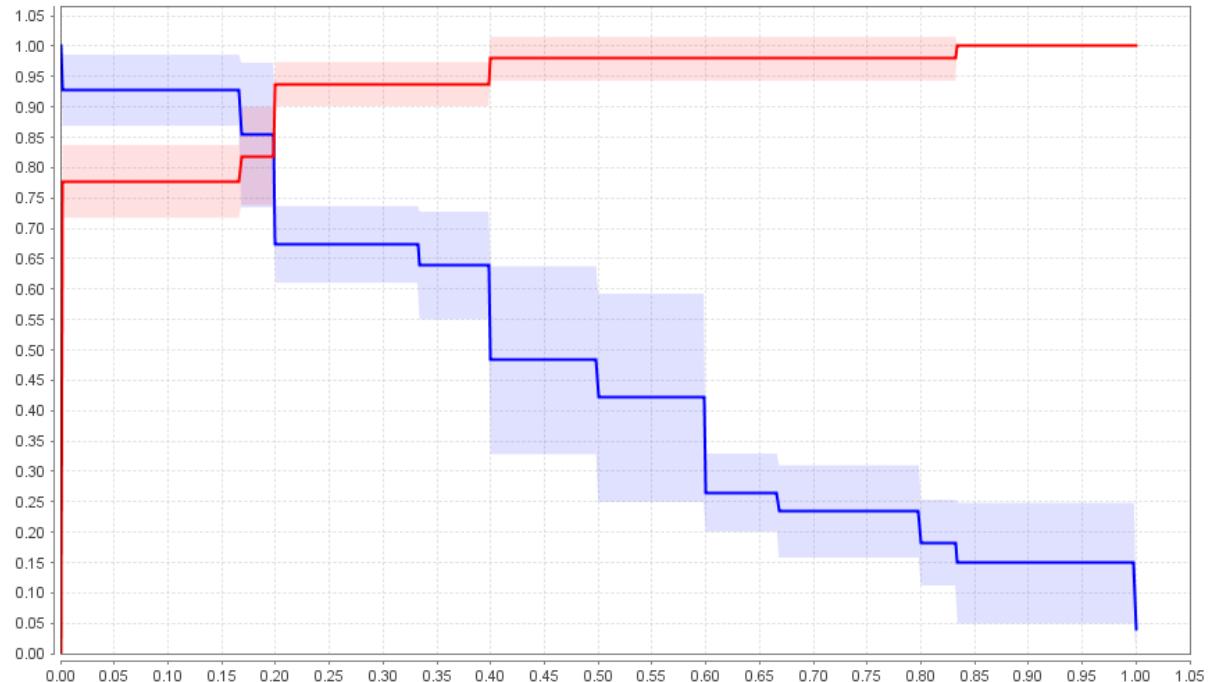


Fig. 6.73 AUC of ANN Classifier

Predictions given by the ANN classifier on 124 datapoints is shown in appendix B.8. It may be worth mentioning that due to software limitation of Rapid miner which only uses momentum backpropagation as training algorithm. To change the training algorithm, same

model was framed in MATLAB using different training algorithm and results are record which are pretty much similar to this. Results for MATLAB ANN classifier are shown in Appendix E.

6.9 Multilayer Perceptron (MLP):

The Multilayer Perceptron (MLP) Classifier classifies the used dataset with an **accuracy of 84.09%** on test dataset. The Process Flow diagram and the Model Parameters of this classifier are shown in Appendix A.9. Performance parameters are shown below:

accuracy: 84.12% +/- 2.34% (micro average: 84.09%)

	true Normal	true Abnormal	class precision
pred. Normal	21	7	75.00%
pred. Abnormal	7	53	88.33%
class recall	75.00%	88.33%	

Fig. 6.74 Accuracy of MLP Classifier

precision: 88.58% +/- 3.20% (micro average: 88.33%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	21	7	75.00%
pred. Abnormal	7	53	88.33%
class recall	75.00%	88.33%	

Fig. 6.75 Precision of MLP Classifier

f_measure: 88.25% +/- 2.25% (micro average: 88.33%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	21	7	75.00%
pred. Abnormal	7	53	88.33%
class recall	75.00%	88.33%	

Fig. 6.76 F_measure of MLP Classifier

sensitivity: 88.16% +/- 5.13% (micro average: 88.33%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	21	7	75.00%
pred. Abnormal	7	53	88.33%
class recall	75.00%	88.33%	

Fig. 6.77 Sensitivity of MLP Classifier

specificity: 74.48% +/- 10.70% (micro average: 75.00%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	21	7	75.00%
pred. Abnormal	7	53	88.33%
class recall	75.00%	88.33%	

Fig.6.78 Specificity of MLP Classifier

attribute	weight
Col6	0.434
Col2	0.076
col5/col10	0.055
Col4	0.042
Col1	0.033
Col5	0.028
Col3	0.020
sqrt(col5...	0.005

Table 6.2. Attributes of Weights of MLP Classifier

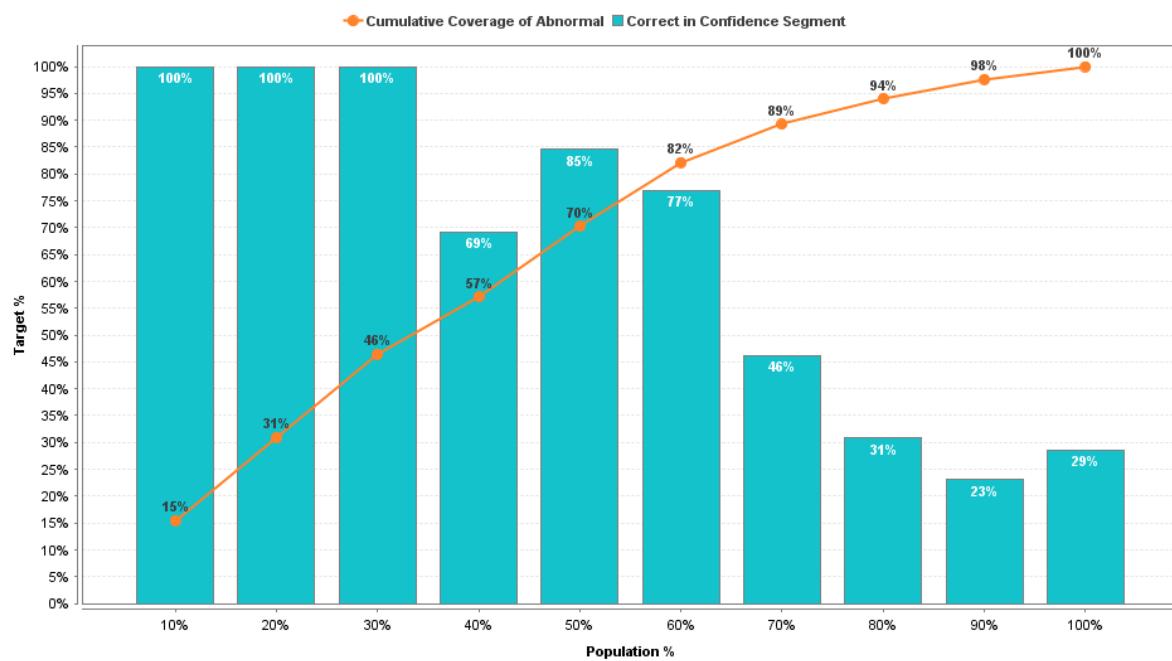


Fig.6.79 Lift Chart of Weights of MLP Classifier

AUC: 0.893 +/- 0.038 (micro average: 0.893) (positive class: Abnormal)

— ROC — ROC (Thresholds)

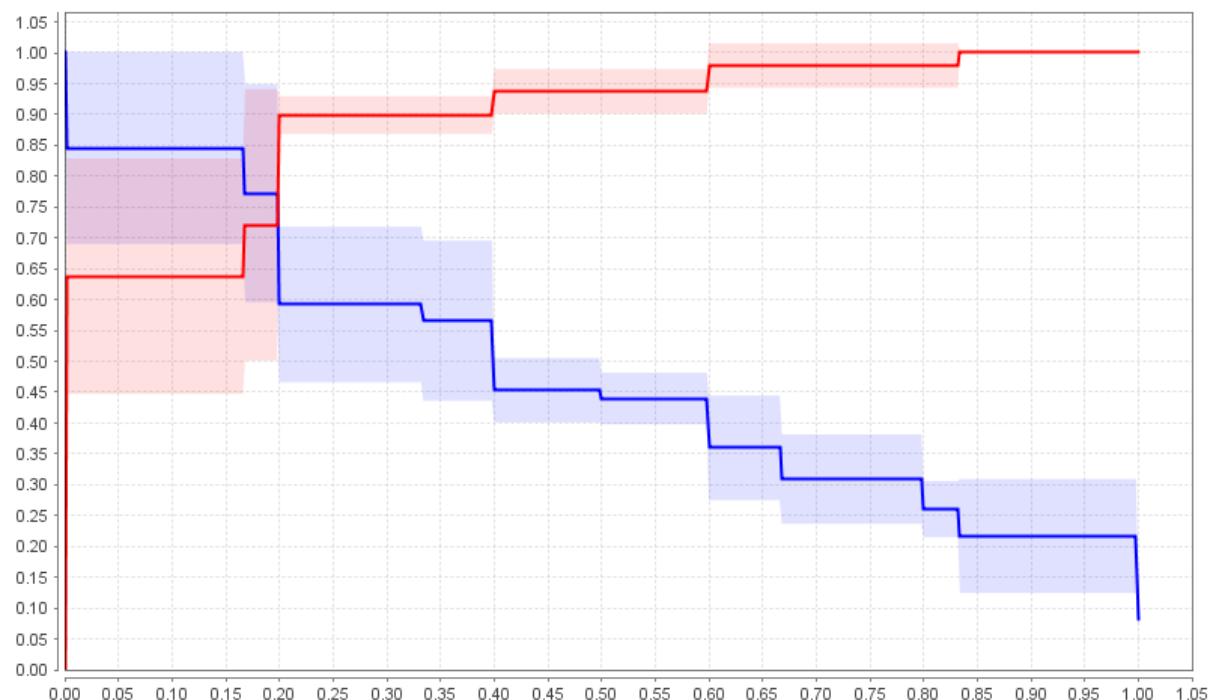


Fig. 6.80 AUC of MLP Classifier

Network Model of MLP Classifier along with final updated weights of each node in Hidden Layer and Output Layer is shown in Appendix C.1 and C.2 respectively.

Predictions given by the MLP classifier on 124 datapoints is shown in appendix B.9.

6.10 KNN Classifier:

The KNN Classifier classifies the used dataset with an **accuracy of 75%** on test dataset.

Process Flow diagram of this classifier is shown in Appendix A.10. Performance parameters are shown below:

accuracy: 74.90% +/- 6.95% (micro average: 75.00%)

	true Normal	true Abnormal	class precision
pred. Normal	14	8	63.64%
pred. Abnormal	14	52	78.79%
class recall	50.00%	86.67%	

Fig. 6.81 Accuracy of KNN Classifier

precision: 79.03% +/- 4.62% (micro average: 78.79%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	14	8	63.64%
pred. Abnormal	14	52	78.79%
class recall	50.00%	86.67%	

Fig. 6.82 Precision of KNN Classifier

f_measure: 82.49% +/- 4.30% (micro average: 82.54%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	14	8	63.64%
pred. Abnormal	14	52	78.79%
class recall	50.00%	86.67%	

Fig. 6.83 F-measure of KNN Classifier

sensitivity: 86.62% +/- 7.54% (micro average: 86.67%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	14	8	63.64%
pred. Abnormal	14	52	78.79%
class recall	50.00%	86.67%	

Fig. 6.84 Sensitivity of KNN Classifier

specificity: 48.29% +/- 19.65% (micro average: 50.00%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	14	8	63.64%
pred. Abnormal	14	52	78.79%
class recall	50.00%	86.67%	

Fig.6.85 Specificity of KNN Classifier

attribute	weight
col5/col10	0.228
Col6	0.057
sqrt(col5...	0.052
Col1	0.049
Col2	0.025
Col3	0.014
Col4	0.008
Col5	0.007

Table 6.3. Attributes of Weights of KNN Classifier

AUC: 0.793 +/- 0.078 (micro average: 0.793) (positive class: Abnormal)

— ROC — ROC (Thresholds)

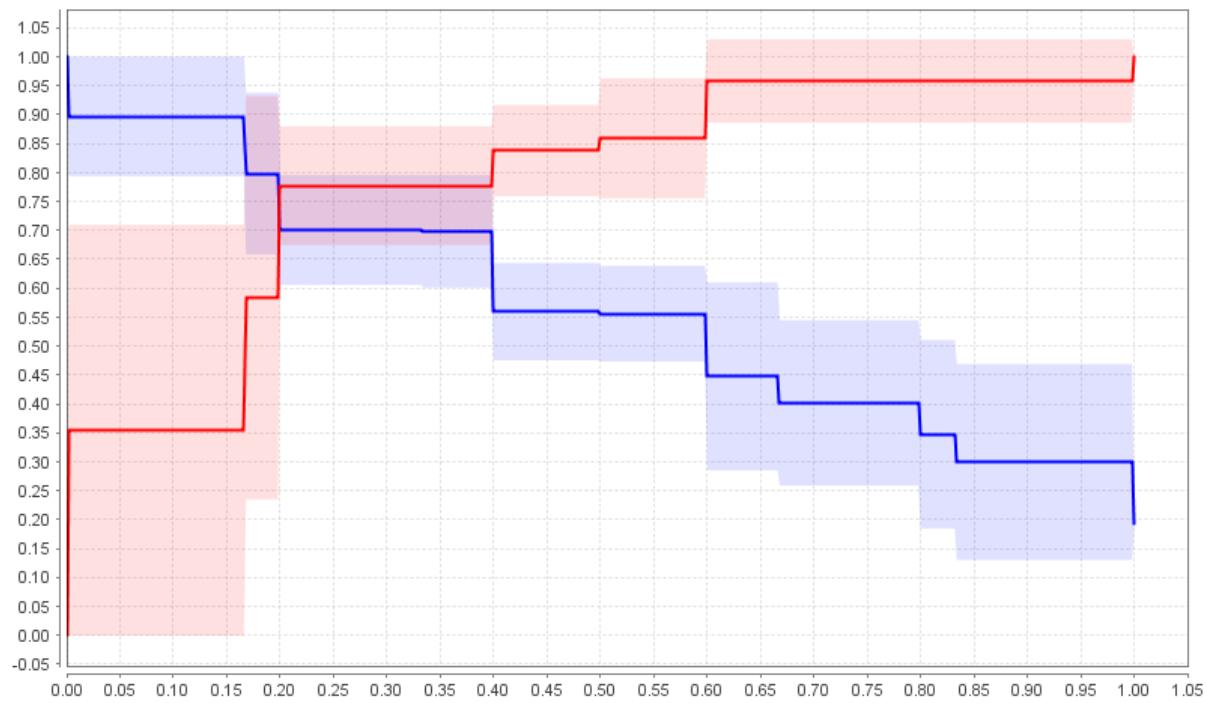


Fig. 6.86 AUC of KNN Classifier

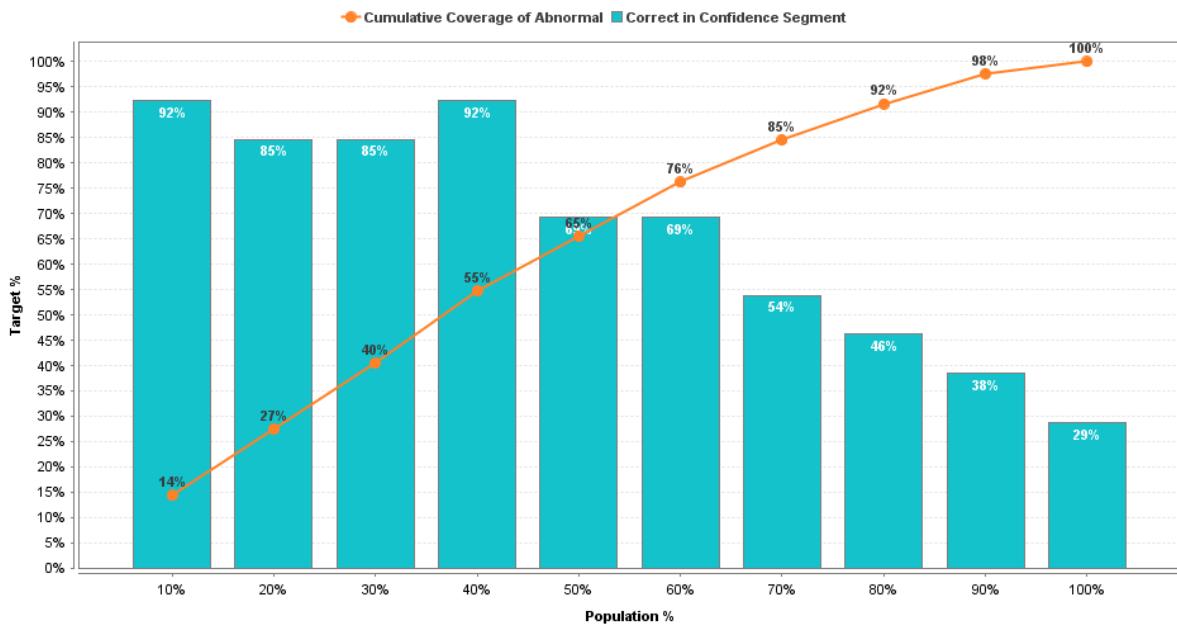


Fig. 6.87 Lift Chart of KNN Classifier

Predictions given by the KNN classifier on 124 datapoints is shown in appendix B.10.

6.11 Fast Large Margin:

The Fast-Large Margin Classifier classifies the used dataset with an **accuracy of 82.95%** on test dataset. The Process Flow diagram of this classifier is shown in Appendix A.6. The Performance parameters are shown below:

accuracy: 82.94% +/- 3.96% (micro average: 82.95%)

	true Normal	true Abnormal	class precision
pred. Normal	12	1	92.31%
pred. Abnormal	14	61	81.33%
class recall	46.15%	98.39%	

Fig. 6.88 Accuracy of Fast Large Margin Classifier

precision: 81.30% +/- 3.15% (micro average: 81.33%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	12	1	92.31%
pred. Abnormal	14	61	81.33%
class recall	46.15%	98.39%	

Fig. 6.89 Precision of Fast Large Margin Classifier

f_measure: 88.98% +/- 2.94% (micro average: 89.05%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	12	1	92.31%
pred. Abnormal	14	61	81.33%
class recall	46.15%	98.39%	

Fig. 6.90 F_measure of Fast Large Margin Classifier

sensitivity: 98.33% +/- 3.73% (micro average: 98.39%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	12	1	92.31%
pred. Abnormal	14	61	81.33%
class recall	46.15%	98.39%	

Fig. 6.91 Sensitivity of Fast Large Margin Classifier

specificity: 46.00% +/- 8.94% (micro average: 46.15%) (positive class: Abnormal)

	true Normal	true Abnormal	class precision
pred. Normal	12	1	92.31%
pred. Abnormal	14	61	81.33%
class recall	46.15%	98.39%	

Fig. 6.92 Specificity of Fast Large Margin Classifier

Fast Large Margin - Model

Fig.6.93 FLM Model

```
- 1.918 * Col1
+ 3.474 * Col2
- 0.144 * Col3
- 3.368 * Col4
- 5.969 * Col5
+ 0.248 * col5/col10
+ 20.827 * Col6
+ 0.959 * sqrt(col5/col10)
+ 1.530
```

Fast Large Margin - Weights

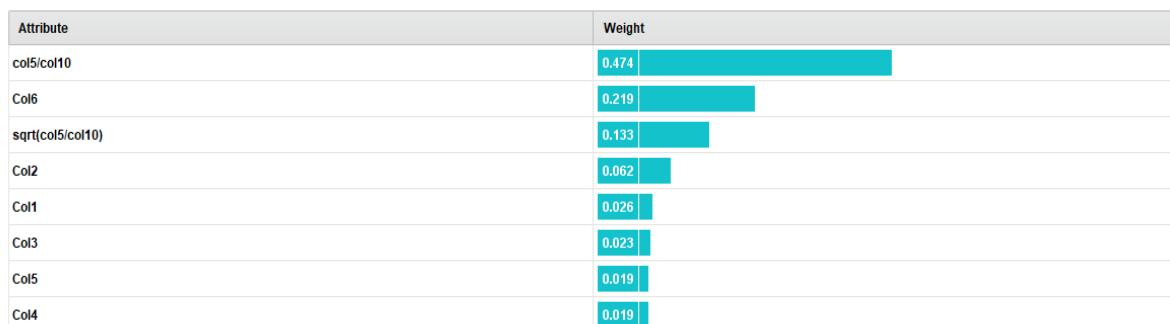


Fig. 6.94 Weights of Attributes of Fast Large Margin Classifier

Fast Large Margin - Optimal Parameters

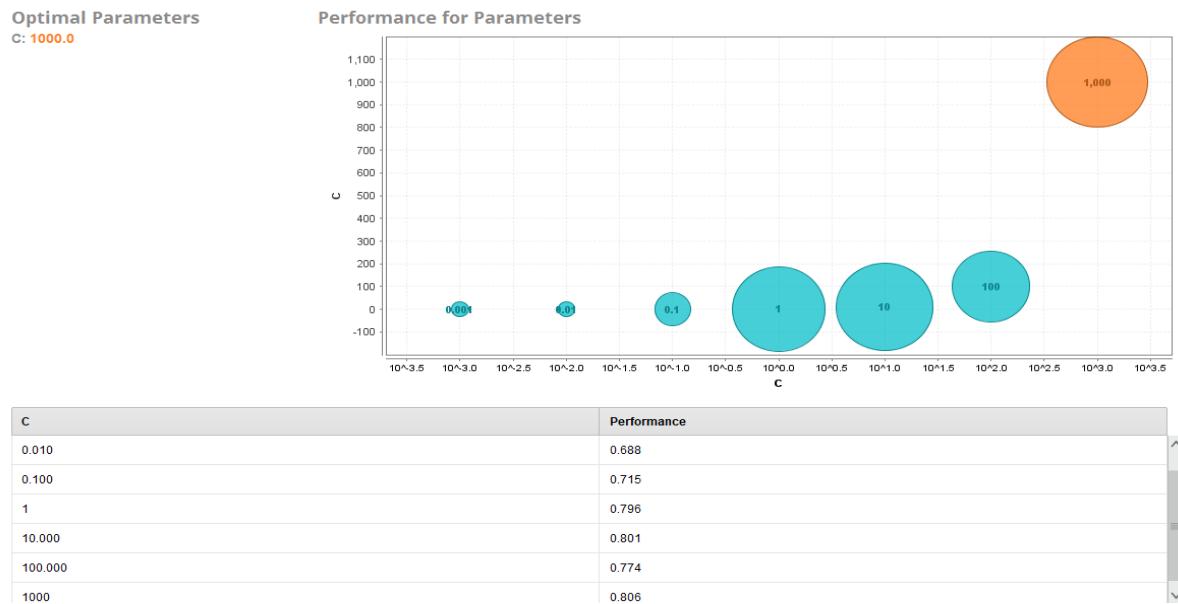


Fig. 6.95 Optimal Parameters' Performance of Fast Large Margin Classifier

AUC: 0.893 +/- 0.032 (micro average: 0.893) (positive class: Abnormal)

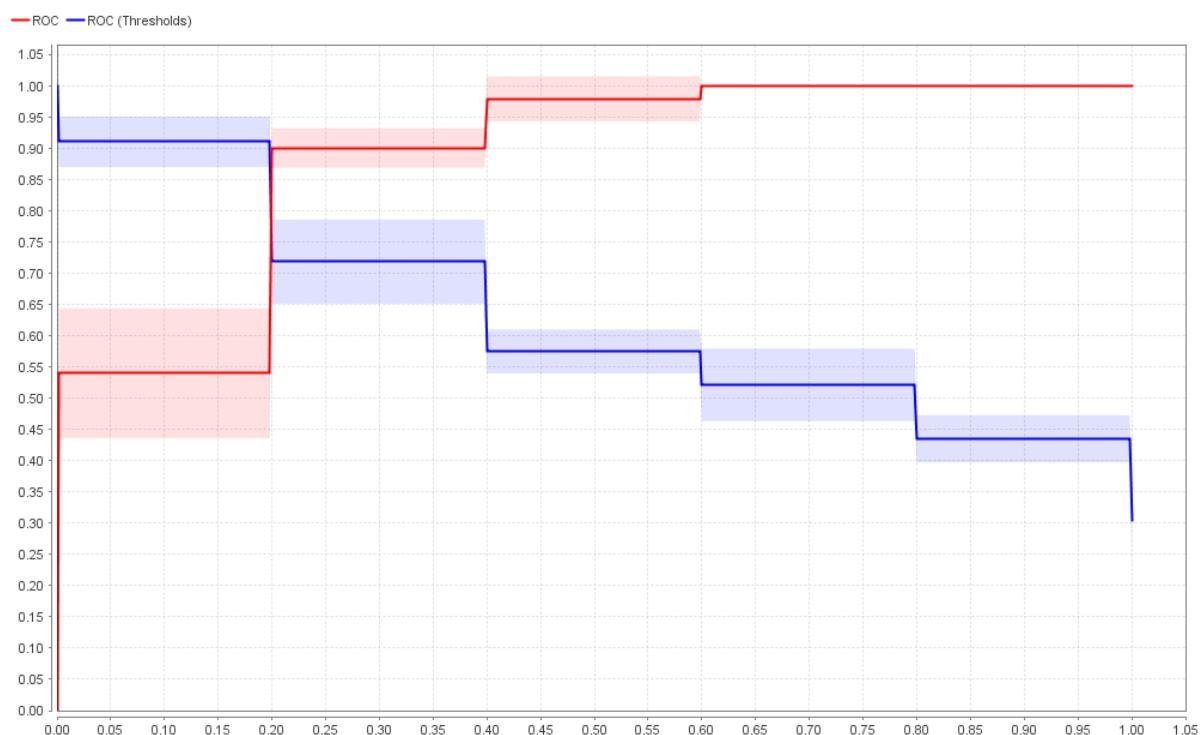


Fig. 6.96 AUC of Fast Large Margin Classifier

Predictions given by the FLM classifier on 124 data points is shown in appendix B.11.

6.12 Comparing Performance of Machine Learning based Classification models:

This section compares various performance parameters of 11 machine learning based classification models used in the study.

6.12.1 Accuracy Comparison:

Accuracy value of each model is compared in shown in bar graph below.

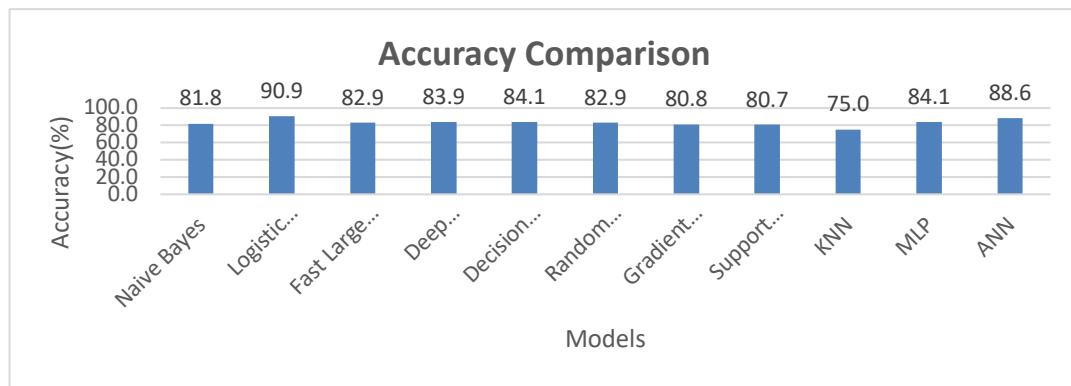


Fig. 6.97 Accuracy value comparison

After seeing the graph, it may be inferred as Logistic Regression classifier is best classifier in terms of accuracy. ANN classifier is second best classifier to classify LBP.

6.12.2 Precision Comparison:

Precision value of each model is compared in shown in bar graph below.

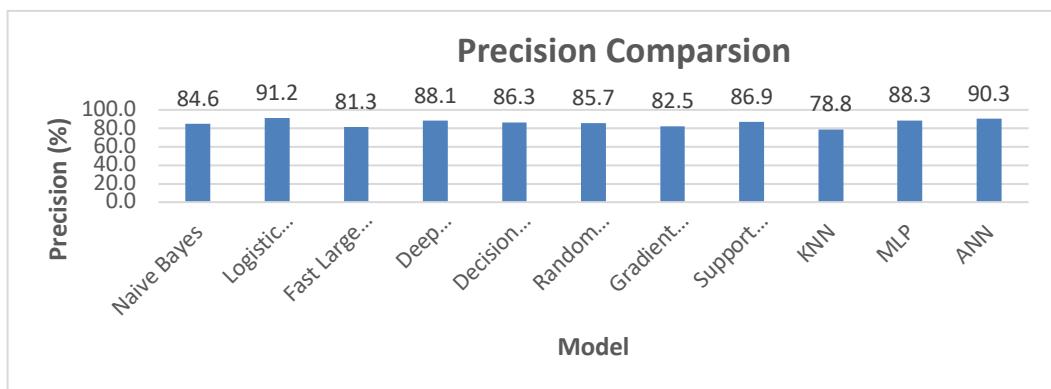


Fig. 6.98 Precision value comparison

Hence it can be stated that as Logistic Regression classifier is best classifier in terms of precision also. ANN classifier is second best classifier to classify LBP in terms of accuracy as well as precision.

6.12.3 F-measure Comparison:

F-measure value of each model is compared in shown in bar graph below.

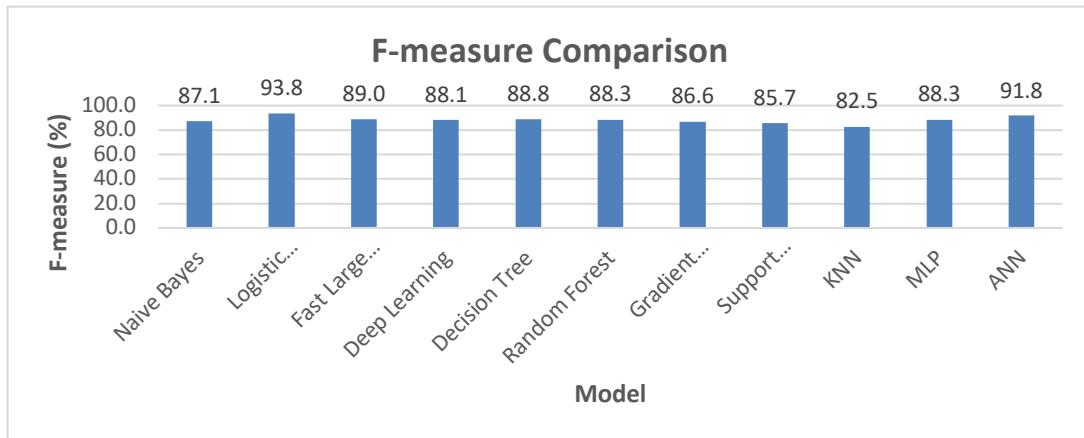


Fig. 6.99 F-measure value comparison

From the graph shown above we may infer that Logistic regression possess largest value of F-measure hence considered as best classifier in this category. ANN classifier is second best in this category as well.

6.12.4 Sensitivity Comparison:

Sensitivity value of each model is compared in shown in bar graph below.

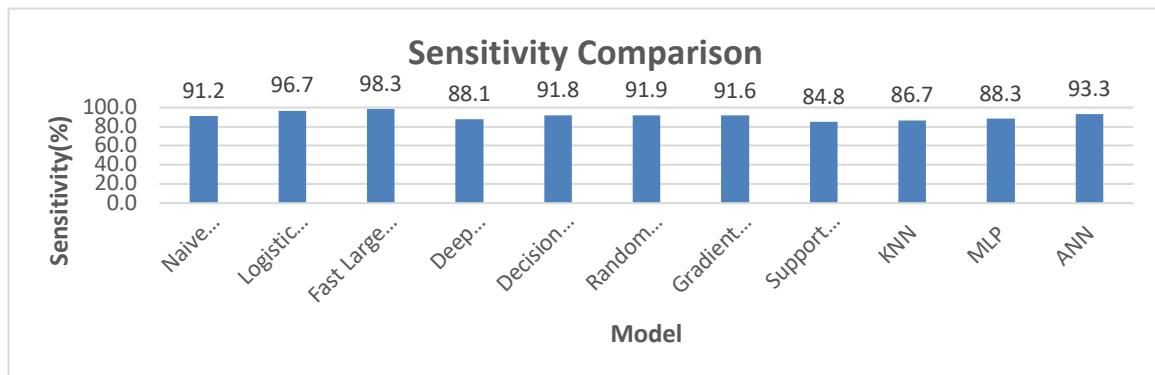


Fig. 6.100 Sensitivity value comparison

It can be inferred that Fast-Large Margin Classifier shows best sensitivity. Logistic Regression is second best in this category.

6.12.5 Specificity Comparison:

Specificity value of each model is compared in shown in bar graph below.

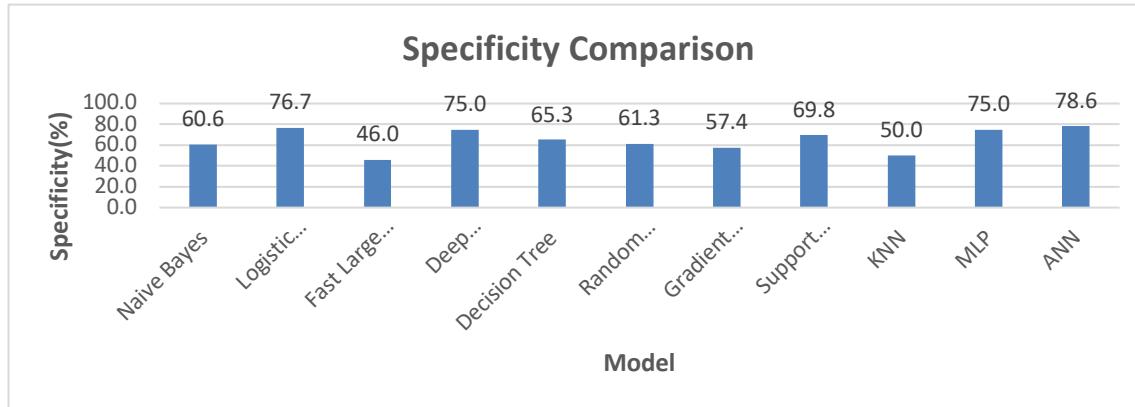


Fig. 6.101 Specificity value comparison

Taking Specificity into consideration, Artificial Neural Network Classification model is best. Second best model in this category is Logistic Regression as seen in the chart above.

6.12.6 Area Under Curve (AUC) Comparison:

AUC value of each model is compared in shown in bar graph below.

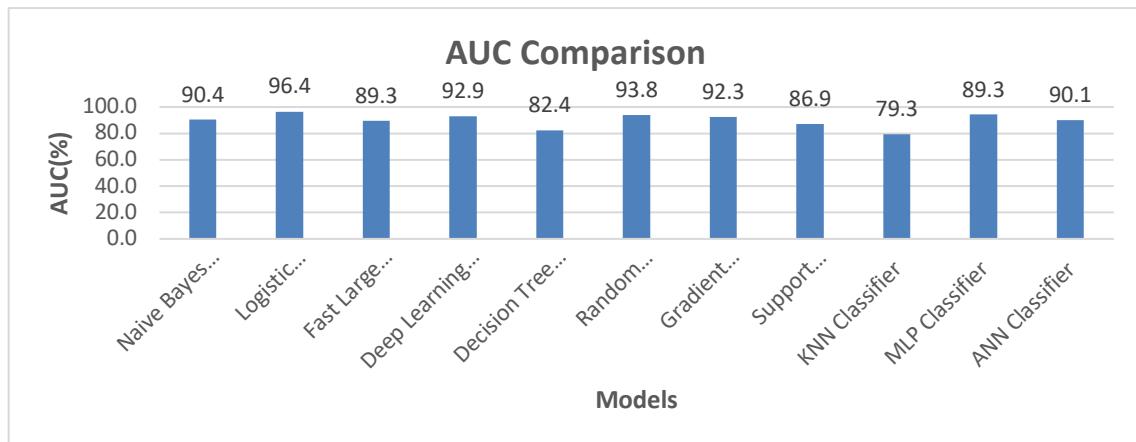


Fig. 6.102 AUC value comparison

In terms of AUC, Logistic Regression Model is best. Random Forest Classifier is second best in this category.

It is worth to mention that Sensitivity indicates the extent to which Actual abnormal cases are not overlooked. In case of Specificity, same thing applies for actual normal cases. Precision and Recall are often in tension; increase in Precision decreases the Recall value. The F-measure is the measure of test's accuracy by using both Precision and Recall.

6.12.7 Computational Times Comparison

Model	Training Time (in sec)	Execution time (in sec)
Naïve Bayes	0.998	0.004
Deep Learning	8.132	0.868
Decision Trees	0.59	0.01
Logistic Regression	7.162	0.851
SVM	1.932	0.125
Random Forest	8.891	0.009
Gradient Boosted Trees	45.172	0.832
Artificial Neural Networks	7.235	0.486
Fast Large Margin	0.991	0.008
Multi Layered Perceptron	1.521	0.168
K-Nearest Neighbor	0.762	0.025

Table 6.4 Computational times comparison

It is evident from the table shown above that Decision Trees classifier is computationally most efficient; but the accuracy and other performance parameters are not efficient. The Gradient boosted trees in computationally most inefficient among all.

6.12.8 Comparison of Accuracy with featured dataset as compared to all attributes

Model	Accuracy (With 8 features)	Accuracy (with all 12 attributes)
Naïve Bayes	81.8	85.23
Deep Learning	83.87	77.43
Decision Trees	84.1	83.15
Logistic Regression	90.91	84.09
SVM	80.7	79.36
Random Forest	82.9	87.5
Gradient Boosted Trees	80.8	80.09
Artificial Neural Networks	88.6	83.15
Fast Large Margin	82.9	81.21
Multi Layered Perceptron	84.1	79.55
K-Nearest Neighbor	75	75

Table 6.5 Comparison of accuracies with features as compared to total attributes

As seen from the table above, the best accuracy that can be achieved by any model is Logistic Regression classifier when it is subjected to featured data. Naïve Bayes and random forest classifiers give higher accuracy considering the total attributes; but still it is not able to surpass the accuracy given by logistic regression classifier with featured data.

6.13 Summary:

This Chapter displays the results of each experimental model designed in this research. The results are then compared and the “best” model is selected based on its value of respective performance parameter. The Logistic Regression is the “best” Non-conventional technique in terms of accuracy, precision, F-measure and AUC. The Fast Large Margin is the “best” classification when sensitivity of the model is the deciding parameter. The ANN model is the “best” in terms of specificity. It is evident that Network structures of Deep Learning Network and ANN classifier used in this research are different in terms of the hidden layer architecture

and training parameters. The ANN and MLP models are different in terms of number of neurons in the hidden layer and the activation functions in each neuron. The Layered Architecture and Model parameters for each of the proposed models are explained in detail in the Appendix. Usually, Deep learning requires more training data to train the dense layers of nodes and weights updates. In this research, despite of having available less training data; the Deep learning classifier still gives 83.9% accuracy on testing data which is not the best but shows that if more training data is provided, the chances of increasing accuracy are high.

The dataset used in the research study gives performance report of 11 machine learning methods used as explained in section 6.12. These results only explain performances of these models based on this specific dataset and not with every case. The Performance of each ML algorithm varies (among some other tuning factors) depends upon size and type of dataset. For a different dataset, the Performance may change and it will depend on to what extent the algorithm is adapting the knowledge given by training dataset.

Chapter 7 Conclusions and Future work

This thesis focuses mainly on designing an Intelligent System which can be used as a clinical decision support system and can help doctors by giving accurate decisions to detect Lower Back Pain symptoms. The main advantage of such kind of Intelligent System is that it can reduce the analysis time by giving quick decisions which can strengthen the doctor's final decision regarding type of Lower back pain detection. Various Machine Learning techniques have been applied on real datasets and the performance of each individual model designed using above mentioned techniques is carefully analysed.

7.1 Conclusions:

In this study, 11 Machine Learning algorithm-based classification models have been designed. The following conclusions can be made from this research.

- Intelligent Systems can be used as clinical decision support systems which can support doctor's decision towards any case.
- The Logistic Regression Classifier was designed and tested which gives an accuracy of 90.91% on test data and hence considered as the most accurate method of all.
- Apart from accuracy, if precision, F-measure and AUC is taken into consideration, the Logistic Regression is the “best” model out of all.
- In terms of Sensitivity Fast Large Margin model is suited as the “best” and Logistic Regression is second “best”.
- Taking Specificity into consideration, the Logistic Regression model is ‘best’ giving a specificity value of 76.7%.

7.2 Future Work:

Current research is facilitating the medical sector by designing Intelligent Systems which can classify LBP symptoms. “Best” models have been identified by rigorous analysis and different performance parameters and depending upon which performance parameter is required, that specific model can be used. Despite the work done is commendable, yet there is future scope of working in this sector more to get better results.

Some of the future works which can be done in this sector are:

- **Analysis with additional data:** The main issue with the current research was limited data. Only 310 data samples are publicly available to do the training as well as testing. For improved performance of models, additional data is required and one may try to get more data and then do the analysis which may render better results.
- **Working more with current techniques:** This thesis presents best use of current possible classification techniques to classify LBP data. Still an effort can be made to work more on current models by changing model parameters, different features selection methods and data pre-processing to get better accuracy.

7.3 Summary:

This Chapter illustrates the conclusions made by this research. This Chapter also shows the paths in direction of which work can be done to get better results.

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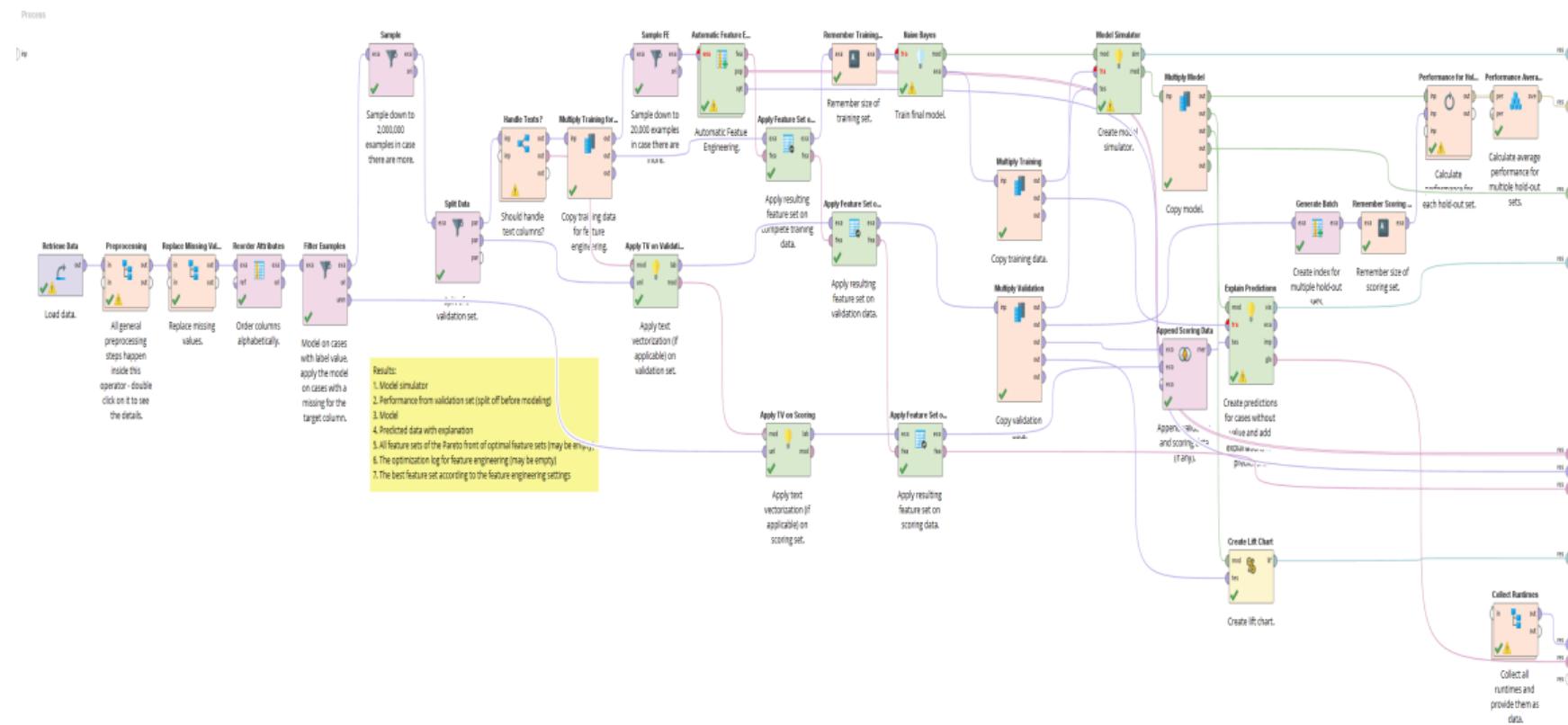
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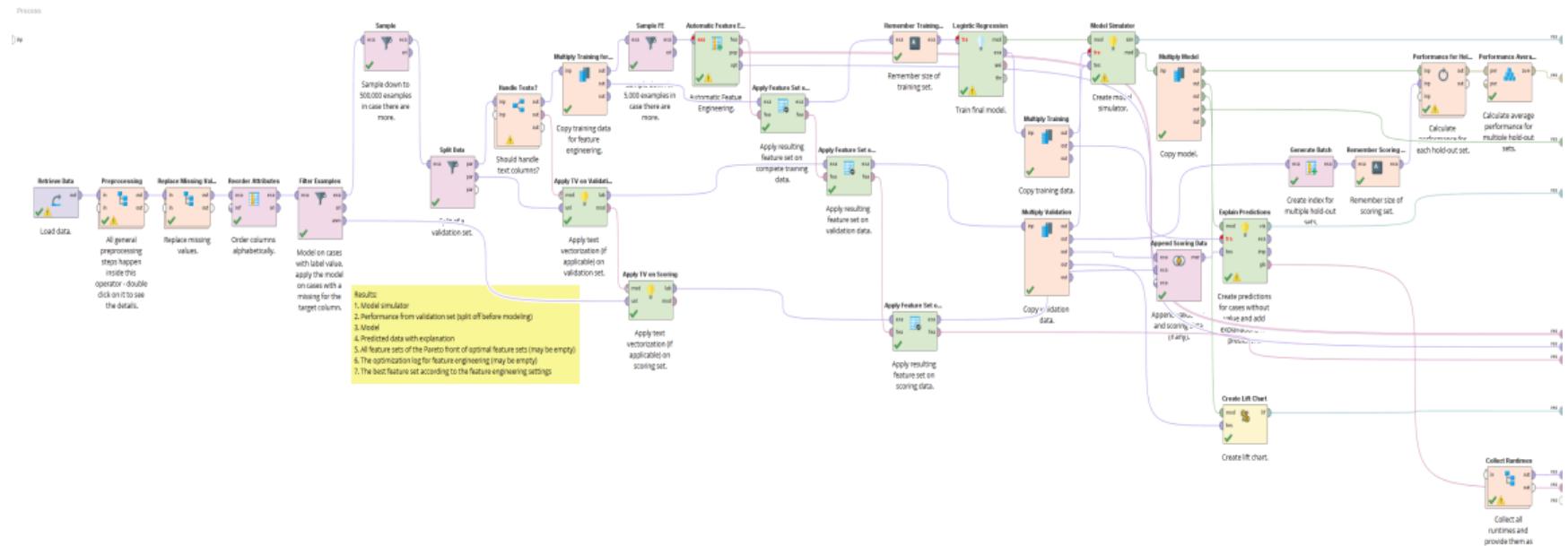
APPENDIX

A. Process Flow Diagrams of Machine Learning algorithms-based classifiers:

A.1 Naïve Bayes Classifier:



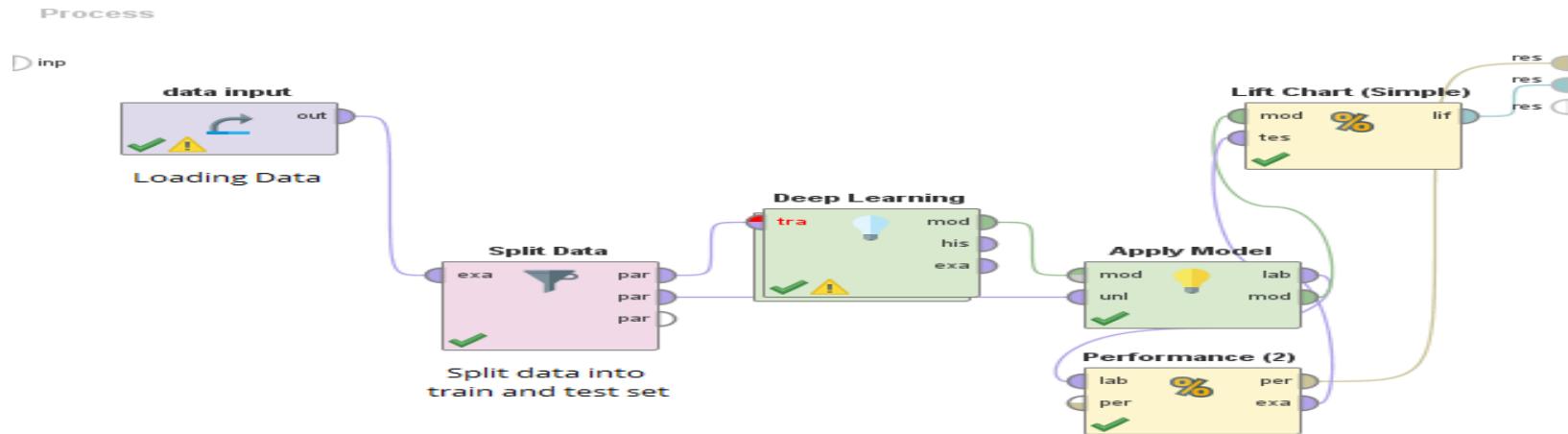
A.2 Logistic Regression Classifier:



Model Parameters:

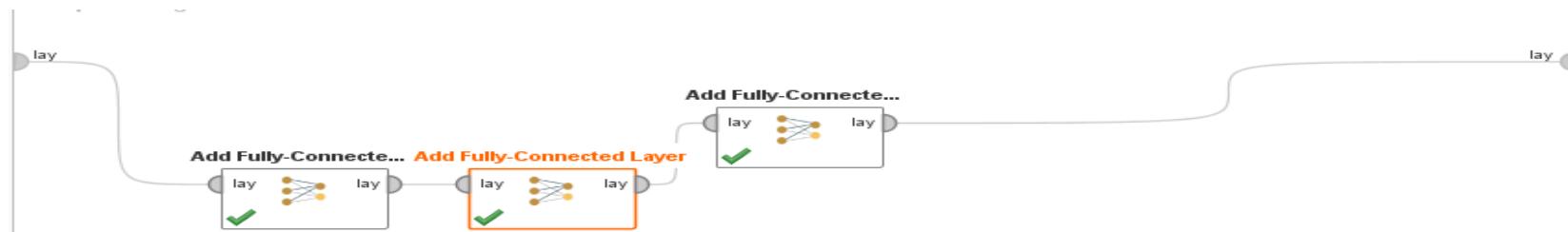
Type of Solver: Auto; data in standardized form

A.3 Deep Learning Classifier:



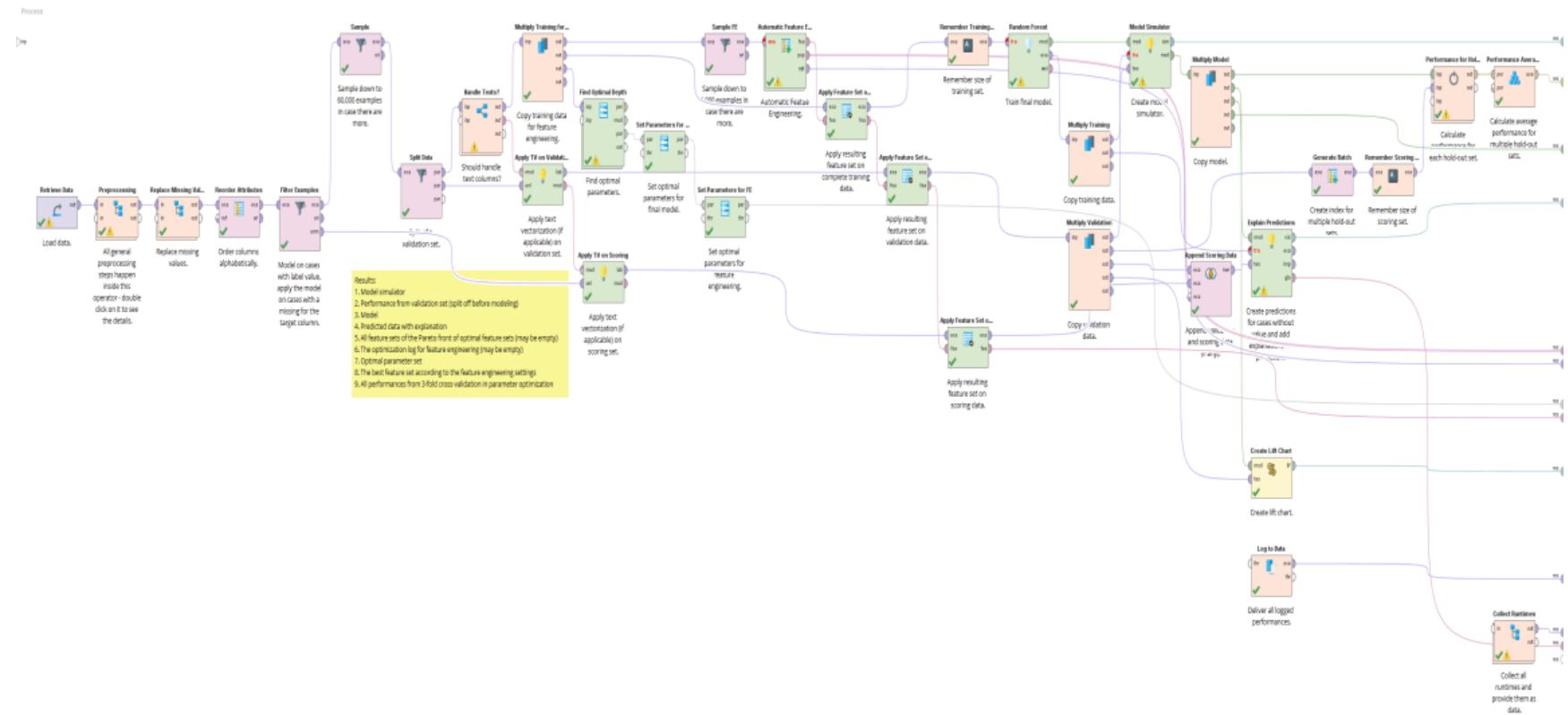
Model Parameters:

Loss function: Multiclass Cross Entropy; **No. of Epochs:** 1000; **Type of updater:** Adam; **Learning rate:** 0.01; **Weight Initialization:** ReLU; **Bias initialization:** 0;



Three fully connected layers in deep learning model with 18, 80 and 2 neurons in layer 1,2 and 3 respectively with activation function ReLU (Rectifier Linear Unit) in first 2 and SoftMax in last layer.

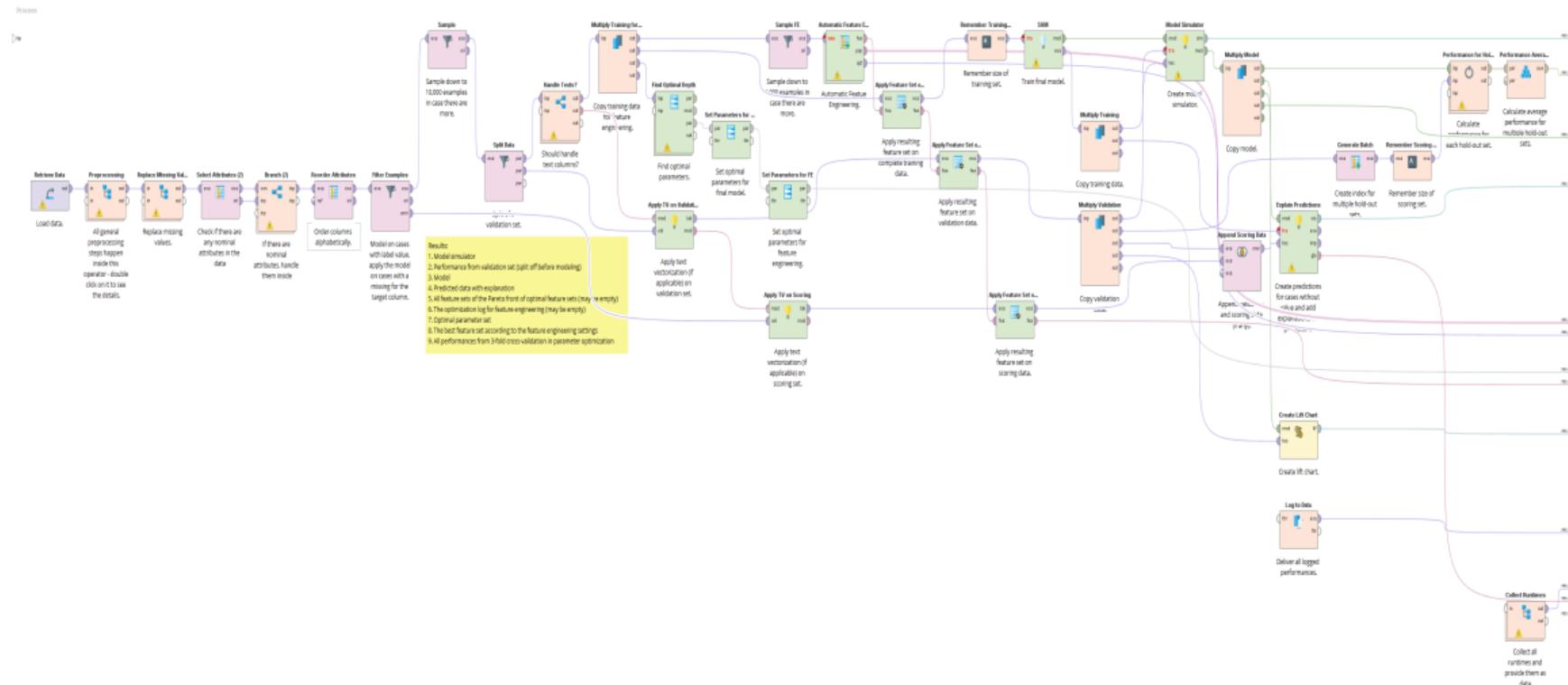
A.4 Random Forests Classifiers:



Model Parameters: No. of trees: 60; Criterion for optimality: Gain ratio; Maximal Depth: 7;

Voting Strategy: Confidence Vote; Minimum Gain: 0.05; Minimum Leaf Size: 2

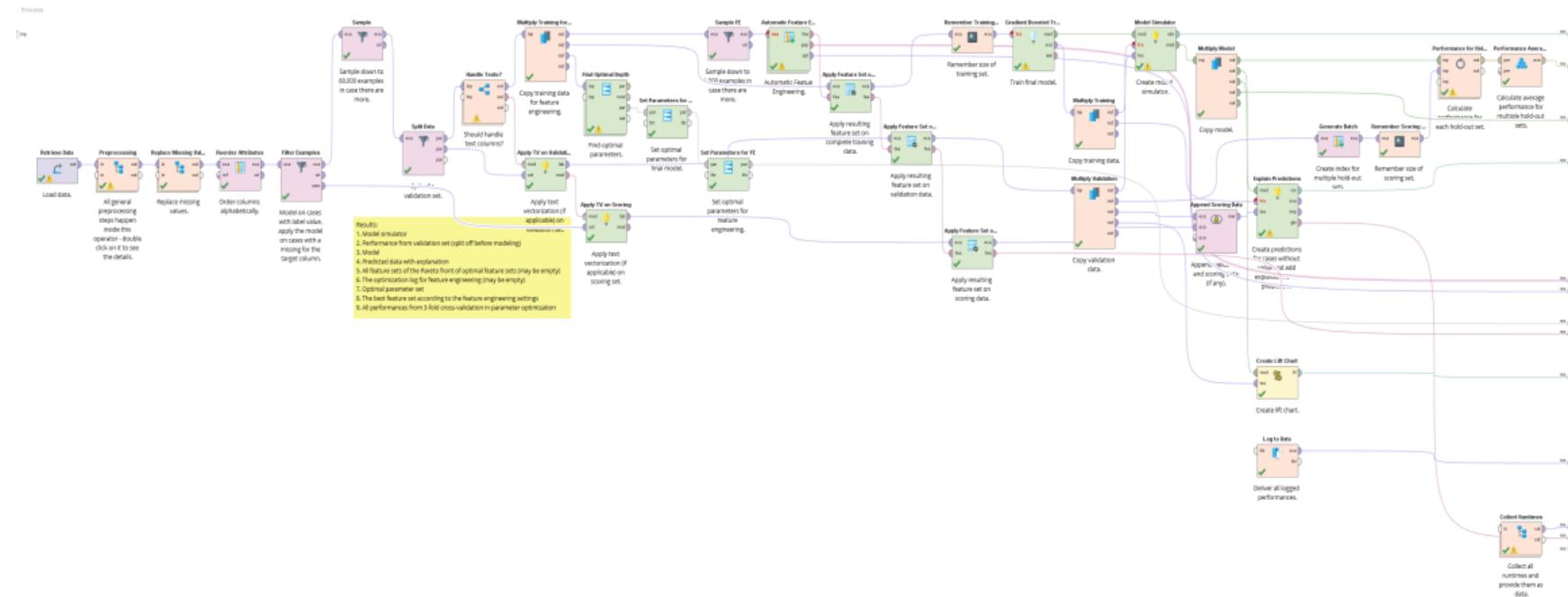
A.5 Support Vector Machines Classifier:



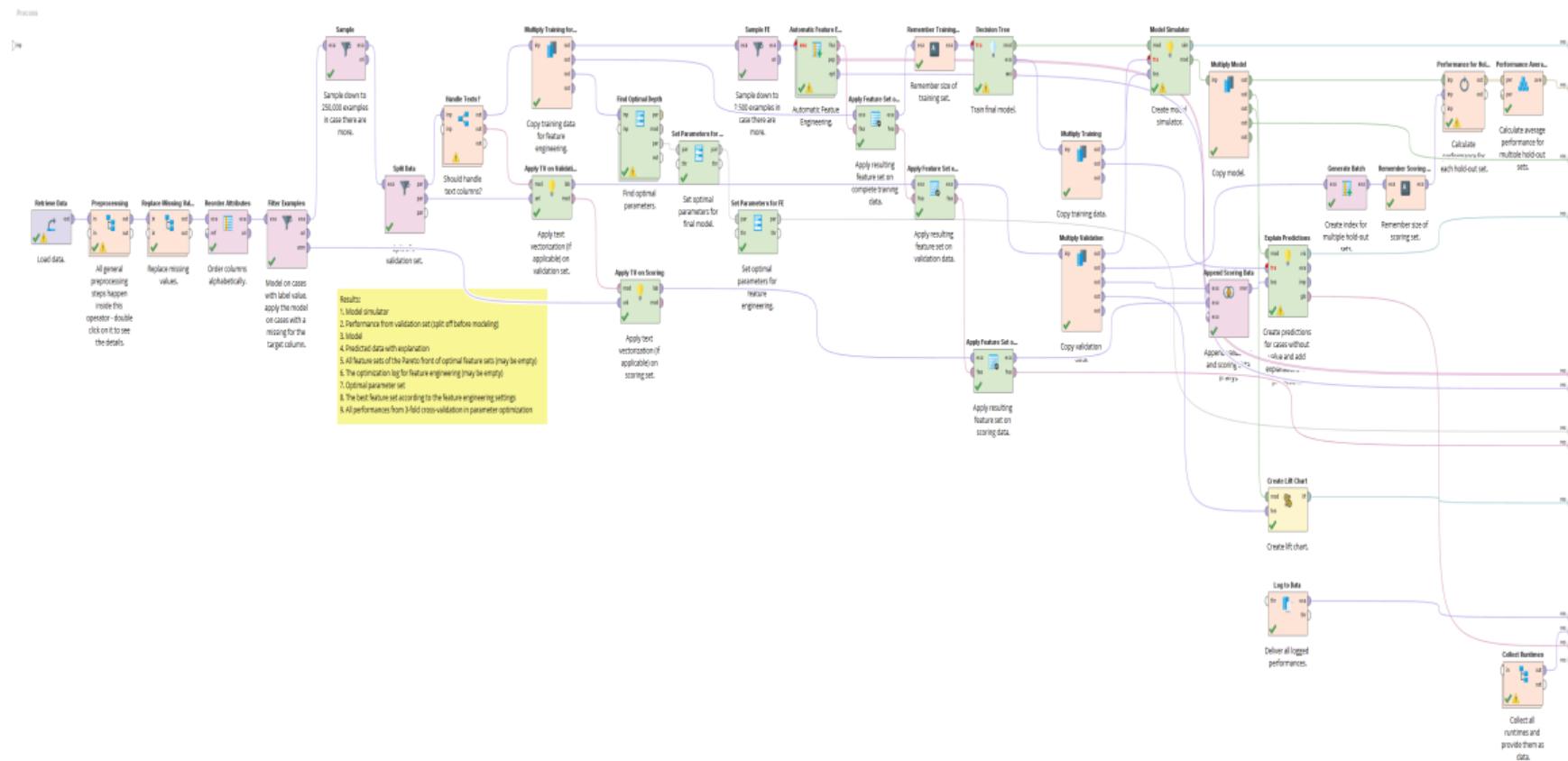
Model Parameters: SVM type: C-SVC; Kernel Type: Rbf; Gamma: 1.0000000000000007;

C: 100; Epsilon: 0.001

A.6 Gradient Boosted Trees Classifier:

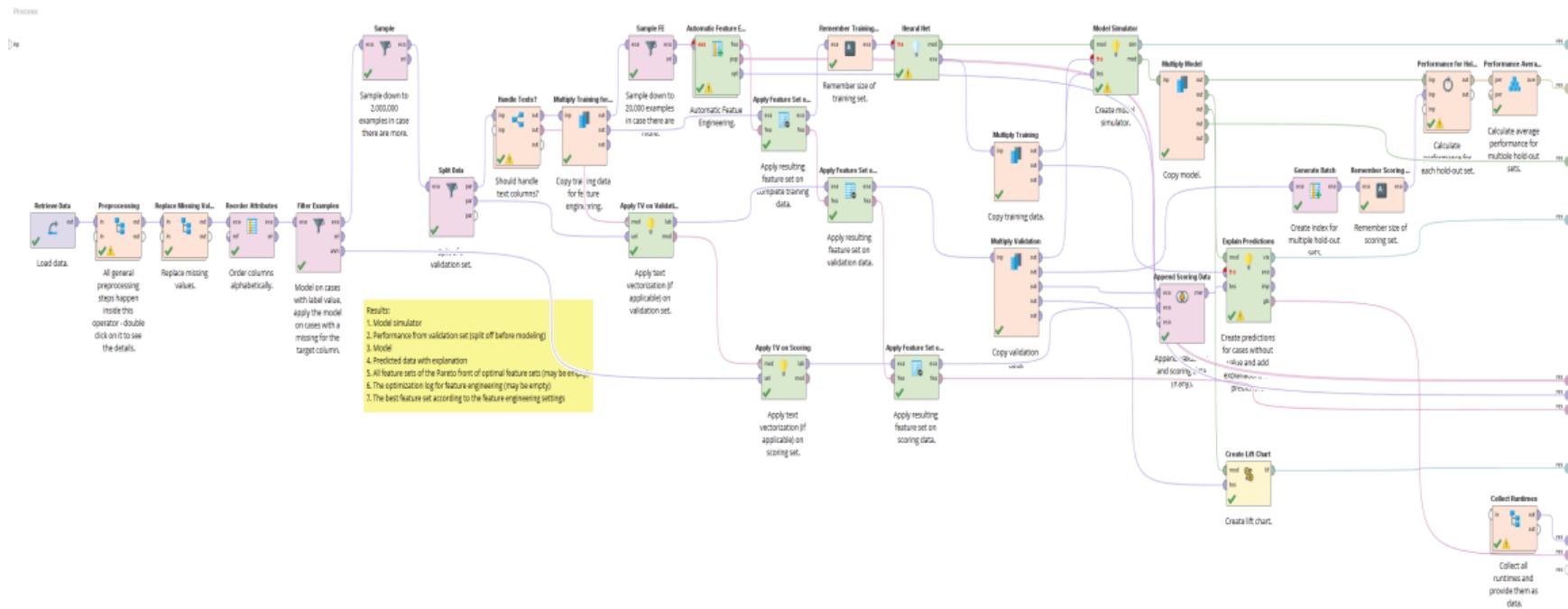


A.7 Decision Trees Classifier:



Model Parameters: Criterion: Gain Ratio; Maximal Depth: 4; Confidence: 0.1; Minimal Gain: 0.01; Minimum Leaf Size: 2.

A.8 ANN Classifier:

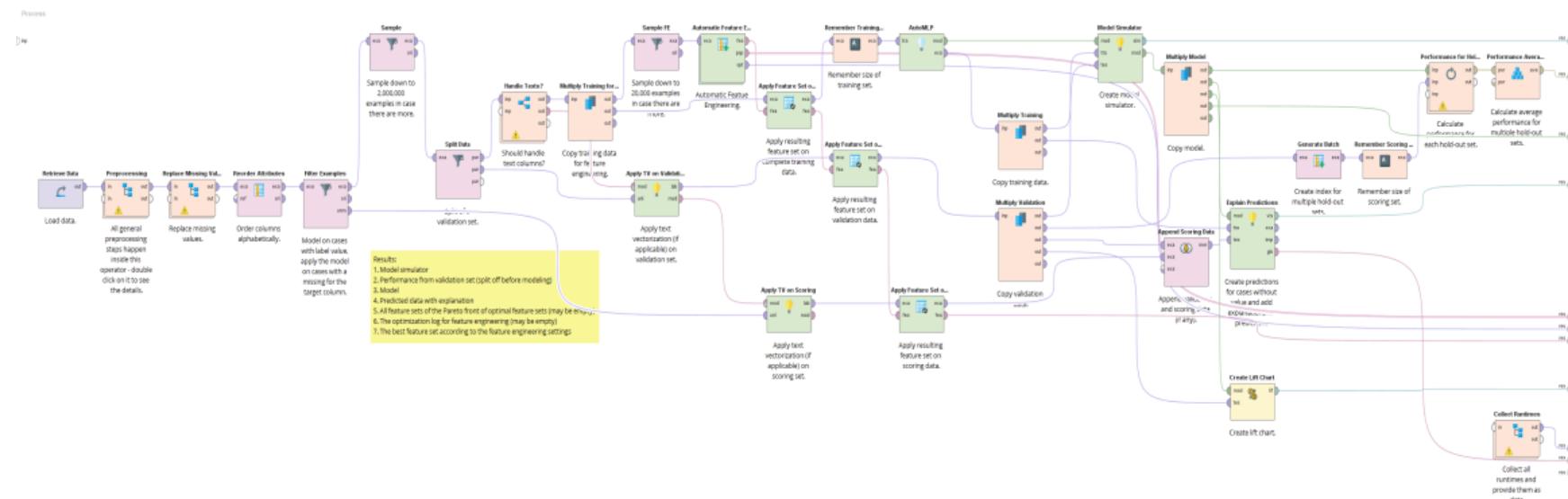


Model Parameters:

Activation Function: Rectifier; **Number of Hidden layers:** 2 (Layer 1= 8 neurons, Layer 2=5 neurons);

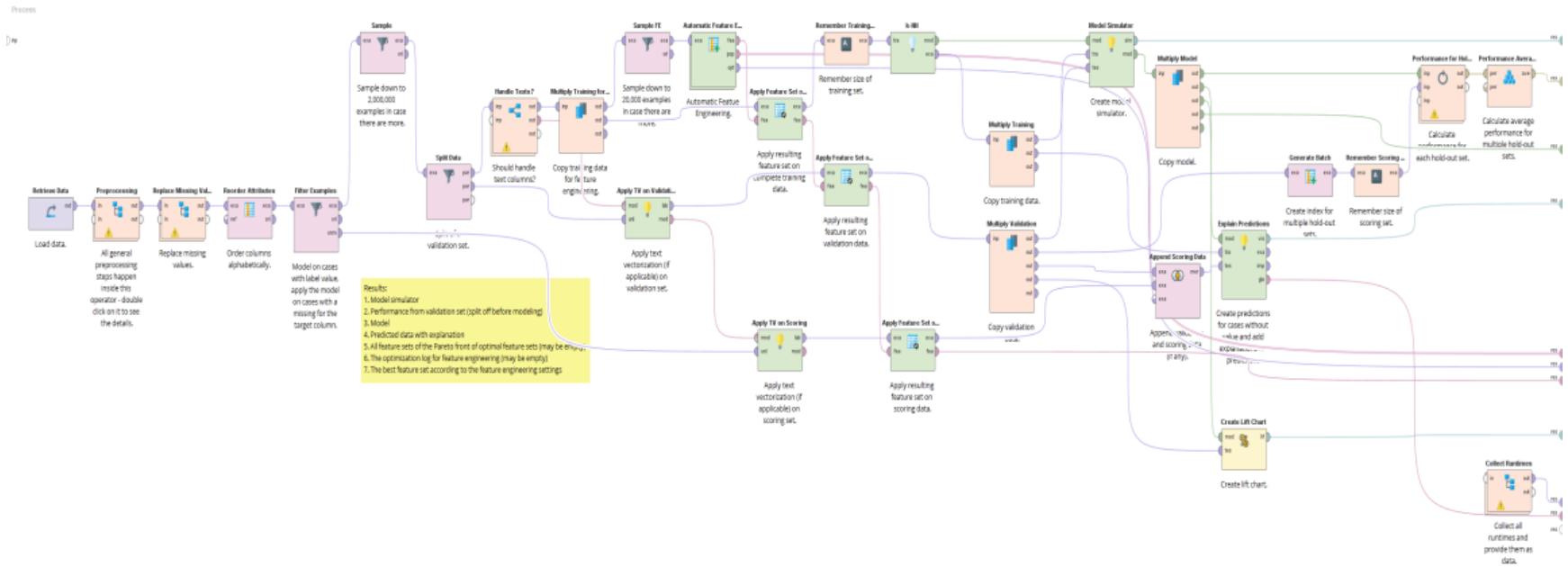
No. of Epochs: 100

A.9 Multilayer Perceptron Classifier:

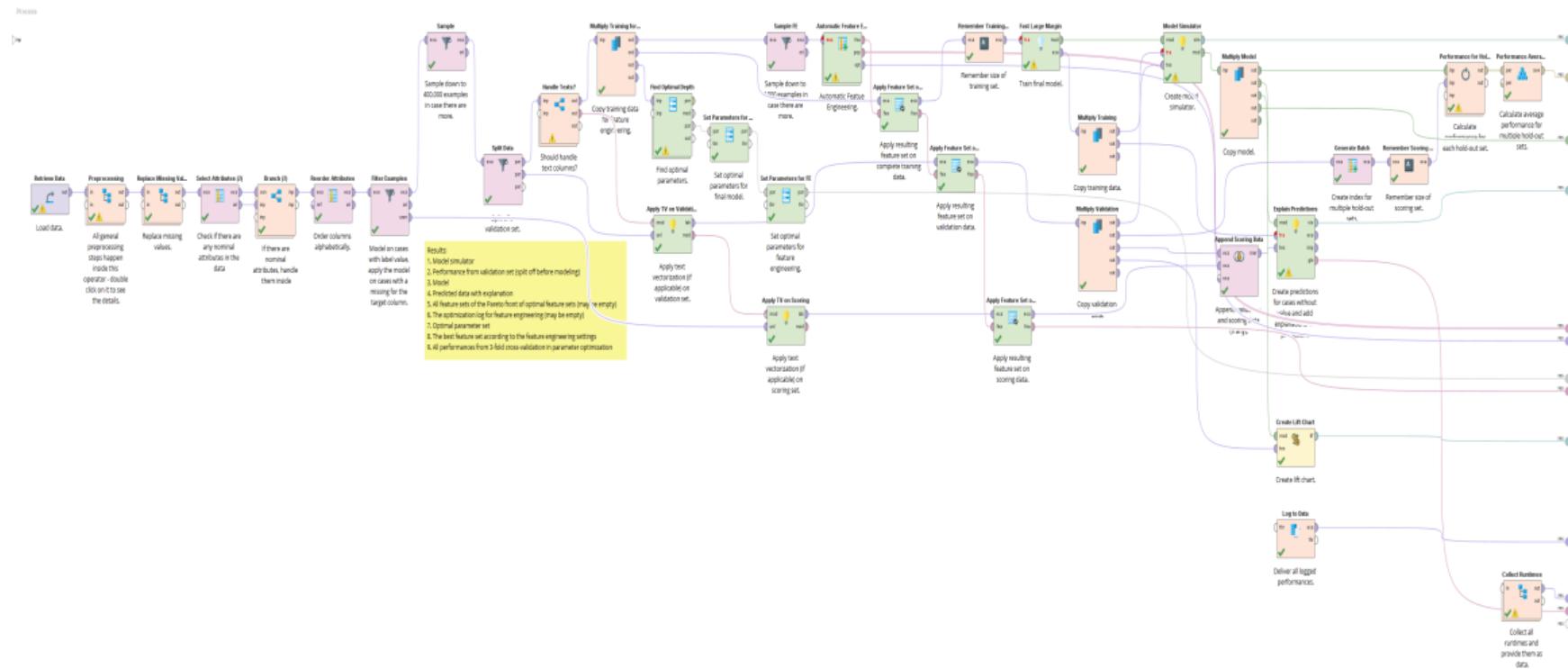


Model Parameters: No. of Neurons in Hidden Layer: 8

A.10 KNN Classifier:



A.11 Fast Large Margin:



B. Classification results given by Machine Learning Classifiers and their comparison with actual outputs:

B.1 Naïve Bayes Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal	Normal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Abnormal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Normal	0.1 9	0.4 5	0.1 8	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnormal	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Abnormal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnormal	Abnormal	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnormal	Abnormal	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnormal	Abnormal	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnormal	Abnormal	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68

10	Normal	Abnormal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma l	Abnormal	0.6 4	0.7 5	0.5 7	0.4 9	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnormal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma l	Abnormal	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma l	Abnormal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma l	Abnormal	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma l	Abnormal	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnorma l	Abnormal	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal	Abnormal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma l	Abnormal	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2 0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnorma l	Abnormal	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Normal	0.2 8	0.2 9	0.3 0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnormal	0.5	0.6	0.4	0.3	0.4	0.45	0.0	0.67

			5	5		7	4		4	
24	Abnormal	Abnormal	0.0 9	0.3 3	0.0 1	0.1	0.4	0.4	0.0 2	0.63
25	Abnormal	Abnormal	0.6 2	0.6 2	0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnormal	Abnormal	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnormal	Abnormal	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnormal	Abnormal	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Normal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38
30	Abnormal	Abnormal	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01	0.0 2	1.01
31	Abnormal	Abnormal	0.1 9	0.2 9	0.2 8	0.2 1	1	1.1	0.0 7	1.05
32	Abnormal	Normal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25	0.0 2	1.12
34	Abnormal	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2	0.6 4	1.43	0.0 4	1.2
36	Abnormal	Abnormal	0.0 5	0.4 3	0.0 1	0	0.5 4	0.68	0.0 3	0.82

37	Abnormal	Abnormal	0.1	0.5	0.1	0	0.4	1.06	0.0		1.03
38	Normal	Normal	0.1	0.4	0.2	0.0	0.6	1.06	0.0		1.03
39	Abnormal	Abnormal	0.5	0.8	0.6	0.3	0.5	1.44	0.1		1.2
40	Normal	Abnormal	0.3	0.4	0.4	0.3	0.7	1.21	0.0		1.1
41	Abnormal	Abnormal	0.4	0.7	0.4	0.2	0.8	2.69	0.3		1.64
42	Normal	Abnormal	0.4	0.3	0.3	0.3	0.6	8.11	0.0		2.85
43	Normal	Abnormal	0.6	0.5	0.6	0.5	0.3	0.81	0.0		0.9
44	Abnormal	Abnormal	0.4	0.4	0.4	0.3	0	0	0.0		0
45	Abnormal	Abnormal	0.5	0.6	0.6	0.3	0.6	2.12	0.1		1.46
46	Abnormal	Abnormal	0.3	0.3	0.3	0.3	0.4	0.44	0.1		0.66
47	Normal	Abnormal	0.3	0.5	0.4	0.2	0.5	3.07	0.0		1.75
48	Abnormal	Normal	0.2	0.2	0.1	0.2	0.4	1.89	0.0		1.38
49	Abnormal	Abnormal	0.6	0.9	0.5	0.2	0.6	0.88	0.3		0.94
50	Abnormal	Abnormal	0.1	0.4	0.0	0.1	0.5	1.82	0.0		1.35

	1		5	4	5		2		3	
51	Abnorma 1	Abnormal	0.3	0.1 2	0.3 1	0.4	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnormal	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnorma 1	Abnormal	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnorma 1	Abnormal	0.5 7	0.4 9	0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Abnormal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma 1	Abnormal	0.1 8	0.2 9	0.3 4	0.2	0.7	0.7	0.0 9	0.84
58	Abnorma 1	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnorma 1	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnorma 1	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5	0.94	0.1	0.97
61	Abnorma 1	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnorma 1	Normal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnorma 1	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84

64	Normal	Normal	0.0 7	0.1 8	0.1 5	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnormal 1	Abnormal	0.5 3	0.4 9	0.7 3	0.4 3	0.6 3	1.14	0.1 1	1.07
66	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 3	1.25	0.0 4	1.12
67	Normal	Abnormal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnormal 1	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2 4	0.2 1	0.3 4	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnormal 1	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Normal	0.1 6	0.3 7	0.1 1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnormal 1	Abnormal	0.2 1	0.1 9	0.4 0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnormal 1	Abnormal	0.2 1	0.5 1	0.2 0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnormal 1	Abnormal	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25	0.2	1.5
77	Abnormal	Abnormal	0.5	0.7	0.3	0.3	0.7	3.59	0.2	1.9

	1		9	1		8		6	
78	Abnorma 1	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4 7	0.76 1	0.1 1
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91 7	0.0 4
80	Normal	Normal	0.2 3	0.4 7	0.2 9	0.1 6	0.5 3	9.41 3	0.0 5
81	Abnorma 1	Abnormal	0.3 3	0.3 7	0.3 9	0.3 8	0.3 8	1.11 1.11	0.1 1.05
82	Abnorma 1	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49 0.49	0.1 2
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6 8	0.0 2
84	Abnorma 1	Abnormal	0.1 1	0.2 5	0.2 7	0.1 5	0.1 5	0.19 0.19	0.0 3
85	Normal	Normal	0.2 6	0.3 1	0.2 5	0.2 1	0.5 5	0.94 0.94	0.0 2
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83 0.83	0.0 3
87	Abnorma 1	Normal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82 0.82	0.0 3
88	Normal	Normal	0.1 4	0.3 1	0.2 6	0.1 6	0.6 2	1.86 1.86	0.0 3
89	Abnorma 1	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6 0.6	0.2 0.2
90	Abnorma 1	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78 0.78	0.1 0.1

91	Normal	Abnormal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnorma l	Abnormal	0.4 9	0.6 6	0.5 0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma l	Abnormal	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma l	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Normal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnorma l	Abnormal	0.3 9	0.3 5	0.4 7	0.2 7	0.5 0.5	0.95	0.1	0.97
99	Abnorma l	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2 9	0.78	0.1 2	0.88
100	Abnorma l	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma l	Abnormal	0.4 1	0.4 8	0.0 5	0.5 9	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma l	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnorma	Abnormal	0.8	0.7	0.5	0.6	0.3	0.82	0.2	0.9

	1		7	9	6		7		1	
105	Abnorma 1	Abnormal	0.5 1	0.5 1	0.4 1	0.4 1	0.5 2	5.08	0.0 9	2.25
106	Abnorma 1	Normal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma 1	Abnormal	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnormal	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma 1	Normal	0.2 9	0.3 1	0.2 7	0.1 7	0.5 0.5	2.83	0.0 3	1.68
110	Abnorma 1	Abnormal	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Normal	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
112	Normal	Abnormal	0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnorma 1	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnorma 1	Abnormal	0.3 7	0.3 9	0.4 0.4	0.3 4	0.4 5	1.38	0.0 8	1.17
115	Abnorma 1	Abnormal	0.2 4	0.5 3	0.3 0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnorma 1	Normal	0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnorma 1	Abnormal	0.4 3	0.5 0.5	0.4 0.4	0.3 3	0.3 5	0.78	0.0 9	0.88

118	Abnormal	Abnormal	0.4 8	0.4 6	0.4 5	0.4 8	0.2 8	0.31	0.1 9	0.56
119	Abnormal	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6	0.51
120	Abnormal	Abnormal	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65	0.1	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2	0.1 4	0.5 8	0.85	0.0 3	0.92
122	Abnormal	Abnormal	0.4 8	0.6 8	0.6 8	0.2 8	0.4	0.4	0.1 5	0.63
123	Abnormal	Abnormal	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3	0.66
124	Abnormal	Abnormal	0.8 9	0.8 3	0.3 1	0.6 1	0.1 2	0.19	0.2	0.44

B.2 Logistic Regression Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Normal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal	0.1 9	0.4	0.1	0.1 2	0.5	0.92	0.0 3	0.96

4	Abnormal	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Abnormal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnormal	Abnormal	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnormal	Abnormal	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnormal	Abnormal	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnormal	Abnormal	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal	Abnormal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnormal	Abnormal	0.6 4	0.7 5	0.5 7	0.4	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnormal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnormal	Abnormal	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnormal	Abnormal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnormal	Abnormal	0.4 3	0.3	0.5 6	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnormal	Abnormal	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnormal	Normal	0.5	0.3	0.5	0.4	0.3	0.59	0.0	0.77

	1			7	9	7	7		5	
18	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma 1	Abnormal	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnorma 1	Abnormal	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Normal	0.2 8	0.2 9	0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnormal	0.5 5	0.6 5	0.4	0.3 7	0.4 4	0.45	0.0 4	0.67
24	Abnorma 1	Abnormal	0.0 9	0.3 3	0.0 1	0.1	0.4	0.4	0.0 2	0.63
25	Abnorma 1	Abnormal	0.6 2	0.6 2	0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnorma 1	Abnormal	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnorma 1	Abnormal	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnorma 1	Abnormal	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Normal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38
30	Abnorma 1	Abnormal	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01	0.0 2	1.01

31	Abnormal	Normal	0.1 9	0.2 9	0.2 8	0.2 1	1	1.1	0.0 7	1.05
32	Abnormal	Abnormal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25	0.0 2	1.12
34	Abnormal	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2	0.6 4	1.43	0.0 4	1.2
36	Abnormal	Abnormal	0.0 5	0.4 3	0.0 1	0	0.5 4	0.68	0.0 3	0.82
37	Abnormal	Abnormal	0.1 2	0.5 3	0.1 3	0	0.4 9	1.06	0.0 2	1.03
38	Normal	Normal	0.1 3	0.4 1	0.2	0.0 9	0.6 7	1.06	0.0 1	1.03
39	Abnormal	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Normal	0.3 6	0.4 4	0.4 2	0.3 2	0.7 8	1.21	0.0 4	1.1
41	Abnormal	Abnormal	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Normal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Normal	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9
44	Abnormal	Abnormal	0.4	0.4	0.4	0.3	0	0	0.0	0

	1		5	1	1	9			5	
45	Abnorma 1	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
46	Abnorma 1	Abnormal	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnormal	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnorma 1	Normal	0.2 7	0.2 3	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma 1	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnorma 1	Abnormal	0.1 5	0.4 4	0.0 5	0.1 8	0.5 2	1.82	0.0 3	1.35
51	Abnorma 1	Abnormal	0.3 2	0.1 1	0.3 0.4	0.4 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnormal	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnorma 1	Abnormal	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnorma 1	Abnormal	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma 1	Abnormal	0.1 8	0.2 9	0.3 4	0.2 0.2	0.7 0.7	0.7	0.0 9	0.84

58	Abnormal	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnormal	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnormal	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5 0.5	0.94	0.1	0.97
61	Abnormal	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnormal	Abnormal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnormal	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1 0.1	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnormal	Abnormal	0.5 3	0.4 9	0.7 0.7	0.4 3	0.6 0.6	1.14	0.1 1	1.07
66	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 0.7	1.25	0.0 4	1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnormal	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2 4	0.2 1	0.3 4	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnormal	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	0.2	0.2	0.3	0.3	0.6	0.64	0.0	0.8

			8	2	5	3	1		2	
72	Normal	Normal	0.1 6	0.3 7	0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnorma 1	Abnormal	0.2 1	0.1 9	0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnorma 1	Abnormal	0.2 1	0.5 1	0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnorma 1	Abnormal	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25	0.2	1.5
77	Abnorma 1	Abnormal	0.5 9	0.7 1	0.3	0.3 8	0.7	3.59	0.2 6	1.9
78	Abnorma 1	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4	0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Abnormal	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnorma 1	Abnormal	0.3 3	0.3 7	0.3 9	0.3 8	0.3	1.11	0.1	1.05
82	Abnorma 1	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnorma 1	Abnormal	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43

85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma 1	Abnormal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnorma 1	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma 1	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Normal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4	0.1 9	0.2 1	0.6 4	1.47	0.0 3	1.21
94	Abnorma 1	Abnormal	0.4 9	0.6 6	0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma 1	Abnormal	0.5 7	0.4	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma 1	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Abnormal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnorma	Abnormal	0.3	0.3	0.4	0.2	0.5	0.95	0.1	0.97

	1			9	5	7				
99	Abnorma 1	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2	0.78	0.1 2	0.88
100	Abnorma 1	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma 1	Abnormal	0.4 1		0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma 1	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnorma 1	Abnormal	0.8 7	0.7 9	0.5 6	0.6 7	0.3 7	0.82	0.2 1	0.9
105	Abnorma 1	Abnormal	0.5 1	0.5 1	0.4 1	0.4 2	0.5 2	5.08	0.0 9	2.25
106	Abnorma 1	Abnormal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma 1	Abnormal	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnormal	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma 1	Abnormal	0.2 9	0.3 1	0.2 1	0.1 7	0.5	2.83	0.0 3	1.68
110	Abnorma 1	Abnormal	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Abnormal	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78

112	Normal	Normal	0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnorma 1	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnorma 1	Abnormal	0.3 7	0.3 9	0.4 0.4	0.3 4	0.4 5	1.38	0.0 8	1.17
115	Abnorma 1	Abnormal	0.2 4	0.5 3	0.3 0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnorma 1	Abnormal	0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnorma 1	Abnormal	0.4 3	0.5 0.5	0.4 0.4	0.3 3	0.3 5	0.78	0.0 9	0.88
118	Abnorma 1	Abnormal	0.4 8	0.4 6	0.4 5	0.4 0.4	0.2 8	0.31	0.1 9	0.56
119	Abnorma 1	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6	0.51
120	Abnorma 1	Abnormal	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65	0.1	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2 0.2	0.1 4	0.5 8	0.85	0.0 3	0.92
122	Abnorma 1	Abnormal	0.4 8	0.6 8	0.6 8	0.2 8	0.4 0.4	0.4	0.1 5	0.63
123	Abnorma 1	Abnormal	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3	0.66
124	Abnorma 1	Abnormal	0.8 9	0.8 0.8	0.3 3	0.6 1	0.1 2	0.19	0.2	0.44

B.3 Deep Learning Classifier:

Row No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.43	0.34	0.43	0.41	0.47	1.12	0.16	1.06
2	Abnormal	Abnormal	0.61	0.7	0.62	0.4	0.64	0.7	0.24	0.83
3	Abnormal	Abnormal	0.12	0.3	0.1	0.14	0.48	0.48	0.04	0.69
4	Abnormal	Abnormal	0.23	0.23	0.35	0.28	0.44	0.47	0.08	0.68
5	Normal	Normal	0.11	0.27	0.11	0.15	0.58	1.4	0.03	1.19
6	Normal	Abnormal	0.19	0.45	0.18	0.12	0.5	0.92	0.03	0.96
7	Abnormal	Abnormal	0.32	0.73	0.33	0.16	0.76	9.48	0.37	3.08
8	Abnormal	Abnormal	0.45	0.24	0.34	0.43	0.3	14.2	0.12	3.77
9	Abnormal	Abnormal	0.31	0.25	0.35	0.35	0.31	1.01	0.15	1
10	Abnormal	Abnormal	0.29	0.28	0.35	0.32	0.31	0.56	0.14	0.75
11	Abnormal	Abnormal	0.29	0.42	0.25	0.24	0.62	0.64	0.08	0.8
12	Abnormal	Abnormal	0.33	0.21	0.41	0.39	0.42	0.83	0.1	0.91
13	Abnormal	Abnormal	0.49	0.66	0.57	0.31	0.44	0.46	0.22	0.68
14	Abnormal	Abnormal	0.34	0.24	0.38	0.34	0.43	0.47	0.11	0.68
15	Normal	Normal	0.41	0.46	0.26	0.35	0.53	0.76	0.04	0.87
16	Normal	Normal	0.45	0.47	0.42	0.37	0.44	184	0.03	13.6
17	Abnormal	Abnormal	0.64	0.75	0.57	0.4	0.49	1.15	0.16	1.07
18	Normal	Normal	0.23	0.06	0.25	0.37	0.66	6.55	0.01	2.56
19	Abnormal	Normal	0.14	0.43	0.17	0.1	0.5	4.56	0	2.14
20	Normal	Normal	0.42	0.43	0.33	0.34	0.73	2.07	0.04	1.44
21	Normal	Normal	0.38	0.53	0.43	0.27	0.58	0.89	0.02	0.95
22	Abnormal	Abnormal	0.48	0.51	0.62	0.38	0.58	1.4	0.05	1.18

23	Abnormal	Abnormal	0.4	0.7	0.7	0.1	0.8	1.86	0.2		1.36
24	Normal	Abnormal	0.2	0.3	0.4	0.2	0.5	0.51	0.1		0.72
25	Abnormal	Abnormal	0.4	0.6	0.4	0.3	0.5	0.75	0.2		0.87
26	Abnormal	Abnormal	0.4	0.4	0.3	0.4	0.4	7.37	0.1		2.71
27	Abnormal	Abnormal	0.3	0.5	0.3	0.2	0.3	6.3	0.0		2.51
28	Normal	Normal	0.2	0.2	0.3	0.2	0.5	0.85	0.0		0.92
29	Abnormal	Abnormal	0.2	0.2	0.1	0.2	0.4	2.18	0.0		1.48
30	Abnormal	Abnormal	0.3	0.3	0.4	0.3	0.2	0.36	0.1		0.6
31	Abnormal	Abnormal	0.3	0.4	0.2	0.2	0.4	0.83	0.1		0.91
32	Normal	Abnormal	0.5	0.6	0.4	0.3	0.4	0.45	0.0		0.67
33	Abnormal	Abnormal	0.6	0.6	0.5	0.4	0.3	0.34	0.1		0.58
34	Normal	Normal	0.4	0.3	0.3	0.4	0.3	0.58	0.0		0.76
35	Abnormal	Normal	0.1	0.3	0.2	0.1	0.5	25.1	0.0		5.01
36	Abnormal	Abnormal	0.3	0.3	0.4	0.3	0.3	0.58	0.1		0.76
37	Normal	Normal	0.1	0.3	0.2	0.1	0.8	2.27	0		1.51
38	Normal	Normal	0.2	0.4	0.3	0.1	0.7	5.67	0.0		2.38
39	Abnormal	Abnormal	0.2	0.4	0.5	0.2	0.7	1.4	0.1		1.18
40	Normal	Abnormal	0.2	0.3	0.2	0.2	0.4	1.22	0.0		1.11
41	Abnormal	Normal	0.2	0.4	0.1	0.2	0.4	0.66	0.0		0.81
42	Abnormal	Normal	0.3	0.4	0.3	0.2	0.4	1.01	0.0		1.01
43	Abnormal	Normal	0.1	0.2	0.2	0.2	1	1.1	0.0		1.05
44	Abnormal	Abnormal	0.2	0.4	0.1	0.2	0.5	1.02	0.0		1.01
45	Abnormal	Normal	0.4	0.3	0.4	0.3	0.5	37.1	0.1		6.09
46	Normal	Normal	0.1	0.3	0.1	0.1	0.6	1.25	0.0		1.12
47	Abnormal	Abnormal	0.1	0.1	0.2	0.2	0.3	1.1	0.0		1.05

48	Abnormal	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
49	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2	0.6 4	1.43	0.0 4	1.2
50	Normal	Normal	0.3 4	0.3 6	0.4 5	0.3 2	0.5 6	4.14	0.0 3	2.03
51	Abnormal	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
52	Abnormal	Abnormal	0.1 7	0.2 5	0.1 3	0.2 1	0.4 6	1.72	0.0 4	1.31
53	Normal	Abnormal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
54	Abnormal	Abnormal	0.4 5	0.4 1	0.4 1	0.3 9	0	0	0.0 5	0
55	Abnormal	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
56	Abnormal	Abnormal	0.1 5	0.4 1	0.1 5	0.1 1	0.4 6	0.49	0.0 2	0.7
57	Abnormal	Abnormal	0.4 7	0.4 7	0.6 2	0.3 8	0.4 2	0.6	0.1	0.77
58	Abnormal	Abnormal	0.2 9	0.3 7	0.2 8	0.2 7	0.3 4	0.47	0.0 9	0.68
59	Normal	Abnormal	0.2 4	0.3 7	0.2	0.2 2	0.4 9	0.7	0.0 4	0.84
60	Abnormal	Normal	0.0 5	0.1 7	0.1 7	0.1 4	0.6 3	4.4	0.0 3	2.1
61	Abnormal	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
62	Normal	Normal	0.1	0.3 6	0.0 6	0.0 8	0.6	24.2	0.0 3	4.92
63	Abnormal	Abnormal	0.1 5	0.4 4	0.0 5	0.1	0.5 2	1.82	0.0 3	1.35
64	Abnormal	Abnormal	0.3 3	0.4 8	0.4 5	0.2 5	0.5 1	0.51	0.2 7	0.71
65	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
66	Abnormal	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
67	Abnormal	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
68	Abnormal	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5	0.94	0.1	0.97
69	Abnormal	Abnormal	0.4 2	0.5 6	0.2 7	0.2 9	0.3 4	0.76	0.0 5	0.87
70	Abnormal	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
71	Abnormal	Abnormal	0.5 2	0.4 2	0.4 7	0.4 6	0.5	0.99	0.1 6	0.99
72	Abnormal	Abnormal	0.2 8	0.4 8	0.2 7	0.2	0.5 7	0.76	0.1 1	0.87

73	Normal	Normal	0.3 2	0.3 8	0.2 6	0.2 9	0.5 5	5.38	0.0 3	2.32
74	Abnormal	Normal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
75	Abnormal	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
76	Abnormal	Abnormal	0.5 3	0.4 9	0.7	0.4 3	0.6	1.14	0.1 1	1.07
77	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7	1.25	0.0 4	1.12
78	Abnormal	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
79	Normal	Normal	0.2 4	0.2	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
80	Abnormal	Normal	0.2 9	0.4 1	0.4 3	0.2 4	0.4 7	0.65	0.0 2	0.81
81	Normal	Normal	0.3 1	0.4	0.2 6	0.2 5	0.4 7	142	0.0 4	11.9
82	Abnormal	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
83	Abnormal	Abnormal	0.0 5	0.2 6	0.0 9	0.1	0.4 7	0.95	0.0 4	0.98
84	Normal	Normal	0.1 6	0.3 7	0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
85	Abnormal	Abnormal	0.5 6	0.4 8	0.5 6	0.4 6	0.6	0.79	0.1 9	0.89
86	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
87	Normal	Normal	0.2 6	0.2 9	0.3	0.2 8	0.5 7	0.81	0.0 3	0.9
88	Normal	Normal	0.3 2	0.2 6	0.3 7	0.3 6	0.5 9	13.3	0.0 3	3.64
89	Abnormal	Abnormal	0.5 9	0.7 1	0.3	0.3 8	0.7	3.59	0.2 6	1.9
90	Abnormal	Abnormal	0.4 3	0.7 9	0.6 3	0.1 9	0.5 9	1.62	0.1 8	1.27
91	Abnormal	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4	0.76	0.1 1	0.87
92	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
93	Abnormal	Abnormal	0.1 9	0.3 5	0.1 5	0.1 8	0.5 2	7.42	0.0 1	2.72
94	Abnormal	Abnormal	0.3 3	0.3 7	0.3 9	0.3	0.3 8	1.11	0.1	1.05
95	Abnormal	Abnormal	0.4 3	0.4	0.4 1	0.3 4	0.4 4	0.9	0.1	0.95
96	Abnormal	Abnormal	0.2 5	0.4 6	0.2	0.1 9	0.5	0.51	0.0 3	0.71
97	Abnormal	Abnormal	0.4 2	0.3 6	0.3 9	0.3 9	0.5 3	5.49	0.0 7	2.34

98	Abnormal	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
99	Abnormal	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
100	Normal	Normal	0.0 8	0.1 5	0.1 6	0.1 8	0.6 3	35.2	0.0 2	5.93
101	Normal	Normal	0.3 9	0.4 9	0.1 6	0.3 3	0.6 3	2.81	0.0 3	1.68
102	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
103	Abnormal	Abnormal	0.4 9	0.6 6	0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
104	Normal	Normal	0.1 4	0.0 9	0.1 5	0.2 6	0.5 3	5.6	0.0 1	2.37
105	Abnormal	Abnormal	0.3 7	0.2 9	0.3 9	0.3 9	0.2 7	0.68	0.1 4	0.83
106	Normal	Abnormal	0.4 2	0.4 5	0.5 5	0.3 4	0.3 6	1.38	0.0 2	1.17
107	Abnormal	Abnormal	0.4 4	0.5 3	0.6 9	0.3 3	0.7 3	0.76	0.1 6	0.87
108	Abnormal	Normal	0.3 9	0.5 9	0.3	0.2 5	0.5 5	0.83	0.0 2	0.91
109	Abnormal	Abnormal	0.4 1	1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
110	Abnormal	Abnormal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
111	Normal	Abnormal	0.1 6	0.4 1	0.2 5	0.1 2	0.5 4	4.57	0.0 4	2.14
112	Abnormal	Abnormal	0.4 3	0.3 6	0.4 2	0.4	0.3 5	0.64	0.0 9	0.8
113	Normal	Normal	0.2 7	0.4 9	0.1 4	0.1 8	0.4 8	82	0.0 2	9.06
114	Normal	Normal	0.1	0.1	0.1 8	0.2 2	0.7 1	1.05	0.0 2	1.03
115	Normal	Normal	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
116	Abnormal	Abnormal	0.5 1	0.5 4	0.2 4	0.3 9	0.3 1	0.32	0.1 1	0.56
117	Abnormal	Abnormal	0.5 3	0.7 8	0.6 5	0.2 8	0.7 6	1.63	0.2 3	1.28
118	Abnormal	Abnormal	0.3 9	0.3 8	0.5 2	0.3 6	0.1 3	0.27	0.1 2	0.52
119	Abnormal	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
120	Abnormal	Abnormal	0.3 6	0.3 7	0.3 1	0.3 3	0.4 5	0.7	0.1	0.84
121	Abnormal	Abnormal	0.4 3	0.5	0.4	0.3 3	0.3 5	0.78	0.0 9	0.88
122	Abnormal	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6	0.51

123	Abnormal	Abnormal	0.2 1	0.2 2	0.3 9	0.2 7	0.2 7	0.62	0.1	0.79
124	Normal	Abnormal	0.1 3	0.2 4	0.2 1	0.1 8	0.5 1	0.56	0.0 3	0.75

B.4 Random Forest Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10 0	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Abnormal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal	0.1 9	0.4 5	0.1 8	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnormal	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Abnormal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnormal	Abnormal	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnormal	Abnormal	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnormal	Abnormal	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnormal	Abnormal	0.4	0.6	0.5	0.3	0.4	0.46	0.2	0.68

	1		9	6	7	1	4		2	
10	Normal	Normal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma 1	Abnormal	0.6 4	0.7 5	0.5 7	0.4 3	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnormal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma 1	Abnormal	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma 1	Abnormal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma 1	Abnormal	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma 1	Abnormal	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnorma 1	Abnormal	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma 1	Abnormal	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2 2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnorma 1	Abnormal	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Abnormal	0.2 8	0.2 9	0.3 3	0.2 9	0.5 7	0.85	0.0 4	0.92

23	Normal	Abnormal	0.5 5	0.6 5	0.4 7	0.3 4	0.4 4	0.45 4	0.0 4	0.67
24	Abnorma 1	Abnormal	0.0 9	0.3 3	0.0 1	0.1 0.4	0.4 0.4	0.0 0.4	0.0 2	0.63
25	Abnorma 1	Abnormal	0.6 2	0.6 2	0.5 0.5	0.4 5	0.3 3	0.34 0.34	0.1 6	0.58
26	Abnorma 1	Abnormal	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79 0.79	0.1 1	0.89
27	Abnorma 1	Abnormal	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58 0.58	0.1 0.1	0.76
28	Abnorma 1	Abnormal	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26 1.26	0.2 6	1.12
29	Normal	Abnormal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67 5.67	0.0 5	2.38
30	Abnorma 1	Normal	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01 1.01	0.0 2	1.01
31	Abnorma 1	Abnormal	0.1 9	0.2 9	0.2 8	0.2 1	1 1	1.1 1.1	0.0 7	1.05
32	Abnorma 1	Abnormal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1 37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25 1.25	0.0 2	1.12
34	Abnorma 1	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2 8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2 4	0.6 4	1.43 1.43	0.0 4	1.2
36	Abnorma	Abnormal	0.0	0.4	0.0	0	0.5	0.68	0.0	0.82

	1		5	3	1		4		3	
37	Abnorma 1	Abnormal	0.1	0.5 2	0.1 3	0	0.4 9	1.06	0.0 2	1.03
38	Normal	Normal	0.1 3	0.4 1	0.2	0.0 9	0.6 7	1.06	0.0 1	1.03
39	Abnorma 1	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Abnormal	0.3 6	0.4 4	0.4 2	0.3 2	0.7 8	1.21	0.0 4	1.1
41	Abnorma 1	Abnormal	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Abnormal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Abnormal	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9
44	Abnorma 1	Abnormal	0.4 5	0.4 1	0.4 1	0.3 9	0 0	0	0.0 5	0
45	Abnorma 1	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
46	Abnorma 1	Abnormal	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnormal	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnorma 1	Normal	0.2	0.2 7	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma 1	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94

50	Abnormal	Abnormal	0.1 5	0.4 4	0.0 5	0.1 2	0.5 2	1.82	0.0 3	1.35
51	Abnormal	Abnormal	0.3 2	0.1 1	0.3 1	0.4 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Normal	0.2 7	0.5 4	0.1 4	0.1 8	0.5 2	0.75	0.0 2	0.86
53	Abnormal	Abnormal	0.2 1	0.4 1	0.2 1	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnormal	Abnormal	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnormal	Abnormal	0.1 8	0.2 9	0.3 4	0.2 0.2	0.7 0.7	0.7	0.0 9	0.84
58	Abnormal	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnormal	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnormal	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5 0.5	0.94	0.1	0.97
61	Abnormal	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnormal	Normal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnormal	Abnormal	0.3	0.2	0.3	0.3	0.3	0.71	0.1	0.84

	1		8	9	3	9	7		2	
64	Normal	Normal	0.0 7	0.1 8	0.1 5	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnorma 1	Abnormal	0.5 3	0.4 9	0.7 3	0.4 3	0.6 3	1.14	0.1 1	1.07
66	Normal	Abnormal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 3	1.25	0.0 4	1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnorma 1	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2 8	0.2 4	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnorma 1	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Abnormal	0.1 6	0.3 7	0.1 0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnorma 1	Abnormal	0.2 1	0.1 9	0.4 0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnorma 1	Abnormal	0.2 1	0.5 1	0.2 0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnorma 1	Abnormal	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25	0.2	1.5

77	Abnormal	Abnormal	0.5 9	0.7 1	0.3 8	0.3 8	0.7 7	3.59	0.2 6	1.9
78	Abnormal	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4 4	0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Abnormal	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnormal	Abnormal	0.3 3	0.3 7	0.3 9	0.3 8	0.3 8	1.11	0.1	1.05
82	Abnormal	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnormal	Abnormal	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnormal	Normal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnormal	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnormal	Abnormal	0.4	0.4	0.3	0.3	0.5	0.78	0.1	0.88

	1		5	3	4	9	3			
91	Normal	Abnormal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnorma l	Abnormal	0.4 9	0.6 6	0.5 0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma l	Abnormal	0.5 7	0.4 2	0.5 2	0.5 8	0.5 8	0.78	0.2	0.88
96	Abnorma l	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Abnormal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnorma l	Abnormal	0.3 9	0.3 5	0.4 7	0.2 9	0.5 0.2	0.95	0.1	0.97
99	Abnorma l	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2 9	0.78	0.1 2	0.88
100	Abnorma l	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma l	Abnormal	0.4 1	1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma l	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9

104	Abnormal	Abnormal	0.8 7	0.7 9	0.5 6	0.6 7	0.3 7	0.82	0.2 1	0.9
105	Abnormal	Abnormal	0.5 1	0.5 1	0.4 1	0.4 2	0.5 2	5.08	0.0 9	2.25
106	Abnormal	Abnormal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnormal	Abnormal	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnormal	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnormal	Normal	0.2 9	0.3 1	0.2 7	0.1 7	0.5 5	2.83	0.0 3	1.68
110	Abnormal	Abnormal	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Normal	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
112	Normal	Abnormal	0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnormal	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnormal	Abnormal	0.3 7	0.3 9	0.4 4	0.3 5	0.4 5	1.38	0.0 8	1.17
115	Abnormal	Abnormal	0.2 4	0.5 3	0.3 0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnormal	Normal	0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnormal	Abnormal	0.4	0.5	0.4	0.3	0.3	0.78	0.0	0.88

	1		3			3	5		9	
118	Abnorma 1	Abnormal	0.4 8	0.4 6	0.4 5	0.4 8	0.2 8	0.31 9	0.1 9	0.56
119	Abnorma 1	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26 9	0.1 6	0.51
120	Abnorma 1	Abnormal	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65 9	0.1 9	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2 0	0.1 4	0.5 8	0.85 9	0.0 3	0.92
122	Abnorma 1	Abnormal	0.4 8	0.6 8	0.6 8	0.2 8	0.4 8	0.4 8	0.1 5	0.63
123	Abnorma 1	Abnormal	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44 9	0.1 3	0.66
124	Abnorma 1	Abnormal	0.8 9	0.8 3	0.3 1	0.6 2	0.1 2	0.19 9	0.2 9	0.44

B.5 Support Vectors Machines Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col1 0	col6	sqrt(col5/col10)
1	Abnorma 1	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48 9	0.0 4	0.69
2	Abnorma 1	Normal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41 9	0.1 9	1.55
3	Normal	Abnormal	0.1	0.4	0.1	0.1	0.5	0.92 9	0.0 9	0.96

			9	5	8	2			3	
4	Abnorma 1	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnorma 1	Abnormal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnorma 1	Abnormal	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnorma 1	Normal	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnorma 1	Abnormal	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnorma 1	Abnormal	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal	Abnormal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma 1	Abnormal	0.6 4	0.7 5	0.5 7	0.4	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnormal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma 1	Abnormal	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma 1	Normal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma 1	Abnormal	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma 1	Abnormal	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69

17	Abnormal	Abnormal	0.5	0.3 7	0.5 9	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnormal	Abnormal	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnormal	Abnormal	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Normal	0.2 8	0.2 9	0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnormal	0.5 5	0.6 5	0.4	0.3 7	0.4 4	0.45	0.0 4	0.67
24	Abnormal	Abnormal	0.0 9	0.3 3	0.0 1	0.1	0.4	0.4	0.0 2	0.63
25	Abnormal	Abnormal	0.6 2	0.6 2	0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnormal	Abnormal	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnormal	Abnormal	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnormal	Abnormal	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Normal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38
30	Abnormal	Abnormal	0.3	0.4	0.3	0.2	0.4	1.01	0.0	1.01

	1		6	8	6	8	5		2	
31	Abnormal	Normal	0.1 9	0.2 9	0.2 8	0.2 1	1	1.1	0.0 7	1.05
32	Abnormal	Abnormal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25	0.0 2	1.12
34	Abnormal	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2	0.6 4	1.43	0.0 4	1.2
36	Abnormal	Abnormal	0.0 5	0.4 3	0.0 1	0	0.5 4	0.68	0.0 3	0.82
37	Abnormal	Abnormal	0.1 2	0.5 3	0.1 3	0	0.4 9	1.06	0.0 2	1.03
38	Normal	Normal	0.1 3	0.4 1	0.2	0.0 9	0.6 7	1.06	0.0 1	1.03
39	Abnormal	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Normal	0.3 6	0.4 4	0.4	0.3 2	0.7 8	1.21	0.0 4	1.1
41	Abnormal	Abnormal	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Normal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Abnormal	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9

44	Abnormal	Abnormal	0.4 5	0.4 1	0.4 1	0.3 9	0	0	0.0 5	0
45	Abnormal	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
46	Abnormal	Abnormal	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnormal	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnormal	Abnormal	0.2 7	0.2 3	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnormal	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnormal	Abnormal	0.1 5	0.4 4	0.0 5	0.1 2	0.5 2	1.82	0.0 3	1.35
51	Abnormal	Normal	0.3 2	0.1 1	0.3 1	0.4 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnormal	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnormal	Abnormal	0.2 1	0.4 1	0.2 1	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnormal	Abnormal	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnormal	Normal	0.1	0.2	0.3	0.2	0.7	0.7	0.0	0.84

	1		8	9	4			9		
58	Abnorma 1	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnorma 1	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnorma 1	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5 0.5	0.94	0.1	0.97
61	Abnorma 1	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnorma 1	Normal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnorma 1	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1 0.1	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnorma 1	Abnormal	0.5 3	0.4 9	0.7 0.7	0.4 3	0.6 0.6	1.14	0.1 1	1.07
66	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 0.7	1.25	0.0 4	1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnorma 1	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2 0.2	0.2 4	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnorma 1	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11

71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Normal	0.1 6	0.3 7	0.1 0.4	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnorma 1	Normal	0.2 1	0.1 9	0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnorma 1	Abnormal	0.2 1	0.5 1	0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnorma 1	Abnormal	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25	0.2	1.5
77	Abnorma 1	Abnormal	0.5 9	0.7 1	0.3	0.3 8	0.7	3.59	0.2 6	1.9
78	Abnorma 1	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4	0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Abnormal	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnorma 1	Abnormal	0.3 3	0.3 7	0.3 9	0.3 0.3	0.3 8	1.11	0.1	1.05
82	Abnorma 1	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnorma	Abnormal	0.1	0.2	0.2	0.1	0.1	0.19	0.0	0.43

	1			1	5	7	5		3	
85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma l	Normal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Abnormal	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnorma l	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma l	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Abnormal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4	0.1 9	0.2 1	0.6 4	1.47	0.0 3	1.21
94	Abnorma l	Abnormal	0.4 9	0.6 6	0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma l	Abnormal	0.5 7	0.4	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma l	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Normal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05

98	Abnormal	Abnormal	0.3	0.3 9	0.4 5	0.2 7	0.5	0.95	0.1	0.97
99	Abnormal	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2	0.78	0.1 2	0.88
100	Abnormal	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnormal	Abnormal	0.4 1		0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Abnormal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnormal	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnormal	Abnormal	0.8 7	0.7 9	0.5 6	0.6	0.3 7	0.82	0.2 1	0.9
105	Abnormal	Normal	0.5 1	0.5 1	0.4 1	0.4	0.5 2	5.08	0.0 9	2.25
106	Abnormal	Normal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnormal	Abnormal	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnormal	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnormal	Abnormal	0.2	0.3 9	0.2 1	0.1 7	0.5	2.83	0.0 3	1.68
110	Abnormal	Abnormal	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Abnormal	0.2	0.4	0.1	0.1	0.5	0.61	0.0	0.78

			3	2	3	8	5		3	
112	Normal	Abnormal	0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnorma 1	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnorma 1	Abnormal	0.3 7	0.3 9	0.4	0.3 4	0.4 5	1.38	0.0 8	1.17
115	Abnorma 1	Abnormal	0.2 4	0.5 3	0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnorma 1	Normal	0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnorma 1	Abnormal	0.4 3	0.5 0.5	0.4	0.3 3	0.3 5	0.78	0.0 9	0.88
118	Abnorma 1	Abnormal	0.4 8	0.4 6	0.4 5	0.4 8	0.2 8	0.31	0.1 9	0.56
119	Abnorma 1	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6	0.51
120	Abnorma 1	Abnormal	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65	0.1	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2	0.1 4	0.5 8	0.85	0.0 3	0.92
122	Abnorma 1	Abnormal	0.4 8	0.6 8	0.6 8	0.2 8	0.4 0.4	0.4	0.1 5	0.63
123	Abnorma 1	Abnormal	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3	0.66
124	Abnorma 1	Abnormal	0.8 9	0.8 0.8	0.3 3	0.6 1	0.1 2	0.19	0.2	0.44

B.6 Gradient Boosted Trees Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10 0	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Abnormal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal	0.1 9	0.4 5	0.1 8	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnormal	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Abnormal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnormal	Abnormal	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnormal	Abnormal	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnormal	Abnormal	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnormal	Abnormal	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal	Normal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1

11	Abnormal	Abnormal	0.6 4	0.7 5	0.5 7	0.4 9	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnormal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnormal	Abnormal	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnormal	Normal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnormal	Abnormal	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnormal	Abnormal	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnormal	Abnormal	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnormal	Abnormal	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2 0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnormal	Abnormal	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Normal	0.2 8	0.2 9	0.3 0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnormal	0.5 5	0.6 5	0.4 0.4	0.3 7	0.4 4	0.45	0.0 4	0.67
24	Abnormal	Abnormal	0.0	0.3	0.0	0.1	0.4	0.4	0.0	0.63

	1		9	3	1			2	
25	Abnorma 1	Abnormal	0.6 2	0.6 2	0.5 5	0.4 3	0.3 6	0.34 6	0.1 0.58
26	Abnorma 1	Abnormal	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79 1	0.1 0.89
27	Abnorma 1	Abnormal	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58 0.1	0.1 0.76
28	Abnorma 1	Abnormal	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26 6	0.2 1.12
29	Normal	Abnormal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67 5	0.0 2.38
30	Abnorma 1	Normal	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01 2	0.0 1.01
31	Abnorma 1	Abnormal	0.1 9	0.2 9	0.2 8	0.2 1	1 1	1.1 7	0.0 1.05
32	Abnorma 1	Abnormal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1 2	0.1 6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25 2	0.0 1.12
34	Abnorma 1	Normal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2 2	0.0 2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2 4	0.6 4	1.43 4	0.0 1.2
36	Abnorma 1	Abnormal	0.0 5	0.4 3	0.0 1	0 0	0.5 4	0.68 3	0.0 0.82
37	Abnorma 1	Abnormal	0.1 0.1	0.5 2	0.1 3	0 0	0.4 9	1.06 2	0.0 1.03

38	Normal	Abnormal	0.1 3	0.4 1	0.2 9	0.0 7	0.6 1.06	0.0 1		1.03
39	Abnorma l	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Abnormal	0.3 6	0.4 4	0.4 2	0.3 2	0.7 8	1.21	0.0 4	1.1
41	Abnorma l	Abnormal	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Abnormal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Normal	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9
44	Abnorma l	Abnormal	0.4 5	0.4 1	0.4 1	0.3 9	0 0	0	0.0 5	0
45	Abnorma l	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
46	Abnorma l	Abnormal	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnormal	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnorma l	Normal	0.2 7	0.2 3	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma l	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnorma l	Abnormal	0.1 5	0.4 4	0.0 5	0.1 0.1	0.5 2	1.82	0.0 3	1.35
51	Abnorma	Abnormal	0.3	0.1	0.3	0.4	0.3	3.6	0.1	1.9

	1			2	1		5		5	
52	Normal	Normal	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75 2	0.0 2	0.86
53	Abnorma 1	Abnormal	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39 0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33 1.33	0.0 2	1.15
55	Abnorma 1	Abnormal	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83 0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61 0.61	0.0 2	0.78
57	Abnorma 1	Abnormal	0.1 8	0.2 9	0.3 4	0.2 0.2	0.7 0.7	0.7 0.7	0.0 9	0.84
58	Abnorma 1	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89 0.89	0.1 8	0.94
59	Abnorma 1	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59 0.59	0.0 3	0.77
60	Abnorma 1	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5 0.5	0.94 0.94	0.1 0.1	0.97
61	Abnorma 1	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62 0.62	0.2 1	0.79
62	Abnorma 1	Abnormal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72 0.72	0.0 3	0.85
63	Abnorma 1	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71 0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1 0.1	0.1 5	0.6 3	0.99 0.99	0.0 2	0.99

65	Abnorma l	Abnormal	0.5 3	0.4 9	0.7 3	0.4 3	0.6 1.14	0.1 1		1.07
66	Normal	Abnormal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 1.25	0.0 4		1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53 4	0.0	1.59
68	Abnorma l	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44 0.0	0.0 3	1.86
69	Normal	Normal	0.2 4	0.2 1	0.3 4	0.2 4	0.6 5	0.79 0.0	0.0 3	0.89
70	Abnorma l	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23 0.1	0.1 7	1.11
71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64 0.0	0.0 2	0.8
72	Normal	Abnormal	0.1 6	0.3 7	0.1 0.1	0.1 4	0.6 3	3.18 0.0	0.0 3	1.78
73	Abnorma l	Abnormal	0.2 1	0.1 9	0.4 0.4	0.2 8	0.5 9	4.4 0.1	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05 0.0	0.0 3	1.43
75	Abnorma l	Abnormal	0.2 1	0.5 1	0.2 0.2	0.1 2	0.5 1	0.81 0.0	0.0 4	0.9
76	Abnorma l	Abnormal	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25 0.2	0.2	1.5
77	Abnorma l	Abnormal	0.5 9	0.7 1	0.3 0.3	0.3 8	0.7 0.7	3.59 0.2	0.2 6	1.9
78	Abnorma	Abnormal	0.4	0.3	0.1	0.4	0.4	0.76	0.1	0.87

	1		7	7	7	4			1	
79	Normal	Abnormal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Normal	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnorma l	Abnormal	0.3 3	0.3 7	0.3 9	0.3 8	0.3 8	1.11	0.1	1.05
82	Abnorma l	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Abnormal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnorma l	Normal	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma l	Normal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnorma l	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma l	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Abnormal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28

92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnormal	Abnormal	0.4 9	0.6 6	0.5 0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnormal	Abnormal	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnormal	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Abnormal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnormal	Abnormal	0.3 9	0.3 5	0.4 5	0.2 7	0.5 0.5	0.95	0.1	0.97
99	Abnormal	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2 9	0.78	0.1 2	0.88
100	Abnormal	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnormal	Abnormal	0.4 1	0.4 8	0.4 5	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnormal	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnormal	Abnormal	0.8 7	0.7 9	0.5 6	0.6 0.6	0.3 7	0.82	0.2 1	0.9
105	Abnormal	Abnormal	0.5	0.5	0.4	0.4	0.5	5.08	0.0	2.25

	1			1	1		2		9	
106	Abnorma 1	Normal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma 1	Abnormal	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Normal	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma 1	Normal	0.2 9	0.3 1	0.2 7	0.1 7	0.5 5	2.83	0.0 3	1.68
110	Abnorma 1	Abnormal	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Normal	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
112	Normal	Abnormal	0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnorma 1	Abnormal	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnorma 1	Abnormal	0.3 7	0.3 9	0.4 0.4	0.3 4	0.4 5	1.38	0.0 8	1.17
115	Abnorma 1	Abnormal	0.2 4	0.5 3	0.3 0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnorma 1	Abnormal	0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnorma 1	Abnormal	0.4 3	0.5 0.5	0.4 0.4	0.3 3	0.3 5	0.78	0.0 9	0.88
118	Abnorma 1	Abnormal	0.4 8	0.4 6	0.4 5	0.4 0.4	0.2 8	0.31	0.1 9	0.56

119	Abnormal	Abnormal	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6	0.51
120	Abnormal	Abnormal	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65	0.1	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2	0.1 4	0.5 8	0.85	0.0 3	0.92
122	Abnormal	Abnormal	0.4 8	0.6 8	0.6 8	0.2 8	0.4	0.4	0.1 5	0.63
123	Abnormal	Abnormal	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3	0.66
124	Abnormal	Abnormal	0.8 9	0.8 8	0.3 3	0.6 1	0.1 2	0.19	0.2	0.44

B.7 Decision Trees Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col1 0	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Normal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal	0.1 9	0.4	0.1	0.1 8	0.5 2	0.92	0.0 3	0.96
4	Abnormal	Abnormal	0.5	0.5	0.4	0.4 5	0.4 8	1.15	0.0 9	1.07

5	Abnorma I	Abnorma I	0.4	0.2 5	0.3 4	0.4 3	0.3 0.3	14.2	0.1 2	3.77
6	Abnorma I	Abnorma I	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnorma I	Abnorma I	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnorma I	Abnorma I	0.6 7	0.9 5	0.4 3	0.3 9	0.2 9	0.54	0.2 1	0.73
9	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal	Normal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma I	Abnorma I	0.6 4	0.7 5	0.5 7	0.4 0.4	0.4 9	1.15	0.1 6	1.07
12	Normal	Normal	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma I	Abnorma I	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma I	Abnorma I	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma I	Abnorma I	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma I	Abnorma I	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnorma	Abnorma	0.5	0.3	0.5	0.4	0.3	0.59	0.0	0.77

	I	I		7	9	7	7		5		
18	Normal	Normal		0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma I	Abnorma I		0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal		0.2 1	0.3 6	0.2 0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnorma I	Abnorma I		0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Abnorma I		0.2 8	0.2 9	0.3 0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnorma I		0.5 5	0.6 5	0.4 0.4	0.3 7	0.4 4	0.45	0.0 4	0.67
24	Abnorma I	Abnorma I		0.0 9	0.3 3	0.0 1	0.1 0.1	0.4 0.4	0.4	0.0 2	0.63
25	Abnorma I	Abnorma I		0.6 2	0.6 2	0.5 0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnorma I	Abnorma I		0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnorma I	Abnorma I		0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnorma I	Abnorma I		0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Abnorma I		0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38

30	Abnorma I	Normal	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5		1.01 2	0.0 2	1.01
31	Abnorma I	Abnorma I	0.1 9	0.2 9	0.2 8	0.2 1		1 1	0.0 7		1.05
32	Abnorma I	Abnorma I	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7		37.1 2	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6		1.25 2	0.0 2	1.12
34	Abnorma I	Normal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7		8.2 2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2 4	0.6 4		1.43 4	0.0 4	1.2
36	Abnorma I	Abnorma I	0.0 5	0.4 3	0.0 1	0 0	0.5 4		0.68 3	0.0 3	0.82
37	Abnorma I	Abnorma I	0.1 2	0.5 3	0.1 3	0 0	0.4 9		1.06 2	0.0 2	1.03
38	Normal	Abnorma I	0.1 3	0.4 1	0.2 0	0.0 9	0.6 7		1.06 1	0.0 1	1.03
39	Abnorma I	Abnorma I	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5		1.44 7	0.1 7	1.2
40	Normal	Abnorma I	0.3 6	0.4 4	0.4 2	0.3 8	0.7 8		1.21 4	0.0 4	1.1
41	Abnorma I	Abnorma I	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2		2.69 2	0.3 2	1.64
42	Normal	Abnorma	0.4	0.3	0.3	0.3	0.6		8.11	0.0	2.85

		I	1	5	7	9	1		5	
43	Normal	Normal	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9
44	Abnorma I	Abnorma I	0.4 5	0.4 1	0.4 1	0.3 9	0.3 1	0	0.0 5	0
45	Abnorma I	Abnorma I	0.5 7	0.6 5	0.6 2	0.3 9	0.3 1	0.6 2.12	0.1 9	1.46
46	Abnorma I	Abnorma I	0.3 8	0.3 1	0.3 8	0.3 9	0.3 2	0.4 0.44	0.1 5	0.66
47	Normal	Abnorma I	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnorma I	Normal	0.2 7	0.2 3	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma I	Abnorma I	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnorma I	Abnorma I	0.1 5	0.4 4	0.0 5	0.1 5	0.5 2	1.82	0.0 3	1.35
51	Abnorma I	Abnorma I	0.3 2	0.1 1	0.3 0.4	0.4 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Normal	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnorma I	Abnorma I	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15

55	Abnorma I	Abnorma I	0.5 7	0.4 9	0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma I	Abnorma I	0.1 8	0.2 9	0.3 4	0.2	0.7	0.7	0.0 9	0.84
58	Abnorma I	Abnorma I	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnorma I	Abnorma I	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnorma I	Abnorma I	0.4 3	0.4 8	0.4 4	0.3 5	0.5	0.94	0.1	0.97
61	Abnorma I	Abnorma I	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnorma I	Abnorma I	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnorma I	Abnorma I	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnorma I	Abnorma I	0.5 3	0.4 9	0.7	0.4 3	0.6	1.14	0.1 1	1.07
66	Normal	Abnorma I	0.2 1	0.2 9	0.2	0.2 3	0.7	1.25	0.0 4	1.12
67	Normal	Normal	0.3	0.3	0.3	0.3	0.6	2.53	0.0	1.59

				5	7	9	2	8		4	
68	Abnorma I	Abnorma I	Abnorma I	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	Normal	0.2	0.2 4	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnorma I	Abnorma I	Abnorma I	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Abnorma I	Abnorma I	0.1 6	0.3 7	0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnorma I	Abnorma I	Abnorma I	0.2 1	0.1 9	0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnorma I	Abnorma I	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnorma I	Abnorma I	Abnorma I	0.2 1	0.5 1	0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnorma I	Abnorma I	Abnorma I	0.5 9	0.4 8	0.7 1	0.5	0.5 5	2.25	0.2	1.5
77	Abnorma I	Abnorma I	Abnorma I	0.5 9	0.7 1	0.3	0.3 8	0.7	3.59	0.2 6	1.9
78	Abnorma I	Abnorma I	Abnorma I	0.4 7	0.3 7	0.1 7	0.4 4	0.4	0.76	0.1 1	0.87
79	Normal	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96

80	Normal	Abnorma l	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnorma l	Abnorma l	0.3 3	0.3 7	0.3 9	0.3 8	0.3 8	1.11	0.1	1.05
82	Abnorma l	Abnorma l	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Abnorma l	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnorma l	Abnorma l	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma l	Normal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnorma l	Abnorma l	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma l	Abnorma l	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Normal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2	0.3	0.3	0.2	0.6	0.68	0.0	0.83

				2	5	4	1	1		3	
93	Normal	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnorma I	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 0.4	0.3 2	0.4 2	0.98	0.1 9	0.99
95	Abnorma I	Abnorma I	Abnorma I	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma I	Abnorma I	Abnorma I	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Abnorma I	Abnorma I	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnorma I	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.2 7	0.5 9	0.95	0.1	0.97
99	Abnorma I	Abnorma I	Abnorma I	0.1 7	0.2 9	0.3 4	0.1 9	0.2 9	0.78	0.1 2	0.88
100	Abnorma I	Abnorma I	Abnorma I	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma I	Abnorma I	Abnorma I	0.4 1	1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma I	Abnorma I	Abnorma I	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnorma I	Abnorma I	Abnorma I	0.8 7	0.7 9	0.5 6	0.6 0.6	0.3 7	0.82	0.2 1	0.9

105	Abnorma I	Abnorma I	0.5	0.5 1	0.4 1	0.4 0.1	0.5 0.5	0.5 2	5.08	0.0 9	2.25
106	Abnorma I	Abnorma I	0.2	0.3 1	0.1 8	0.1 9	0.5 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma I	Abnorma I	0.5	0.4 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Normal	0.1	0.4 1	0.0 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma I	Normal	0.2	0.3 9	0.2 1	0.1 7	0.5 0.5	0.5 2.83	0.0 3	0.0 1.68	
110	Abnorma I	Abnorma I	0.3	0.3 7	0.4 4	0.3 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Normal	0.2	0.4 3	0.1 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
112	Normal	Abnorma I	0.6	0.5 1	0.4 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4	1.04
113	Abnorma I	Abnorma I	0.5	0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7	1.02
114	Abnorma I	Abnorma I	0.3	0.3 7	0.4 9	0.4 4	0.3 4	0.4 5	1.38	0.0 8	1.17
115	Abnorma I	Abnorma I	0.2	0.5 4	0.5 3	0.3 0.3	0.1 3	0.5 1	0.58	0.0 2	0.76
116	Abnorma I	Abnorma I	0.1	0.4 6	0.1 7	0.0 9	0.0 9	0.5 9	0.75	0.0 2	0.86
117	Abnorma	Abnorma	0.4	0.5	0.4	0.4	0.3	0.3	0.78	0.0	0.88

	I	I	3			3	5		9	
118	Abnorma I	Abnorma I	0.4 8	0.4 6	0.4 5	0.4 8	0.2 8	0.31 9	0.1 9	0.56
119	Abnorma I	Abnorma I	0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26 9	0.1 6	0.51
120	Abnorma I	Abnorma I	0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65 9	0.1 0.1	0.8
121	Normal	Normal	0.0 7	0.2 1	0.2 4	0.1 4	0.5 8	0.85 8	0.0 3	0.92
122	Abnorma I	Abnorma I	0.4 8	0.6 8	0.6 8	0.2 8	0.4 8	0.4 8	0.1 5	0.63
123	Abnorma I	Abnorma I	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44 1	0.1 3	0.66
124	Abnorma I	Abnorma I	0.8 9	0.8 3	0.3 1	0.6 2	0.1 2	0.19 2	0.2 0.2	0.44

B.8 ANN Classifier:

Row No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal I	Abnormal I	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal I	Normal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal I	0.1 9	0.4 5	0.1 8	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnormal I	Abnormal I	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Abnormal	0.4	0.2	0.3	0.4	0.3	14.2	0.1	3.77

	I	I		5	4	3			2	
6	Abnorma I	Abnorma I	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnorma I	Abnorma I	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnorma I	Abnorma I	0.6 7	0.9 5	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal	Normal	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma I	Abnorma I	0.6 4	0.7 5	0.5 7	0.4	0.4 9	1.15	0.1 6	1.07
12	Normal	Abnorma I	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma I	Abnorma I	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma I	Normal	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma I	Abnorma I	0.4 3	0.3	0.5 6	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma I	Abnorma I	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnorma I	Abnorma I	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma I	Abnorma I	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal	Normal	0.2 1	0.3 6	0.2	0.1 9	0.5 1	3.35	0.0 2	1.83
21	Abnorma I	Abnorma I	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6	0.0 8	0.77
22	Normal	Normal	0.2 8	0.2 9	0.3	0.2 9	0.5 7	0.85	0.0 4	0.92
23	Normal	Abnorma I	0.5 5	0.6 5	0.4	0.3 7	0.4 4	0.45	0.0 4	0.67
24	Abnorma I	Abnorma I	0.0 9	0.3 3	0.0 1	0.1	0.4	0.4	0.0 2	0.63
25	Abnorma I	Abnorma I	0.6 2	0.6 2	0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnorma I	Abnorma I	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnorma I	Abnorma I	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Normal	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38
30	Abnorma	Abnorma	0.3	0.4	0.3	0.2	0.4	1.01	0.0	1.01

	I	I	6	8	6	8	5		2	
31	Abnormal	Normal	0.1 9	0.2 9	0.2 8	0.2 1	1	1.1	0.0 7	1.05
32	Abnormal	Abnormal	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25	0.0 2	1.12
34	Abnormal	Abnormal	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2 0	0.6 4	1.43	0.0 4	1.2
36	Abnormal	Abnormal	0.0 5	0.4 3	0.0 1	0	0.5 4	0.68	0.0 3	0.82
37	Abnormal	Abnormal	0.1 2	0.5 3	0.1 3	0	0.4 9	1.06	0.0 2	1.03
38	Normal	Normal	0.1 3	0.4 1	0.2	0.0 9	0.6 7	1.06	0.0 1	1.03
39	Abnormal	Abnormal	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Normal	0.3 6	0.4	0.4 4	0.3 2	0.7 8	1.21	0.0 4	1.1
41	Abnormal	Abnormal	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Normal	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Abnormal	0.6 1	0.5 2	0.6 9	0.5	0.3 3	0.81	0.0 3	0.9
44	Abnormal	Abnormal	0.4 5	0.4 1	0.4 1	0.3 9	0	0	0.0 5	0
45	Abnormal	Abnormal	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46
46	Abnormal	Abnormal	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnormal	0.3 6	0.5	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnormal	Normal	0.2	0.2	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnormal	Abnormal	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnormal	Abnormal	0.1 5	0.4 4	0.0 5	0.1	0.5 2	1.82	0.0 3	1.35
51	Abnormal	Abnormal	0.3	0.1	0.3 1	0.4	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnormal	0.2 7	0.5	0.1 4	0.1 8	0.5 2	0.75	0.0 2	0.86
53	Abnormal	Abnormal	0.2 1	0.4 1	0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnormal	Abnormal	0.5	0.4	0.7	0.4	0.4	0.83	0.1	0.91

	I	I	7	9		7	2		1	
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnormal	Normal	0.1 8	0.2 9	0.3 4	0.2	0.7	0.7	0.0 9	0.84
58	Abnormal	Abnormal	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnormal	Abnormal	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnormal	Abnormal	0.4 3	0.4 8	0.4 4	0.3 5	0.5	0.94	0.1	0.97
61	Abnormal	Abnormal	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnormal	Abnormal	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnormal	Abnormal	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnormal	Abnormal	0.5 3	0.4 9	0.7	0.4 3	0.6	1.14	0.1 1	1.07
66	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7	1.25	0.0 4	1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnormal	Abnormal	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2	0.2 4	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnormal	Abnormal	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Normal	0.1 6	0.3 7	0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnormal	Abnormal	0.2 1	0.1 9	0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnormal	Abnormal	0.2 1	0.5 1	0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnormal	Abnormal	0.5 9	0.4 8	0.7 1	0.5	0.5 5	2.25	0.2	1.5
77	Abnormal	Abnormal	0.5 9	0.7 1	0.3	0.3 8	0.7	3.59	0.2 6	1.9
78	Abnormal	Abnormal	0.4 7	0.3 7	0.1 7	0.4 4	0.4	0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Abnormal	0.2	0.4	0.2	0.1	0.5	9.41	0.0	3.07

		I			3	6	3		5	
81	Abnormal	Abnormal	0.3 3	0.3 7	0.3 9	0.3 8	0.3 8	1.11	0.1	1.05
82	Abnormal	Abnormal	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnormal	Abnormal	0.1 1	0.2 5	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	0.2 2	0.3 3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnormal	Abnormal	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3 3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnormal	Abnormal	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnormal	Abnormal	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Normal	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 4	0.1 9	0.2 1	0.6 4	1.47	0.0 3	1.21
94	Abnormal	Abnormal	0.4 9	0.6 6	0.5 5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnormal	Abnormal	0.5 7	0.4 4	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnormal	Abnormal	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Normal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnormal	Abnormal	0.3 3	0.3 9	0.4 5	0.2 7	0.5	0.95	0.1	0.97
99	Abnormal	Abnormal	0.1 7	0.2 9	0.3 4	0.1 9	0.2	0.78	0.1 2	0.88
100	Abnormal	Abnormal	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnormal	Abnormal	0.4 1	1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnormal	Abnormal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnormal	Abnormal	0.8 7	0.7 9	0.5 6	0.6 7	0.3 7	0.82	0.2 1	0.9
105	Abnormal	Abnormal	0.5	0.5	0.4	0.4	0.5	5.08	0.0	2.25

	I	I		1	1		2		9	
106	Abnormal	Abnormal		0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4
107	Abnormal	Abnormal		0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2
108	Normal	Abnormal		0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4
109	Abnormal	Abnormal		0.2 9	0.3 1	0.2 1	0.1 7	0.5 7	2.83	0.0 3
110	Abnormal	Abnormal		0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2
111	Normal	Abnormal		0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3
112	Normal	Abnormal		0.6 1	0.5 8	0.4 9	0.4 6	0.4 5	1.08	0.0 4
113	Abnormal	Abnormal		0.5 1	0.5 9	0.5 1	0.3 6	0.5 2	1.04	0.1 7
114	Abnormal	Abnormal		0.3 7	0.3 9	0.4 4	0.3 4	0.4 5	1.38	0.0 8
115	Abnormal	Abnormal		0.2 4	0.5 3	0.3 3	0.1 3	0.5 1	0.58	0.0 2
116	Abnormal	Abnormal		0.1 6	0.4 7	0.1 9	0.0 9	0.5 9	0.75	0.0 2
117	Abnormal	Abnormal		0.4 3	0.5 5	0.4 4	0.3 3	0.3 5	0.78	0.0 9
118	Abnormal	Abnormal		0.4 8	0.4 6	0.4 5	0.4 4	0.2 8	0.31	0.1 9
119	Abnormal	Abnormal		0.3 6	0.3 5	0.4 6	0.3 5	0.2 1	0.26	0.1 6
120	Abnormal	Abnormal		0.4 7	0.3 7	0.4 4	0.4 4	0.4 9	0.65	0.1
121	Normal	Normal		0.0 7	0.2 1	0.2 2	0.1 4	0.5 8	0.85	0.0 3
122	Abnormal	Abnormal		0.4 8	0.6 8	0.6 8	0.2 8	0.4 4	0.4	0.1 5
123	Abnormal	Abnormal		0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3
124	Abnormal	Abnormal		0.8 9	0.8 8	0.3 3	0.6 1	0.1 2	0.19	0.2
										0.44

B.9 MLP Classifier:

Ro	Class Att.	Class	Test Inputs
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w No.		Predicted	col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.12	0.3	0.1	0.4	0.48	0.04		0.69
2	Abnormal	Normal	0.11	0.2	0.1	0.19	0.94	2.41	0.1	1.55
3	Normal	Abnormal	0.19	0.45	0.18	0.12	0.5	0.92	0.03	0.96
4	Abnormal	Abnormal	0.5	0.5	0.45	0.4	0.48	1.15	0.09	1.07
5	Abnormal	Abnormal	0.4	0.25	0.34	0.43	0.3	14.2	0.12	3.77
6	Abnormal	Abnormal	0.29	0.28	0.35	0.32	0.31	0.56	0.14	0.75
7	Abnormal	Abnormal	0.29	0.42	0.25	0.24	0.62	0.64	0.08	0.8
8	Abnormal	Abnormal	0.67	0.95	0.43	0.33	0.29	0.54	0.21	0.73
9	Abnormal	Abnormal	0.49	0.66	0.57	0.31	0.44	0.46	0.22	0.68
10	Normal	Abnormal	0.34	0.47	0.35	0.26	0.52	1.01	0.04	1
11	Abnormal	Abnormal	0.64	0.75	0.57	0.49	0.49	1.15	0.16	1.07
12	Normal	Abnormal	0.3	0.5	0.3	0.2	0.3	0.56	0.0	0.75

		I		7	9	3	3	9		3	
13	Abnorma	Abnorma	0.4	0.5	0.2	0.3	0.5		3.82	0.0	1.41
			3	4	7	1	4		9		
14	Abnorma	Abnorma	0.2	0.2	0.2	0.2	0.5		0.59	0.0	0.77
			7	8	6	9	8		8		
15	Abnorma	Abnorma	0.4	0.3	0.5	0.4	0.5		10.1	0.1	3.18
			3		6	3	3				
16	Abnorma	Abnorma	0.5	0.9	0.3	0.1	0.4		0.48	0.1	0.69
			2	8	4	7	4		8		
17	Abnorma	Abnorma	0.5	0.3	0.5	0.4	0.3		0.59	0.0	0.77
				7	9	7	7		5		
18	Normal	Normal	0.1	0.0	0.3	0.3	0.5		2.65	0.0	1.63
			6	1	9	3	5			2	
19	Abnorma	Abnorma	0.4	0.4	0.3	0.4	0.4		7.37	0.1	2.71
			9	2	2	4	4		2		
20	Normal	Abnorma	0.2	0.3		0.2	0.1	0.5		3.35	0.0
			1	6			9	1		2	1.83
21	Abnorma	Abnorma	0.3	0.5	0.2	0.2	0.3		0.6	0.0	0.77
			4	7	2	1	6		8		
22	Normal	Normal	0.2	0.2		0.3	0.2	0.5		0.85	0.0
			8	9			9	7		4	0.92
23	Normal	Abnorma	0.5	0.6		0.4	0.3	0.4		0.45	0.0
			5	5			7	4		4	0.67
24	Abnorma	Abnorma	0.0	0.3	0.0		0.1	0.4		0.4	0.0
			9	3	1				2		0.63

25	Abnorma I	Abnorma I	0.6 2	0.6 2	0.5	0.4 5	0.3 3	0.34	0.1 6	0.58
26	Abnorma I	Abnorma I	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79	0.1 1	0.89
27	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58	0.1	0.76
28	Abnorma I	Abnorma I	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26	0.2 6	1.12
29	Normal	Abnorma I	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67	0.0 5	2.38
30	Abnorma I	Abnorma I	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01	0.0 2	1.01
31	Abnorma I	Normal	0.1 9	0.2 9	0.2 8	0.2 1	1	1.1	0.0 7	1.05
32	Abnorma I	Abnorma I	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1	0.1 2	6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25	0.0 2	1.12
34	Abnorma I	Abnorma I	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2	0.6 4	1.43	0.0 4	1.2
36	Abnorma I	Abnorma I	0.0 5	0.4 3	0.0 1	0	0.5 4	0.68	0.0 3	0.82
37	Abnorma	Abnorma	0.1	0.5	0.1	0	0.4	1.06	0.0	1.03

	I	I		2	3		9		2	
38	Normal	Abnorma	0.1	0.4	0.2	0.0	0.6	1.06	0.0	1.03
	I	I	3	1	9	7			1	
39	Abnorma	Abnorma	0.5	0.8	0.6	0.3	0.5	1.44	0.1	1.2
	I	I	7	1	1	1	5		7	
40	Normal	Normal	0.3	0.4	0.4	0.3	0.7	1.21	0.0	1.1
			6	4	2	8			4	
41	Abnorma	Abnorma	0.4	0.7	0.4	0.2	0.8	2.69	0.3	1.64
	I	I	7	1	7	6	2		2	
42	Normal	Normal	0.4	0.3	0.3	0.3	0.6	8.11	0.0	2.85
			1	5	7	9	1		5	
43	Normal	Abnorma	0.6	0.5	0.6	0.5	0.3	0.81	0.0	0.9
	I	I	1	2	9		3		3	
44	Abnorma	Abnorma	0.4	0.4	0.4	0.3	0	0	0.0	0
	I	I	5	1	1	9			5	
45	Abnorma	Abnorma	0.5	0.6	0.6	0.3	0.6	2.12	0.1	1.46
	I	I	7	5	2	9	1		9	
46	Abnorma	Abnorma	0.3	0.3	0.3	0.3	0.4	0.44	0.1	0.66
	I	I	8	1	8	9	2		5	
47	Normal	Abnorma	0.3	0.5	0.4	0.2	0.5	3.07	0.0	1.75
	I	I	6		7	7	3		5	
48	Abnorma	Abnorma	0.2	0.2	0.1	0.2	0.4	1.89	0.0	1.38
	I	I	7		3	3	9		3	
49	Abnorma	Abnorma	0.6	0.9	0.5	0.2	0.6	0.88	0.3	0.94
	I	I	1	9	2	5	9			

50	Abnorma I	Abnorma I	0.1 5	0.4 4	0.0 5	0.1 2	0.5 2	1.82	0.0 3	1.35
51	Abnorma I	Abnorma I	0.3 2	0.1 1	0.3 4	0.4 8	0.3 2	3.6	0.1 5	1.9
52	Normal	Abnorma I	0.2 7	0.5 4	0.1 4	0.1 8	0.5 2	0.75	0.0 2	0.86
53	Abnorma I	Abnorma I	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnorma I	Abnorma I	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma I	Abnorma I	0.1 8	0.2 9	0.3 4	0.2 0.2	0.7 0.7	0.7	0.0 9	0.84
58	Abnorma I	Abnorma I	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnorma I	Abnorma I	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnorma I	Abnorma I	0.4 3	0.4 8	0.4 4	0.3 5	0.5 0.5	0.94	0.1	0.97
61	Abnorma I	Abnorma I	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnorma	Abnorma	0.1	0.3	0.1	0.1	0.5	0.72	0.0	0.85

	I	I	2	6	5	1	7		3	
63	Abnorma I	Abnorma I	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	0.0 7	0.1 8	0.1 5	0.1 5	0.6 3	0.99	0.0 2	0.99
65	Abnorma I	Abnorma I	0.5 3	0.4 9	0.7 0.7	0.4 3	0.6 0.6	1.14	0.1 1	1.07
66	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7 0.7	1.25	0.0 4	1.12
67	Normal	Normal	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnorma I	Abnorma I	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	0.2 4	0.2 1	0.3 4	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnorma I	Abnorma I	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Abnorma I	0.1 6	0.3 7	0.1 0.1	0.1 4	0.6 3	3.18	0.0 3	1.78
73	Abnorma I	Abnorma I	0.2 1	0.1 9	0.4 0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnorma I	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43

75	Abnorma I	Abnorma I	0.2 1	0.5 1	0.2 0.2	0.1 2	0.5 1		0.81 0.4	0.0 4	0.9
76	Abnorma I	Abnorma I	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5		2.25	0.2	1.5
77	Abnorma I	Abnorma I	0.5 9	0.7 1	0.3 0.3	0.3 8	0.7 0.7		3.59	0.2 6	1.9
78	Abnorma I	Abnorma I	0.4 7	0.3 7	0.1 7	0.4 4	0.4 0.4		0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7		0.91	0.0 4	0.96
80	Normal	Abnorma I	0.2 3	0.4 7	0.2 9	0.1 3	0.5 3		9.41	0.0 5	3.07
81	Abnorma I	Abnorma I	0.3 3	0.3 7	0.3 9	0.3 0.3	0.3 8		1.11	0.1	1.05
82	Abnorma I	Abnorma I	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7		0.49	0.1 2	0.7
83	Normal	Abnorma I	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8		0.6	0.0 2	0.77
84	Abnorma I	Abnorma I	0.1 1	0.2 5	0.2 7	0.1 5	0.1 5		0.19	0.0 3	0.43
85	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5		0.94	0.0 2	0.97
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4		0.83	0.0 3	0.91
87	Abnorma	Abnorma	0.2	0.4	0.2	0.1	0.5		0.82	0.0	0.9

	I	I	8	9	5	9	9		3	
88	Normal	Abnorma	0.1 I 4	0.3 1	0.2 6	0.1 2	0.6	1.86	0.0 3	1.36
89	Abnorma I	Abnorma I	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma I	Abnorma I	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Abnorma	0.1 I 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6	1.47	0.0 3	1.21
94	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 0.5	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma I	Abnorma I	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma I	Abnorma I	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Abnorma	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05
98	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.2 7	0.5	0.95	0.1	0.97
99	Abnorma I	Abnorma I	0.1 7	0.2 9	0.3 4	0.1 9	0.2	0.78	0.1 2	0.88

100	Abnorma I	Abnorma I	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma I	Abnorma I	0.4 1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88	
102	Normal	Abnorma I	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma I	Abnorma I	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnorma I	Abnorma I	0.8 7	0.7 9	0.5 6	0.6 7	0.3 7	0.82	0.2 1	0.9
105	Abnorma I	Abnorma I	0.5 1	0.5 1	0.4 1	0.4 2	0.5 2	5.08	0.0 9	2.25
106	Abnorma I	Abnorma I	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma I	Abnorma I	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnorma I	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma I	Abnorma I	0.2 9	0.3 1	0.2 7	0.1 7	0.5 7	2.83	0.0 3	1.68
110	Abnorma I	Abnorma I	0.3 7	0.3 4	0.4 9	0.3 6	0.2 7	0.39	0.1 2	0.62
111	Normal	Abnorma I	0.2 3	0.4 2	0.1 3	0.1 8	0.5 5	0.61	0.0 3	0.78
112	Normal	Abnorma	0.6	0.5	0.4	0.4	0.4	1.08	0.0	1.04

		I		1	8	9	6	5		4	
113	Abnorma	Abnorma	0.5	0.5	0.5	0.3	0.5		1.04	0.1	1.02
				1	9	1	6	2		7	
114	Abnorma	Abnorma	0.3	0.3	0.4	0.3	0.4		1.38	0.0	1.17
				7	9		4	5		8	
115	Abnorma	Abnorma	0.2	0.5	0.3	0.1	0.5		0.58	0.0	0.76
				4	3		3	1		2	
116	Abnorma	Abnorma	0.1	0.4	0.1	0.0	0.5		0.75	0.0	0.86
				6	7	9	9	9		2	
117	Abnorma	Abnorma	0.4	0.5	0.4	0.3	0.3		0.78	0.0	0.88
				3			3	5		9	
118	Abnorma	Abnorma	0.4	0.4	0.4	0.4	0.2		0.31	0.1	0.56
				8	6	5		8		9	
119	Abnorma	Abnorma	0.3	0.3	0.4	0.3	0.2		0.26	0.1	0.51
				6	5	6	5	1		6	
120	Abnorma	Abnorma	0.4	0.3	0.4	0.4	0.4		0.65	0.1	0.8
				7	7	4	4	9			
121	Normal	Abnorma	0.0	0.2	0.2	0.1	0.5		0.85	0.0	0.92
				7	1		4	8		3	
122	Abnorma	Abnorma	0.4	0.6	0.6	0.2	0.4		0.4	0.1	0.63
				8	8	8	8			5	
123	Abnorma	Abnorma	0.5	0.4	0.4	0.4	0.2		0.44	0.1	0.66
				3	6	3	5	1		3	
124	Abnorma	Abnorma	0.8	0.8	0.3	0.6	0.1		0.19	0.2	0.44
				9		3	1	2			

B.10 KNN Classifier:

Ro w No.	Class Att.	Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnormal	Abnormal	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnormal	Abnormal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnormal	0.1 9	0.4	0.1	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnormal	Abnormal	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnormal	Normal	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnormal	Abnormal	0.2 9	0.2	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnormal	Abnormal	0.2 9	0.4	0.2 2	0.2 5	0.6 4	0.64	0.0 8	0.8
8	Abnormal	Abnormal	0.6 7	0.9	0.4	0.3 3	0.2 9	0.54	0.2 1	0.73
9	Abnormal	Abnormal	0.4 9	0.6	0.5 6	0.3 7	0.4 1	0.46	0.2 2	0.68
10	Normal	Abnormal	0.3	0.4	0.3	0.2	0.5	1.01	0.0	1

		I		4	7	5	6	2		4	
11	Abnorma	Abnorma	Abnorma	0.6 4	0.7 5	0.5 7	0.4 9	0.4 9	1.15 6	0.1 6	1.07
12	Normal	Abnorma	Abnorma	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56 9	0.0 3	0.75
13	Abnorma	Abnorma	Abnorma	0.4 3	0.5 4	0.2 7	0.3 1	0.3 4	0.5 4	3.82 9	0.0 9
14	Abnorma	Normal	Abnorma	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59 8	0.0 8	0.77
15	Abnorma	Abnorma	Abnorma	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1 3	0.1 3	3.18
16	Abnorma	Abnorma	Abnorma	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48 4	0.1 8	0.69
17	Abnorma	Abnorma	Abnorma	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59 7	0.0 5	0.77
18	Normal	Normal	Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65 5	0.0 2	1.63
19	Abnorma	Abnorma	Abnorma	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37 4	0.1 2	2.71
20	Normal	Abnorma	Abnorma	0.2 1	0.3 6	0.2 9	0.1 1	0.5 1	3.35 1	0.0 2	1.83
21	Abnorma	Abnorma	Abnorma	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6 6	0.0 8	0.77
22	Normal	Normal	Normal	0.2 8	0.2 9	0.3 9	0.2 9	0.5 7	0.85 7	0.0 4	0.92

23	Normal	Abnorma	0.5 	0.6 5	0.4 5	0.3 7	0.4 4	0.45 0.45	0.0 4	0.67 0.67
24	Abnorma	Abnorma	0.0 	0.3 9	0.0 3	0.1 1	0.4 0.4	0.4 0.4	0.0 2	0.63 0.63
25	Abnorma	Abnorma	0.6 	0.6 2	0.5 2	0.4 5	0.3 3	0.34 0.34	0.1 6	0.58 0.58
26	Abnorma	Abnorma	0.3 	0.4 6	0.4 7	0.2 8	0.6 8	0.79 0.79	0.1 1	0.89 0.89
27	Abnorma	Abnorma	0.3 	0.3 9	0.4 5	0.3 7	0.3 7	0.58 0.58	0.1 0.1	0.76 0.76
28	Abnorma	Abnorma	0.4 	0.8 8	0.7 7	0.1 1	0.6 9	1.26 0.7	0.2 6	1.12 1.12
29	Normal	Abnorma	0.2 	0.4 2	0.3 4	0.1 4	0.7 6	5.67 4	0.0 5	2.38 2.38
30	Abnorma	Abnorma	0.3 	0.4 6	0.3 8	0.2 6	0.4 8	1.01 5	0.0 2	1.01 1.01
31	Abnorma	Normal	0.1 	0.2 9	0.2 9	0.2 8	0.2 1	1.1 1	0.0 7	1.05 1.05
32	Abnorma	Abnorma	0.4 	0.3 1	0.4 9	0.3 4	0.5 7	37.1 7	0.1 2	6.09 6.09
33	Normal	Normal	0.1 8	0.3 7	0.1 6	0.1 6	0.6 6	1.25 6	0.0 2	1.12 1.12
34	Abnorma	Abnorma	0.3 	0.5 9	0.3 6	0.2 2	0.4 6	8.2 7	0.0 2	2.86 2.86
35	Normal	Normal	0.1	0.2	0.2	0.2	0.6	1.43	0.0	1.2

				8	8	9		4		4	
36	Abnorma 	Abnorma 	Abnorma 	0.0 5	0.4 3	0.0 1	0 4	0.5 4	0.68 0.3	0.0 3	0.82
37	Abnorma 	Abnorma 	Abnorma 	0.1 2	0.5 3	0.1 3	0 0	0.4 9	1.06 1.06	0.0 2	1.03
38	Normal		Abnorma 	0.1 3	0.4 1	0.2 9	0.0 7	0.6 7	1.06 1.06	0.0 1	1.03
39	Abnorma 	Abnorma 	Abnorma 	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44 1.44	0.1 7	1.2
40	Normal		Abnorma 	0.3 6	0.4 4	0.4 2	0.3 8	0.7 8	1.21 1.21	0.0 4	1.1
41	Abnorma 	Abnorma 	Abnorma 	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69 2.69	0.3 2	1.64
42	Normal		Abnorma 	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11 8.11	0.0 5	2.85
43	Normal		Abnorma 	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81 0.81	0.0 3	0.9
44	Abnorma 	Abnorma 	Abnorma 	0.4 5	0.4 1	0.4 1	0.3 9	0 0	0 0	0.0 5	0
45	Abnorma 	Abnorma 	Abnorma 	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12 2.12	0.1 9	1.46
46	Abnorma 	Abnorma 	Abnorma 	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44 0.44	0.1 5	0.66
47	Normal		Abnorma 	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07 3.07	0.0 5	1.75

48	Abnorma I	Normal	0.2	0.2 7	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma I	Abnorma I	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnorma I	Abnorma I	0.1 5	0.4 4	0.0 5	0.1 2	0.5 2	1.82	0.0 3	1.35
51	Abnorma I	Abnorma I	0.3 2	0.1 1	0.3 0.4	0.4 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnorma I	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnorma I	Abnorma I	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnorma I	Abnorma I	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Abnorma I	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma I	Normal	0.1 8	0.2 9	0.3 4	0.2 0.2	0.7 0.7	0.7	0.0 9	0.84
58	Abnorma I	Abnorma I	0.5 7	0.6 6	0.5 7	0.3 9	0.4 8	0.89	0.1 8	0.94
59	Abnorma I	Abnorma I	0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59	0.0 3	0.77
60	Abnorma	Abnorma	0.4	0.4	0.4	0.3	0.5	0.94	0.1	0.97

	I	I		3	8	4	5				
61	Abnorma I	Abnorma I	Abnorma	0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62	0.2 1	0.79
62	Abnorma I	Normal	Abnorma	0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72	0.0 3	0.85
63	Abnorma I	Abnorma I	Abnorma	0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71	0.1 2	0.84
64	Normal	Normal	Normal	0.0 7	0.1 8	0.1 5	0.1 3	0.6 3	0.99	0.0 2	0.99
65	Abnorma I	Abnorma I	Abnorma	0.5 3	0.4 9	0.7	0.4 3	0.6	1.14	0.1 1	1.07
66	Normal	Normal	Normal	0.2 1	0.2 9	0.2 3	0.2 3	0.7	1.25	0.0 4	1.12
67	Normal	Abnorma I	Abnorma	0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53	0.0 4	1.59
68	Abnorma I	Abnorma I	Abnorma	0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44	0.0 3	1.86
69	Normal	Normal	Normal	0.2	0.2 4	0.3 1	0.2 4	0.6 5	0.79	0.0 3	0.89
70	Abnorma I	Abnorma I	Abnorma	0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23	0.1 7	1.11
71	Normal	Normal	Normal	0.2 8	0.2 2	0.3 5	0.3 3	0.6 1	0.64	0.0 2	0.8
72	Normal	Abnorma I	Abnorma	0.1 6	0.3 7	0.1	0.1 4	0.6 3	3.18	0.0 3	1.78

73	Abnormal 	Normal	0.2 1	0.1 9	0.4	0.2 8	0.5 9	4.4	0.1 1	2.1
74	Normal	Abnormal 	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7	2.05	0.0 3	1.43
75	Abnormal 	Abnormal 	0.2 1	0.5 1	0.2	0.1 2	0.5 1	0.81	0.0 4	0.9
76	Abnormal 	Abnormal 	0.5 9	0.4 8	0.7 1	0.5 0.5	0.5 5	2.25	0.2	1.5
77	Abnormal 	Abnormal 	0.5 9	0.7 1	0.3 0.3	0.3 8	0.7 0.7	3.59	0.2 6	1.9
78	Abnormal 	Abnormal 	0.4 7	0.3 7	0.1 7	0.4 4	0.4 0.4	0.76	0.1 1	0.87
79	Normal	Normal	0.1 2	0.2 3	0.3 3	0.1 7	0.6 7	0.91	0.0 4	0.96
80	Normal	Abnormal 	0.2	0.4	0.2 3	0.1 6	0.5 3	9.41	0.0 5	3.07
81	Abnormal 	Abnormal 	0.3 3	0.3 7	0.3 9	0.3 0.3	0.3 8	1.11	0.1	1.05
82	Abnormal 	Abnormal 	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7	0.49	0.1 2	0.7
83	Normal	Normal	0.0 8	0.2 5	0.2 6	0.1 3	0.5 8	0.6	0.0 2	0.77
84	Abnormal 	Abnormal 	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	0.2	0.3	0.2	0.2	0.5	0.94	0.0	0.97

					6	1	5		2	
86	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma I	Abnorma I	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Normal	0.1 4	0.3 1	0.2 6	0.1 2	0.6 2	1.86	0.0 3	1.36
89	Abnorma I	Abnorma I	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma I	Abnorma I	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Abnorma I	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Normal	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 1	0.3 1	0.4 5	0.98	0.1 9	0.99
95	Abnorma I	Abnorma I	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88
96	Abnorma I	Abnorma I	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3	0.55	0.1	0.74
97	Normal	Normal	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1	1.11	0.0 6	1.05

98	Abnorma I	Abnorma I	0.3	0.3 9	0.4 5	0.2 7	0.5	0.95	0.1	0.97
99	Abnorma I	Abnorma I	0.1 7	0.2 9	0.3 4	0.1 9	0.2	0.78	0.1 2	0.88
100	Abnorma I	Abnorma I	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3	0.68	0.1 5	0.82
101	Abnorma I	Abnorma I	0.4 1	1	0.4 8	0.0 5	0.5 9	0.78	0.1 5	0.88
102	Normal	Normal	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2	1.87	0.0 3	1.37
103	Abnorma I	Normal	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1	0.82	0.1 3	0.9
104	Abnorma I	Abnorma I	0.8 7	0.7 9	0.5 6	0.6	0.3 7	0.82	0.2 1	0.9
105	Abnorma I	Normal	0.5 0.5	0.5 1	0.4 1	0.4	0.5 2	5.08	0.0 9	2.25
106	Abnorma I	Normal	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8	0.64	0.0 4	0.8
107	Abnorma I	Abnorma I	0.5 3	0.4 9	0.4 2	0.4 4	0.2 6	11	0.1 2	3.31
108	Normal	Abnorma I	0.1 1	0.4 1	0.0 9	0.0 7	0.5 9	2.42	0.0 4	1.56
109	Abnorma I	Abnorma I	0.2	0.3 9	0.2 1	0.1 7	0.5	2.83	0.0 3	1.68
110	Abnorma	Abnorma	0.3	0.3	0.4	0.3	0.2	0.39	0.1	0.62

	I	I		7	4	9	6	7		2	
111	Normal	Abnorma	0.2	0.4	0.1	0.1	0.5		0.61	0.0	0.78
	I	I	3	2	3	8	5			3	
112	Normal	Abnorma	0.6	0.5	0.4	0.4	0.4		1.08	0.0	1.04
	I	I	1	8	9	6	5			4	
113	Abnorma	Abnorma	0.5	0.5	0.5	0.3	0.5		1.04	0.1	1.02
	I	I	1	9	1	6	2			7	
114	Abnorma	Abnorma	0.3	0.3	0.4	0.3	0.4		1.38	0.0	1.17
	I	I	7	9		4	5			8	
115	Abnorma	Abnorma	0.2	0.5	0.3	0.1	0.5		0.58	0.0	0.76
	I	I	4	3		3	1			2	
116	Abnorma	Abnorma	0.1	0.4	0.1	0.0	0.5		0.75	0.0	0.86
	I	I	6	7	9	9	9			2	
117	Abnorma	Abnorma	0.4	0.5	0.4	0.3	0.3		0.78	0.0	0.88
	I	I	3			3	5			9	
118	Abnorma	Abnorma	0.4	0.4	0.4	0.4	0.2		0.31	0.1	0.56
	I	I	8	6	5		8			9	
119	Abnorma	Abnorma	0.3	0.3	0.4	0.3	0.2		0.26	0.1	0.51
	I	I	6	5	6	5	1			6	
120	Abnorma	Abnorma	0.4	0.3	0.4	0.4	0.4		0.65	0.1	0.8
	I	I	7	7	4	4	9				
121	Normal	Abnorma	0.0	0.2	0.2	0.1	0.5		0.85	0.0	0.92
	I	I	7	1		4	8			3	
122	Abnorma	Abnorma	0.4	0.6	0.6	0.2	0.4		0.4	0.1	0.63
	I	I	8	8	8	8				5	

123	Abnorma I	Abnorma I	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44	0.1 3	0.66
124	Abnorma I	Abnorma I	0.8 9	0.8	0.3 3	0.6 1	0.1 2	0.19	0.2	0.44

B.11 Fast Large Margin Classifier:

Ro w No.	Class Att.	Class Predicted	Test Inputs							
			col1	col2	col3	col4	col5	col5/col10	col6	sqrt(col5/col10)
1	Abnorma I	Abnorma I	0.1 2	0.3	0.1	0.1 4	0.4 8	0.48	0.0 4	0.69
2	Abnorma I	Normal	0.1 1	0.2	0.1	0.1 9	0.9 4	2.41	0.1	1.55
3	Normal	Abnorma I	0.1 9	0.4 5	0.1 8	0.1 2	0.5	0.92	0.0 3	0.96
4	Abnorma I	Abnorma I	0.5	0.5	0.4 5	0.4	0.4 8	1.15	0.0 9	1.07
5	Abnorma I	Abnorma I	0.4	0.2 5	0.3 4	0.4 3	0.3	14.2	0.1 2	3.77
6	Abnorma I	Abnorma I	0.2 9	0.2 8	0.3 5	0.3 2	0.3 1	0.56	0.1 4	0.75
7	Abnorma I	Abnorma I	0.2 9	0.4 2	0.2 5	0.2 4	0.6 2	0.64	0.0 8	0.8
8	Abnorma	Abnorma	0.6	0.9	0.4	0.3	0.2	0.54	0.2	0.73

	I	I	7	5		3	9		1	
9	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 7	0.3 1	0.4 4	0.46	0.2 2	0.68
10	Normal I	Abnorma I	0.3 4	0.4 7	0.3 5	0.2 6	0.5 2	1.01	0.0 4	1
11	Abnorma I	Abnorma I	0.6 4	0.7 5	0.5 7	0.4 0.4	0.4 9	1.15	0.1 6	1.07
12	Normal I	Abnorma I	0.3 7	0.5 9	0.3 3	0.2 3	0.3 9	0.56	0.0 3	0.75
13	Abnorma I	Abnorma I	0.4 3	0.5 4	0.2 7	0.3 1	0.5 4	3.82	0.0 9	1.41
14	Abnorma I	Abnorma I	0.2 7	0.2 8	0.2 6	0.2 9	0.5 8	0.59	0.0 8	0.77
15	Abnorma I	Abnorma I	0.4 3	0.3 6	0.5 3	0.4 3	0.5 3	10.1	0.1	3.18
16	Abnorma I	Abnorma I	0.5 2	0.9 8	0.3 4	0.1 7	0.4 4	0.48	0.1 8	0.69
17	Abnorma I	Normal Normal	0.5 7	0.3 9	0.5 7	0.4 7	0.3 7	0.59	0.0 5	0.77
18	Normal Normal	Normal Normal	0.1 6	0.0 1	0.3 9	0.3 3	0.5 5	2.65	0.0 2	1.63
19	Abnorma I	Abnorma I	0.4 9	0.4 2	0.3 2	0.4 4	0.4 4	7.37	0.1 2	2.71
20	Normal Normal	Abnorma I	0.2 1	0.3 6	0.2 0.2	0.1 9	0.5 1	3.35	0.0 2	1.83

21	Abnorma I	Abnorma I	0.3 4	0.5 7	0.2 2	0.2 1	0.3 6	0.6 8	0.0 8		0.77
22	Normal	Normal	0.2 8	0.2 9	0.3 9	0.2 9	0.5 7	0.85 8	0.0 4		0.92
23	Normal	Abnorma I	0.5 5	0.6 5	0.4 7	0.3 7	0.4 4	0.45 4	0.0 4		0.67
24	Abnorma I	Abnorma I	0.0 9	0.3 3	0.0 1	0.1 1	0.4 4	0.4 4	0.0 2		0.63
25	Abnorma I	Abnorma I	0.6 2	0.6 2	0.5 5	0.4 5	0.3 3	0.34 34	0.1 6		0.58
26	Abnorma I	Abnorma I	0.3 6	0.4 7	0.4 8	0.2 8	0.6 6	0.79 79	0.1 1		0.89
27	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.3 7	0.3 3	0.58 58	0.1 1		0.76
28	Abnorma I	Abnorma I	0.4 8	0.8 7	0.7 1	0.1 9	0.6 7	1.26 126	0.2 6		1.12
29	Normal	Abnorma I	0.2 2	0.4 4	0.3 4	0.1 6	0.7 4	5.67 567	0.0 5		2.38
30	Abnorma I	Abnorma I	0.3 6	0.4 8	0.3 6	0.2 8	0.4 5	1.01 101	0.0 2		1.01
31	Abnorma I	Normal	0.1 9	0.2 9	0.2 8	0.2 1	1 1	1.1 11	0.0 7		1.05
32	Abnorma I	Abnorma I	0.4 1	0.3 9	0.4 4	0.3 7	0.5 7	37.1 371	0.1 2		6.09
33	Normal	Normal	0.1 0.1	0.3 0.3	0.1 0.1	0.1 0.1	0.6 0.6	1.25 125	0.0 0.0		1.12

				8	7	6	6	6		2	
34	Abnorma I	Abnorma I	Abnorma I	0.3 9	0.5 6	0.3 2	0.2 6	0.4 7	8.2	0.0 2	2.86
35	Normal	Normal	Normal	0.1 8	0.2 8	0.2 9	0.2 4	0.6 4	1.43	0.0 4	1.2
36	Abnorma I	Abnorma I	Abnorma I	0.0 5	0.4 3	0.0 1	0 0	0.5 4	0.68	0.0 3	0.82
37	Abnorma I	Abnorma I	Abnorma I	0.1 2	0.5 3	0.1 3	0 0	0.4 9	1.06	0.0 2	1.03
38	Normal	Normal	Normal	0.1 3	0.4 1	0.2 0	0.0 9	0.6 7	1.06	0.0 1	1.03
39	Abnorma I	Abnorma I	Abnorma I	0.5 7	0.8 1	0.6 1	0.3 1	0.5 5	1.44	0.1 7	1.2
40	Normal	Normal	Normal	0.3 6	0.4 4	0.4 2	0.3 8	0.7 8	1.21	0.0 4	1.1
41	Abnorma I	Abnorma I	Abnorma I	0.4 7	0.7 1	0.4 7	0.2 6	0.8 2	2.69	0.3 2	1.64
42	Normal	Abnorma I	Abnorma I	0.4 1	0.3 5	0.3 7	0.3 9	0.6 1	8.11	0.0 5	2.85
43	Normal	Abnorma I	Abnorma I	0.6 1	0.5 2	0.6 9	0.5 3	0.3 3	0.81	0.0 3	0.9
44	Abnorma I	Abnorma I	Abnorma I	0.4 5	0.4 1	0.4 1	0.3 9	0 0	0	0.0 5	0
45	Abnorma I	Abnorma I	Abnorma I	0.5 7	0.6 5	0.6 2	0.3 9	0.6 1	2.12	0.1 9	1.46

46	Abnorma I	Abnorma I	0.3 8	0.3 1	0.3 8	0.3 9	0.4 2	0.44	0.1 5	0.66
47	Normal	Abnorma I	0.3 6	0.5 7	0.4 7	0.2 7	0.5 3	3.07	0.0 5	1.75
48	Abnorma I	Abnorma I	0.2 7	0.2 3	0.1 3	0.2 3	0.4 9	1.89	0.0 3	1.38
49	Abnorma I	Abnorma I	0.6 1	0.9 9	0.5 2	0.2 5	0.6 9	0.88	0.3	0.94
50	Abnorma I	Abnorma I	0.1 5	0.4 4	0.0 5	0.1 2	0.5 2	1.82	0.0 3	1.35
51	Abnorma I	Abnorma I	0.3 2	0.1 1	0.3 0.4	0.3 5	0.3 5	3.6	0.1 5	1.9
52	Normal	Abnorma I	0.2 7	0.5 4	0.1 8	0.1 2	0.5 2	0.75	0.0 2	0.86
53	Abnorma I	Abnorma I	0.2 1	0.4 1	0.2 0.2	0.1 7	0.2 7	0.39	0.0 9	0.62
54	Normal	Normal	0.0 8	0.1 6	0.1 4	0.1 7	0.6 1	1.33	0.0 2	1.15
55	Abnorma I	Abnorma I	0.5 7	0.4 9	0.7 0.7	0.4 7	0.4 2	0.83	0.1 1	0.91
56	Normal	Normal	0.3 6	0.4 2	0.3 2	0.3 1	0.5 1	0.61	0.0 2	0.78
57	Abnorma I	Abnorma I	0.1 8	0.2 9	0.3 4	0.2 0.7	0.7 0.7	0.7	0.0 9	0.84
58	Abnorma	Abnorma	0.5	0.6	0.5	0.3	0.4	0.89	0.1	0.94

	I	I		7	6	7	9	8		8	
59	Abnorma I	Abnorma I		0.2 7	0.5 9	0.1 9	0.1 3	0.5 5	0.59 0.59	0.0 3	0.77 0.77
60	Abnorma I	Abnorma I		0.4 3	0.4 8	0.4 4	0.3 5	0.5 5	0.94 0.94	0.1 0.1	0.97 0.97
61	Abnorma I	Abnorma I		0.5 6	0.5 3	0.6 5	0.4 4	0.5 9	0.62 0.62	0.2 1	0.79 0.79
62	Abnorma I	Abnorma I		0.1 2	0.3 6	0.1 5	0.1 1	0.5 7	0.72 0.72	0.0 3	0.85 0.85
63	Abnorma I	Abnorma I		0.3 8	0.2 9	0.3 3	0.3 9	0.3 7	0.71 0.71	0.1 2	0.84 0.84
64	Normal	Normal		0.0 7	0.1 8	0.1 0.1	0.1 5	0.6 3	0.99 0.99	0.0 2	0.99 0.99
65	Abnorma I	Abnorma I		0.5 3	0.4 9	0.7 0.7	0.4 3	0.6 0.6	1.14 1.14	0.1 1	1.07 1.07
66	Normal	Normal		0.2 1	0.2 9	0.2 3	0.2 3	0.7 0.7	1.25 1.25	0.0 4	1.12 1.12
67	Normal	Normal		0.3 5	0.3 7	0.3 9	0.3 2	0.6 8	2.53 2.53	0.0 4	1.59 1.59
68	Abnorma I	Abnorma I		0.3 2	0.6 9	0.2 9	0.1 3	0.5 3	3.44 3.44	0.0 3	1.86 1.86
69	Normal	Normal		0.2 4	0.2 1	0.3 4	0.2 4	0.6 5	0.79 0.79	0.0 3	0.89 0.89
70	Abnorma I	Abnorma I		0.6 8	0.4 6	0.6 8	0.5 9	0.5 4	1.23 1.23	0.1 7	1.11 1.11

71	Normal	Normal		0.2 8	0.2 2	0.3 5	0.3 3	0.6 1		0.64	0.0 2		0.8	
72	Normal	Abnorma	I	0.1 6	0.3 7		0.1 4	0.6 3		3.18	0.0 3		1.78	
73	Abnorma	Abnorma	I	0.2 1	0.1 9		0.4 8	0.5 9		4.4	0.1 1		2.1	
74	Normal	Abnorma	I	0.1 8	0.5 1	0.1 6	0.0 9	0.4 7		2.05	0.0 3		1.43	
75	Abnorma	Abnorma	I	0.2 1	0.5 1		0.2 2	0.5 1		0.81	0.0 4		0.9	
76	Abnorma	Abnorma	I	0.5 9	0.4 8	0.7 1		0.5 5		2.25	0.2		1.5	
77	Abnorma	Abnorma	I	0.5 9	0.7 1	0.3 8	0.3 8	0.7 7		3.59	0.2 6		1.9	
78	Abnorma	Abnorma	I	0.4 7	0.3 7	0.1 7	0.4 4	0.4 3		0.76	0.1 1		0.87	
79	Normal	Normal		0.1 2	0.2 3	0.3 3	0.1 7	0.6 7		0.91	0.0 4		0.96	
80	Normal	Abnorma	I		0.2 3	0.4 6	0.2 3	0.1 6	0.5 3		9.41	0.0 5		3.07
81	Abnorma	Abnorma	I	0.3 3	0.3 7	0.3 9		0.3 8		1.11	0.1		1.05	
82	Abnorma	Abnorma	I	0.3 6	0.3 6	0.4 3	0.3 4	0.4 7		0.49	0.1 2		0.7	
83	Normal	Normal		0.0	0.2	0.2	0.1	0.5		0.6	0.0		0.77	

				8	5	6	3	8		2	
84	Abnorma I	Abnorma I	Abnorma I	0.1	0.2 1	0.2 5	0.1 7	0.1 5	0.19	0.0 3	0.43
85	Normal	Normal	Normal	0.2	0.3	0.2 6	0.2 1	0.5 5	0.94	0.0 2	0.97
86	Normal	Normal	Normal	0.1 4	0.1 5	0.3 2	0.2 4	0.7 4	0.83	0.0 3	0.91
87	Abnorma I	Abnorma I	Abnorma I	0.2 8	0.4 9	0.2 5	0.1 9	0.5 9	0.82	0.0 3	0.9
88	Normal	Abnorma I	Abnorma I	0.1 4	0.3	0.2 1	0.1 6	0.6 2	1.86	0.0 3	1.36
89	Abnorma I	Abnorma I	Abnorma I	0.4 6	0.4 9	0.3 9	0.3 7	0.5 4	0.6	0.2	0.77
90	Abnorma I	Abnorma I	Abnorma I	0.4 5	0.4 3	0.3 4	0.3 9	0.5 3	0.78	0.1	0.88
91	Normal	Abnorma I	Abnorma I	0.1 1	0.2 8	0.2 5	0.1 4	0.7 1	1.64	0.0 6	1.28
92	Normal	Normal	Abnorma	0.2 2	0.3 5	0.3 4	0.2 1	0.6 1	0.68	0.0 3	0.83
93	Normal	Abnorma I	Abnorma I	0.2 5	0.4 9	0.1 1	0.2 4	0.6 4	1.47	0.0 3	1.21
94	Abnorma I	Abnorma I	Abnorma I	0.4 9	0.6 6	0.5 1	0.3 5	0.4 5	0.98	0.1 9	0.99
95	Abnorma I	Abnorma I	Abnorma I	0.5 7	0.4 2	0.5 2	0.5 2	0.5 8	0.78	0.2	0.88

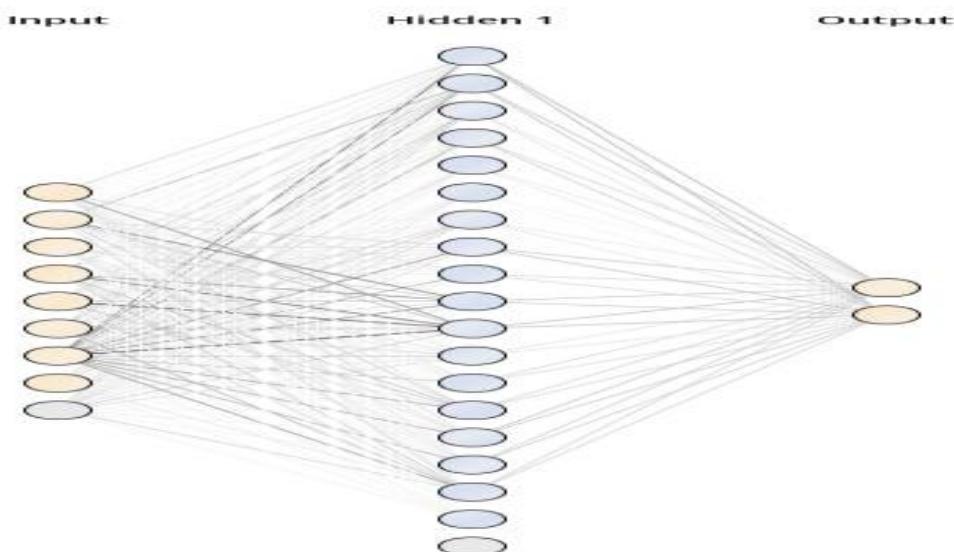
96	Abnorma I	Abnorma I	0.2 8	0.0 5	0.3 8	0.4 2	0.4 3		0.55	0.1		0.74
97	Normal	Abnorma I	0.2 4	0.3 6	0.1 9	0.2 3	0.6 1		1.11	0.0 6		1.05
98	Abnorma I	Abnorma I	0.3 9	0.3 5	0.4 7	0.2 0.5		0.95	0.1			0.97
99	Abnorma I	Abnorma I	0.1 7	0.2 9	0.3 4	0.1 9	0.2 0.2		0.78	0.1 2		0.88
100	Abnorma I	Abnorma I	0.5 4	0.4 8	0.5 1	0.4 5	0.5 3		0.68	0.1 5		0.82
101	Abnorma I	Abnorma I	0.4 1	1	0.4 8	0.0 5	0.5 9		0.78	0.1 5		0.88
102	Normal	Abnorma I	0.1 8	0.2 7	0.2 5	0.2 1	0.5 2		1.87	0.0 3		1.37
103	Abnorma I	Abnorma I	0.1 7	0.1 4	0.2 9	0.2 7	0.4 1		0.82	0.1 3		0.9
104	Abnorma I	Abnorma I	0.8 7	0.7 9	0.5 6	0.6 0.6	0.3 7		0.82	0.2 1		0.9
105	Abnorma I	Abnorma I	0.5 1	0.5 1	0.4 1	0.4 0.4	0.5 2		5.08	0.0 9		2.25
106	Abnorma I	Abnorma I	0.2 1	0.3 8	0.1 9	0.1 8	0.5 8		0.64	0.0 4		0.8
107	Abnorma I	Abnorma I	0.5 3	0.4 9	0.4 2	0.4 4	0.2 0.6		11	0.1 2		3.31
108	Normal	Abnorma	0.1	0.4	0.0	0.0	0.5		2.42	0.0		1.56

		I		1	1	9	7	9		4	
109	Abnorma	Abnorma		0.2	0.3	0.2	0.1	0.5	2.83	0.0	1.68
	I	I			9	1	7			3	
110	Abnorma	Abnorma		0.3	0.3	0.4	0.3	0.2	0.39	0.1	0.62
	I	I		7	4	9	6	7		2	
111	Normal	Abnorma		0.2	0.4	0.1	0.1	0.5	0.61	0.0	0.78
	I	I		3	2	3	8	5		3	
112	Normal	Abnorma		0.6	0.5	0.4	0.4	0.4	1.08	0.0	1.04
	I	I		1	8	9	6	5		4	
113	Abnorma	Abnorma		0.5	0.5	0.5	0.3	0.5	1.04	0.1	1.02
	I	I		1	9	1	6	2		7	
114	Abnorma	Abnorma		0.3	0.3	0.4	0.3	0.4	1.38	0.0	1.17
	I	I		7	9		4	5		8	
115	Abnorma	Abnorma		0.2	0.5	0.3	0.1	0.5	0.58	0.0	0.76
	I	I		4	3		3	1		2	
116	Abnorma	Abnorma		0.1	0.4	0.1	0.0	0.5	0.75	0.0	0.86
	I	I		6	7	9	9	9		2	
117	Abnorma	Abnorma		0.4	0.5	0.4	0.3	0.3	0.78	0.0	0.88
	I	I		3			3	5		9	
118	Abnorma	Abnorma		0.4	0.4	0.4	0.4	0.2	0.31	0.1	0.56
	I	I		8	6	5		8		9	
119	Abnorma	Abnorma		0.3	0.3	0.4	0.3	0.2	0.26	0.1	0.51
	I	I		6	5	6	5	1		6	
120	Abnorma	Abnorma		0.4	0.3	0.4	0.4	0.4	0.65	0.1	0.8
	I	I		7	7	4	4	9			

121	Normal	Normal	0.0 7	0.2 1	0.2 4	0.1 8	0.5 8	0.85 3	0.0 3	0.92
122	Abnorma I	Abnorma I	0.4 8	0.6 8	0.6 8	0.2 8	0.4 8	0.4 0.4	0.1 5	0.63
123	Abnorma I	Abnorma I	0.5 3	0.4 6	0.4 3	0.4 5	0.2 1	0.44 0.44	0.1 3	0.66
124	Abnorma I	Abnorma I	0.8 9	0.8 3	0.3 1	0.6 1	0.1 2	0.19 0.19	0.2 0.2	0.44

C. MLP Model Diagram and Model Parameters:

C.1 MLP Model Network:



C.2 Nodal Final Weights of Hidden layer and Output layer neurons:

Hidden 1

=====

Node 1 (Sigmoid)

```
Col1: 1.496
Col2: 0.734
Col3: 0.581
Col4: 0.942
Col5: -0.423
col5/col10: -0.999
Col6: 4.419
sqrt(col5/col10): 0.396
Threshold: 0.980

Node 2 (Sigmoid)
-----
Col1: 0.380
Col2: 2.616
Col3: -0.568
Col4: -1.688
Col5: -1.316
col5/col10: -1.286
Col6: 3.839
sqrt(col5/col10): 0.202
Threshold: 0.664

Node 3 (Sigmoid)
-----
Col1: 0.256
Col2: -0.445
Col3: 0.093
Col4: 0.754
Col5: 0.554
col5/col10: 1.705
Col6: -1.618
sqrt(col5/col10): 1.079
Threshold: -1.137

Node 4 (Sigmoid)
-----
Col1: 0.163
Col2: -0.261
Col3: 0.728
Col4: 0.302
Col5: -0.942
col5/col10: -0.415
Col6: 2.803
sqrt(col5/col10): 0.335
Threshold: 0.275

Node 5 (Sigmoid)
-----
Col1: 0.169
Col2: 0.217
Col3: 0.410
Col4: 0.077
Col5: -0.255
col5/col10: 0.199
Col6: 1.434
sqrt(col5/col10): 0.524
Threshold: -0.511

Node 6 (Sigmoid)
-----
Col1: 0.123
```

```
Col2: 0.226
Col3: 0.291
Col4: 0.070
Col5: -0.111
col5/col10: 0.538
Col6: 0.841
sqrt(col5/col10): 0.604
Threshold: -0.765
```

```
Node 7 (Sigmoid)
-----
Col1: 0.254
Col2: -0.527
Col3: 0.143
Col4: 0.887
Col5: 0.661
col5/col10: 1.757
Col6: -1.949
sqrt(col5/col10): 1.074
Threshold: -1.229
```

```
Node 8 (Sigmoid)
-----
Col1: 0.133
Col2: -1.580
Col3: 1.269
Col4: 1.204
Col5: -1.245
col5/col10: -1.046
Col6: 4.331
sqrt(col5/col10): 0.378
Threshold: 1.139
```

```
Node 9 (Sigmoid)
-----
Col1: 1.244
Col2: 0.674
Col3: 0.762
Col4: 0.797
Col5: -0.096
col5/col10: -0.523
Col6: 3.019
sqrt(col5/col10): 0.329
Threshold: 0.487
```

```
Node 10 (Sigmoid)
-----
Col1: -0.653
Col2: 5.186
Col3: -1.982
Col4: -4.895
Col5: -2.569
col5/col10: -1.584
Col6: 4.809
sqrt(col5/col10): 0.718
Threshold: 0.983
```

```
Node 11 (Sigmoid)
-----
Col1: 3.902
Col2: -2.241
```

```
Col3: -0.215
Col4: 6.320
Col5: 7.831
col5/col10: 3.059
Col6: -8.771
sqrt(col5/col10): 0.521
Threshold: -2.093
```

```
Node 12 (Sigmoid)
-----
Col1: 0.348
Col2: -0.790
Col3: 0.017
Col4: 1.187
Col5: 0.865
col5/col10: 1.953
Col6: -2.584
sqrt(col5/col10): 0.996
Threshold: -1.428
```

```
Node 13 (Sigmoid)
-----
Col1: 0.798
Col2: 0.456
Col3: 0.714
Col4: 0.464
Col5: -0.420
col5/col10: -0.466
Col6: 2.856
sqrt(col5/col10): 0.326
Threshold: 0.368
```

```
Node 14 (Sigmoid)
-----
Col1: -0.820
Col2: 1.555
Col3: -0.662
Col4: -2.202
Col5: -2.114
col5/col10: -1.088
Col6: 4.215
sqrt(col5/col10): 0.503
Threshold: 0.497
```

```
Node 15 (Sigmoid)
-----
Col1: 1.080
Col2: 0.044
Col3: 0.927
Col4: 1.042
Col5: -0.374
col5/col10: -0.648
Col6: 3.575
sqrt(col5/col10): 0.369
Threshold: 0.720
```

```
Node 16 (Sigmoid)
-----
Col1: 0.805
Col2: 0.271
Col3: 0.833
```

```
Col4: 0.660
Col5: -0.438
col5/col10: -0.517
Col6: 2.998
sqrt(col5/col10): 0.344
Threshold: 0.451
```

```
Node 17 (Sigmoid)
-----
Col1: 0.482
Col2: -1.173
Col3: -0.083
Col4: 1.660
Col5: 1.232
col5/col10: 2.389
Col6: -3.731
sqrt(col5/col10): 0.897
Threshold: -1.826
```

```
Node 18 (Sigmoid)
-----
Col1: 0.137
Col2: 0.138
Col3: 0.218
Col4: 0.176
Col5: -0.024
col5/col10: 0.448
Col6: 0.428
sqrt(col5/col10): 0.439
Threshold: -0.484
```

Output

=====

```
Class 'Normal' (Sigmoid)
-----
Node 1: -2.259
Node 2: -1.744
Node 3: 0.910
Node 4: -1.442
Node 5: -0.744
Node 6: -0.405
Node 7: 0.959
Node 8: -2.449
Node 9: -1.695
Node 10: -2.270
Node 11: 2.752
Node 12: 1.127
Node 13: -1.540
Node 14: -1.619
Node 15: -1.972
Node 16: -1.593
Node 17: 1.403
Node 18: -0.049
Threshold: -0.050
```

```
Class 'Abnormal' (Sigmoid)
-----
```

```
Node 1: 2.214
Node 2: 1.773
```

```
Node 3: -0.845
Node 4: 1.511
Node 5: 0.738
Node 6: 0.405
Node 7: -0.957
Node 8: 2.468
Node 9: 1.698
Node 10: 2.270
Node 11: -2.751
Node 12: -1.136
Node 13: 1.525
Node 14: 1.592
Node 15: 1.898
Node 16: 1.655
Node 17: -1.454
Node 18: 0.079
Threshold: 0.044
```

D. Deep Learning Model Parameters:

DeepLearning

Sequential Model:

Layer Configuration:

Input Layer:

0, 8

Layer 1: (FullyConnectedLayer)

 type: DenseLayer
 input: 8
 output: 18
 activation: relu

Layer 2: (Hidden Layer 2)

 type: DenseLayer
 input: 18
 output: 80
 activation: relu

Layer 3: (output layer)

 type: OutputLayer
 input: 80
 output: 2
 activation: softmax

Detailed network configuration (json):

```
{  
    "backprop" : true,  
    "backpropType" : "Standard",  
    "cacheMode" : "NONE",  
    "confs" : [ {  
        "cacheMode" : "NONE",  
        "epochCount" : 0,
```

```

"iterationCount" : 0,
"l1ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"l2ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"layer" : {
  "@class" : "org.deeplearning4j.nn.conf.layers.DenseLayer",
  "activationFn" : {
    "@class" : "org.nd4j.linalg.activations.impl.ActivationReLU"
  },
  "biasInit" : 0.0,
  "biasUpdater" : null,
  "constraints" : null,
  "dist" : null,
  "gradientNormalization" : "None",
  "gradientNormalizationThreshold" : 1.0,
  "hasBias" : true,
  "idropout" : null,
  "iupdater" : {
    "@class" : "org.nd4j.linalg.learning.config.Adam",
    "beta1" : 0.9,
    "beta2" : 0.999,
    "epsilon" : 1.0E-6,
    "learningRate" : 0.01
  },
  "l1" : 0.0,
  "l1Bias" : 0.0,
  "l2" : 0.0,
  "l2Bias" : 0.0,
  "layerName" : "FullyConnectedLayer",
  "nin" : 8,
  "nout" : 18,
  "weightInit" : "RELU",
  "weightNoise" : null
},
"maxNumLineSearchIterations" : 5,
"miniBatch" : false,
"minimize" : true,
"optimizationAlgo" : "STOCHASTIC_GRADIENT_DESCENT",
"pretrain" : false,
"seed" : 2001,
"stepFunction" : null,
"variables" : [ "W", "b" ]
}, {
  "cacheMode" : "NONE",
  "epochCount" : 0
}

```

```

"iterationCount" : 0,
"l1ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"l2ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"layer" : {
  "@class" : "org.deeplearning4j.nn.conf.layers.DenseLayer",
  "activationFn" : {
    "@class" : "org.nd4j.linalg.activations.impl.ActivationReLU"
  },
  "biasInit" : 0.0,
  "biasUpdater" : null,
  "constraints" : null,
  "dist" : null,
  "gradientNormalization" : "None",
  "gradientNormalizationThreshold" : 1.0,
  "hasBias" : true,
  "idropout" : null,
  "iupdater" : {
    "@class" : "org.nd4j.linalg.learning.config.Adam",
    "beta1" : 0.9,
    "beta2" : 0.999,
    "epsilon" : 1.0E-6,
    "learningRate" : 0.01
  },
  "l1" : 0.0,
  "l1Bias" : 0.0,
  "l2" : 0.0,
  "l2Bias" : 0.0,
  "layerName" : "Hidden Layer 2",
  "nin" : 18,
  "nout" : 80,
  "weightInit" : "RELU",
  "weightNoise" : null
},
"maxNumLineSearchIterations" : 5,
"miniBatch" : false,
"minimize" : true,
"optimizationAlgo" : "STOCHASTIC_GRADIENT_DESCENT",
"pretrain" : false,
"seed" : 2001,
"stepFunction" : null,
"variables" : [ "W", "b" ]
}, {
  "cacheMode" : "NONE",
  "epochCount" : 0
}

```

```

"iterationCount" : 0,
"l1ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"l2ByParam" : {
  "b" : 0.0,
  "W" : 0.0
},
"layer" : {
  "@class" : "org.deeplearning4j.nn.conf.layers.OutputLayer",
  "activationFn" : {
    "@class" : "org.nd4j.linalg.activations.impl.ActivationSoftmax"
  },
  "biasInit" : 0.0,
  "biasUpdater" : null,
  "constraints" : null,
  "dist" : null,
  "gradientNormalization" : "None",
  "gradientNormalizationThreshold" : 1.0,
  "hasBias" : true,
  "idropout" : null,
  "iupdater" : {
    "@class" : "org.nd4j.linalg.learning.config.Adam",
    "beta1" : 0.9,
    "beta2" : 0.999,
    "epsilon" : 1.0E-6,
    "learningRate" : 0.01
  },
  "l1" : 0.0,
  "l1Bias" : 0.0,
  "l2" : 0.0,
  "l2Bias" : 0.0,
  "layerName" : "output layer",
  "lossFn" : {
    "@class" : "org.nd4j.linalg.lossfunctions.impl.LossMCXENT",
    "softmaxClipEps" : 1.0E-10,
    "configProperties" : false
  },
  "nin" : 80,
  "nout" : 2,
  "weightInit" : "RELU",
  "weightNoise" : null
},
"maxNumLineSearchIterations" : 5,
"miniBatch" : false,
"minimize" : true,
  "optimizationAlgo" : "STOCHASTIC_GRADIENT_DESCENT",
  "pretrain" : false,
  "seed" : 2001,
  "stepFunction" : null,

```

```

    "variables" : [ "W", "b" ]
  } ],
  "epochCount" : 1000,
  "inferenceWorkspaceMode" : "ENABLED",
  "inputPreProcessors" : { },
  "iterationCount" : 1000,
  "pretrain" : false,
  "tbpttBackLength" : 20,
  "tbpttFwdLength" : 20,
  "trainingWorkspaceMode" : "ENABLED"
}
Model Weights:
[[ 0.0126, -0.2346, 0.1993 ... -0.3382 -0.1045, 0.1045]]

```

E. Results for ANN classifier designed in MATLAB:

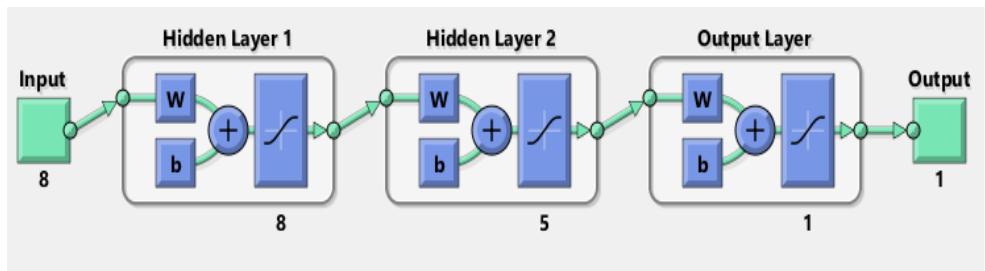


Fig. G.1 MATLAB ANN Classifier Model

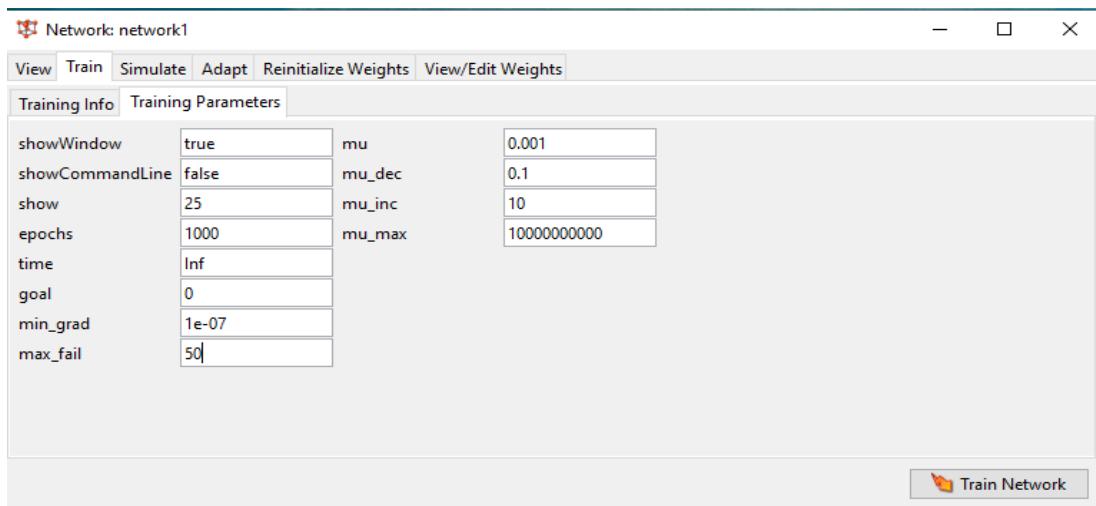


Fig. G.2 Model Training Parameters

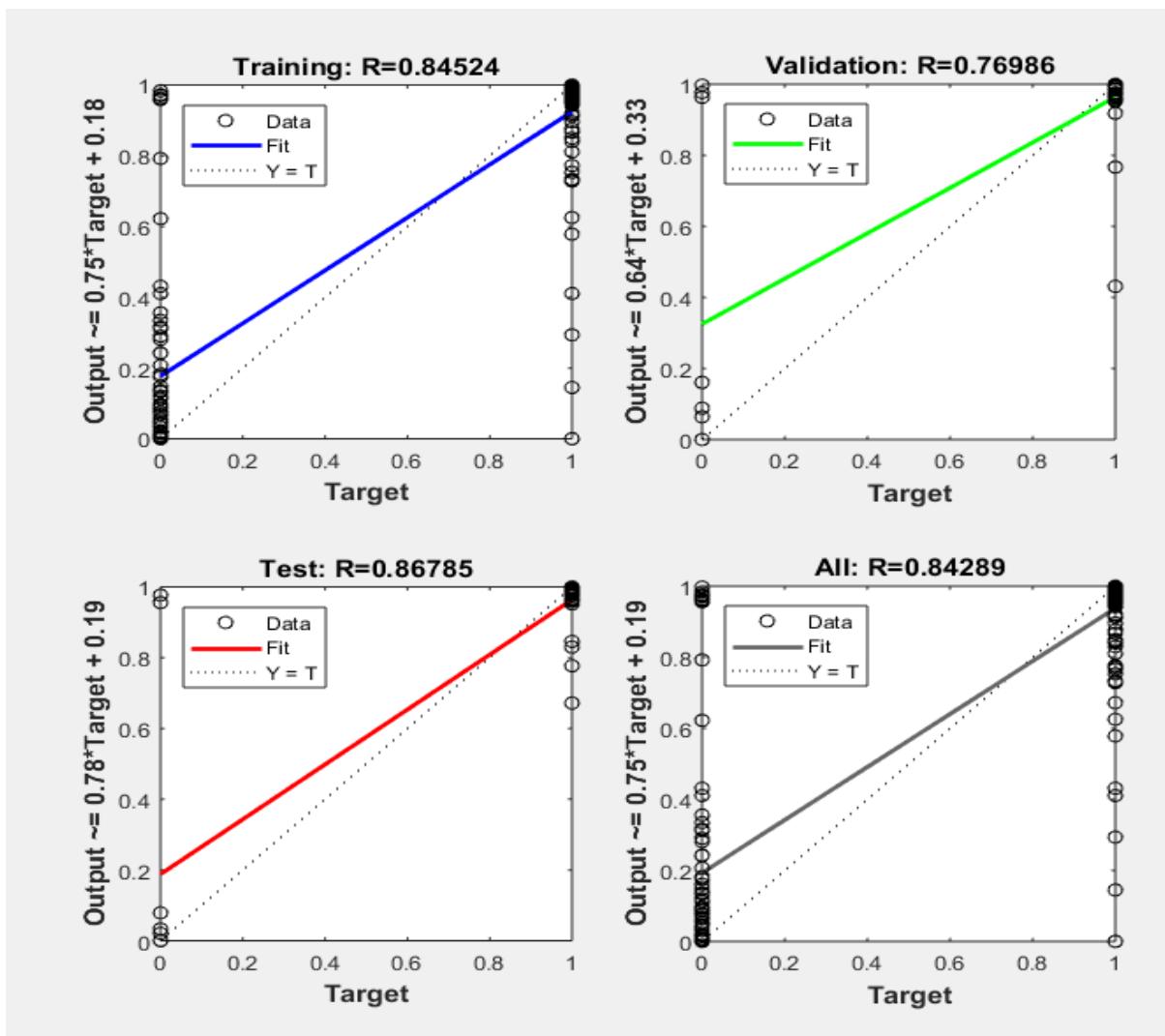


Fig. G.3 Model Performance

