Classification of Indoor vs Outdoor induction labour success

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Declaration

I certify that this research work titled "*Classification of Indoor vs Outdoor Induction Labour Success*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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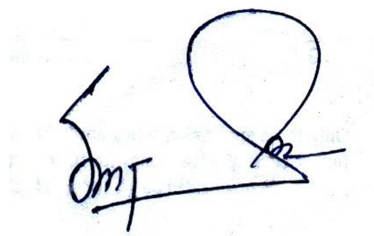
This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.



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Copyright Statement

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Abstract

Induction of labour is a procedure which is performed when benefits of interrupting or stopping the pregnancy outweighs rather it is continued further. According to studies and surveys it is found that about 25% of the women requires induction for delivery in developed countries and the number slightly decreases in developing countries. Different methods are available to induce labour induction including mechanical and chemical. Various protocols suggest hospitalization before induction of labour but necessity of admission is not proven. Induction in a familiar home like environment may have benefits psychologically as well as financially.

This study is about indoor and outdoor induction of labour, their outcomes and comparison of results based on success. Firstly data of pregnant women was collected with singleton pregnancies excluding complexities; patients were admitted in wards and emergency. Then machine learning algorithms are applied on collected data to find out the success rate of outcomes using features obtained at the time of admission. As hospitals of Pakistan are not much developed especially in rural areas. This study will assist patient as well as doctor to make decisions either to refer the patient to highly equipped hospital or not, also they will be able to predict the fetomaternal outcomes.

A novel approach to present the comparative study of indoor and outdoor patients with future prediction of four fetomaternal outcomes using supervised machine learning algorithms; with best accuracy achieved by Ensemble Bagged Tree algorithms which is 87.9%, also concluded that outdoor induction is better than indoor induction in terms of outcomes success.

Key Words: Induction of Labour, Fetomaternal outcomes, Accuracies, Prediction

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1 CHAPTER: INDUCTION OF LABOUR

1.1 Objective and Motivation

Objective of this study is to compare the fetomaternal outcomes of indoor and outdoor induction in local population. The study can be beneficial for patients, doctors and for hospitals as well. Tertiary hospitals in developing countries often lack the resources to cater the number of incoming patients. So by managing low risk patients by outdoor induction, the indoor patients care can be improved due to decrease hospitalization.

1.2 Introduction

Over recent decades, number of pregnant women undergoing labour induction is increased more and more to deliver babies. About one fourth of women undergo labour induction in developed countries. This rate is lower in developing countries but often in some setting this rate approaches to the rate as in developed countries [1]. Induction of labour only should be done when clear indications are there and outcomes benefits are more than their harms.

Labour is physiological intervention in which Placenta, membranes, umbilical cord and the fetus (i.e. conceptions products) are pushed out from uterus. It is achieved during connective tissues biochemical changes and uterine cervix dilation and effacement, resulting rhythmic shrinking frequency, duration and intensity. There are different indications for diagnosis of labour. Beginning of labour is explained as smooth and painful contraction of uterine that will lead towards effacement and dilation of cervix. During contraction of uterine if cervical dilation is absent then it suggest cervical insufficiency and contraction of uterine without any significant change in cervix does not fulfil requirements of labour. Pregnancy is divided into four distant phases i.e. is early term (between start of 37 week and end of 38 week), full term (between start of 39 week and end of 40 week), Later term (between start of 41 week and end of 41 week), and post term (Start of 42^{nd} week and beyond) [2]. Studies have shown that once the pregnancy reaches full term, baby has best health outcomes [3]. Usually induction consists of multiple processes; not only a single intervention and it present challenges for both clinicians and mother [4].

Studies have shown that best outcomes can be achieved when pregnancy reaches at full term. But due to complications it is necessary to interrupt pregnancy to induce labour to prevent the risk for mother and child. Vaginal prostaglandin E2 and Misoprostol are commonly used drugs for induction. A study was conducted by Lilungulu A et al [5] for comparison of indoor and outdoor to compare the fetomaternal outcomes in indoor and outdoor patients and recorded cesarean section, Apgar score <7 at 5 minutes, meconium stained liquor and admission in NICU and concluded that cesarean section rate is higher in indoor patients.

As I am comparing induction of labour success between indoor patient and outdoor patients. There are only three randomized studies (total of 612 women) comparing inpatient to outpatients induction of labour which have been published previously [5] and do not describe significant variances in medical outcomes. Besides clinical studies there is no may be rare or any research which deals in outcomes/ success rate prediction using deep learning and machine learning algorithms to predict future outcomes using previous data of indoor and outdoor patients. In this study I am using Support Vector Machines (including Linear, Quadratic and Cubic SVMs), K Nearest Neighbors (KNN), Decision Tree algorithm and Ensemble Bagged Tree classifiers to predict fetomaternal outcomes of patients retained as indoor and outdoor. I have compared the results and on the basis of these machine learning algorithms we were able to conclude classification of indoor vs outdoor induction of labour success. I have shown results in the form of accuracies, recall, precision, F score, Confusion Matrices, ROC curves and AUC (Area under the curve).

1.3 What is Induction of Labour?

Labour induction is an artificial stimulation process of contraction of uterine to complete delivery rather going into spontaneous labour. In United States this gynecological process is most widely and commonly used [6]. From 1990-2004 occurrence of induction labour is almost doubled from 9.5 to 21%. This is because better cervical ripening agents are available. Clinicians and patients want for a suitable time of delivery and relaxed attitude for indications of labour [7]. Reasons behind the increase rate of induction are also the patient or clinician concern for threat of neonatal death on near term or post term [8].

1.4 Indications

Induction should be examined at the time when sensed. Also the vaginal delivery outcomes success exceeds the possible fetal and maternal induction risks. Before initiation of induction these problems must be conferred with woman. Mostly induction of labour is observed in post term pregnancies. Pregnancy with at least 41 weeks of Gestational period completion. This indication of induction has shown decrease in the possibility of perinatal death. Other indications include before time rupture of membrane, [9], [10] restriction in growth of fetal, medical conditions of mother (renal disease, hypertension, Pulmonary disease or renal disease), death of fetal, early separation of placenta from uterus, chorioamnionitis. This list does not cover all.

Also sometimes there are Social or geographic reason for induction without an obstetric or medical indication [11]. There are just few studies which explain induction indications. Two clinical randomized trials [10] [11] propose no amplified threats to mother or newborn but as the trial magnitude is not too big to conclude conclusion. Another study says that elective induction in nulliparous woman should be discouraged because due to elective induction cesarean section has increased. A case control study does not conclude that cesarean delivery prediction is not due to elective induction. Also analysis of early trials conclude that elective induction has no benefits and for it there is no room in term pregnancy [12]. According obstetricians and Gynecologists college of America, "logistic reasons may induce labour including hospital distance, psychosocial reasons and rapid labour" [13].

1.5 Predicting a successful induction

Most common factor for estimating the likelihood of labour induction success is cervical status. So before starting the induction attempt cervical examination should be performed. Several scoring systems are available to examine cervix status including Bishop System, Burnett, Friedman modifications etc. [12].

Other indications associated with successful induction include postern pregnancy, BMI of women, infant weight, tall stature and multi parity [13]. These factors or predictors for success also present in spontaneous labour.

1.5.1 Bishop score

Most commonly Bishop Score is applied in clinical Practice [14]. This system consists of four characteristics of cervix; position, consistency, dilation and effacement. Also this system score is a scoring system to predict either induction is required or not.

Chances of operative delivery becomes double when a nulliparous woman undergo elective induction [15]. Bishop score ≤5 on admission time means unfavorable cervix leads to increase in cesarean delivery risks as most of the studies include random trials [16]. If Bishop Score is higher i.e. ≥5 or ≥8 (differently defined) chances of vaginal delivery is high whether labour is induced or spontaneous [17].

On other hand if Bishop Score is low than it is predicted vaginal delivery will fail after induction [13]. Above said relationships are relatively high in nulliparous woman undergoing induction.

To predict the possibility that vaginal delivery is the result of induction, best tool that is available is Bishop Score. This opinion is based on controlled studies systematic reviews that Bishop Score was more predictive regarding outcomes than sonographic amount of cervical length [18] and most important factor of Bishop Score was dilation [12].

1.6 MONITORING DURING LABOUR

Pregnancies with higher risks may contain up to 80% of overall perinatal mortality and morbidity. Other perinatal complexities appear in gestations without recognizable risk features for worse consequences [19]. Hence gestations need overall complete assessment of risks and close observation. As early as the woman reaches health facility for labour and appropriate delivery monitoring and evaluation can be done. Also fetal heart rate and duration of uterine contraction can be calculated.

During labour continuation observing the uterine contraction with the help of tocodynamometry is mostly enough. But if labouring is confirmed by rapture of membranes and if contraction duration/intensity cannot be measured then intrauterine pressure catheter is passed into the uterine cavity to assess the contraction intensity and duration. As the external tocometer just records the contraction timing, to measure the pressure produced while contraction of uterine, if strength is concerned pressure catheter is used. Because it is a safe method hence rare complications are recorded of placental abruption while using intrauterine pressure catheter [20].

Mostly cardiotography is used for fetal assessment using cardiotograpy in labour was reviewed having randomized controlled trials. Comparing cardiotograpy with no monitoring study concluded that a decrease in neonatal seizure was recorded in cardiotograpy but not in neonatal mortality or cerebral palsy. Also an increase was observed in operative vaginal deliveries and cesarean with continuous monitoring [21].

If non reassuring neonatal heart rate record by cardiotocagraphy is noted, beat to beat sensitive reading can be generated by applying electrode, but should not be used if mother has hepatitis B, C or HIV infection. Recently a model is proposed for classification and of fetal heart rate pattern [22].

To assess whether the fetal pulse anxiety is useful for neonatal monitoring in labour was examined in a study review comparison of cardiotography. Concluded that adding up fetal pulse oximetry feature does not decrease cesarean section [23]. Further assessment can be done with sampling of blood from capillaries of fetal scalp. With this technique fetal oxygenation and blood PH can be calculated. If PH is less than 7.20 then further investigation is required for possible resuscitation or surgery.

2 CHAPTER: Literature Review

As discussed in introduction section that there are rare (about three) clinical studies comparing fetomaternal outcomes of indoor patients and outdoor patients but still there is no predictive/ estimation study which uses machine learning or any other technical algorithms to predict future outcomes using previous data and features of patients. This study is novel in this case as I am classifying outdoor vs indoor induction success. Previous studies/ researches are mostly inclined towards prediction of cesarean section.

According to WHO, number of women who under gone labour induction (Labour initiated artificially) for delivery of babies has increased more and more in recent decades. In developed countries one fourth of deliveries involve induction of labour. This rate is lower in developing countries but often in some setting this rate approaches to the rate as in developed countries [11]. Induction of labour only should be done when clear indications are there and outcomes benefits are more than their harms. Since the practice involve the risk of uterine rupture and fetal distress, labour induction should be accomplished with care. Also induction of labour should be achieved in those facilities where cesarean section can be performed [30].

According to WHO statement on cesarean section, recently there is no classification system defining cesarean deliveries which is internationally acceptable and that can be used for comparison of cesarean section rates in different cities, regions or health facilities. Cesarean deliveries are useful in saving infant and maternal lives but this should only be performed when there is clear symptom for this. Cesarean sections rates higher than 10% are not considered as decrease in fetus maternal death rates. Cesarean section may also lead to outstanding and sometimes everlasting disability, complexities or can cause death especially in setting that do not have proper facilities and to conduct properly safe surgery and also treatment of surgical complications [31].

Marjo Riitta Jarvelin et.al in their study, inspect indications for labour induction and policy of induction. Also compared outcomes of induced and spontaneous labour. Found that labour was induced more often at lowest level of specialization (29.4%), (23.6%) at local level and (17.7%) at specialized health centers. Practice of labour induction is not same in various hospitals. Individual consultant's opinion and staff routine effect the induction policy. Also a liberal induction policy lead to increase in operative deliveries [32].

Hye In Kim et.al in surveying observational study described the benefits and risk of labour induction at thirty nine or more weeks of singleton gestation were included in this study and compared both maternal (Rate of Cesarean Section) and fetal outcomes in spontaneous and induced labour groups. Spontaneous and induced labour had 17.7% vs 12.3% incidence of cesarean section. Other neonatal outcomes had also similar incidence and hence concluded that it may be acceptable to schedule labour induction 7 days before the expected date [33].

Philippa Middleton et.al devised a study to investigate the improvement in birth outcomes for induction of labour at or beyond terms. Because beyond terms, the risk of neonatal death or stillbirth increases. This study basically assesses the effects of labour induction policy at or beyond term with spontaneous labour policy. 30 RCTs were included (recording on 12,749 women) and the trial took place in different countries. Concluded that as absolute death risk is low so it may be supportive to offer women counselling to help choose between post term pregnancies planned induction labour or monitoring without induction [34].

Ekaterina Mishanina MBBS et.al in systematic review and analysis of labour induction examined either the cesarean delivery risk is lower or higher in induction labour vs expectant. Concluded that the cesarean section risk is twelve percent less in induction of labour vs expectant management. Also observed a reduced risk of fetal death and admission to NICU. No impact on maternal death was recorded with induction labour [35].

Sarwat mumtaz et.al in demographic health survey of Pakistan describes increasing trends and differences in cesarean section rates in Pakistan. Compared socioeconomic inequalities in cesarean section rates and found lower utilization in illiterate women (7.5%) vs highly educated (40.3%) and in poor women it was recorded 5.5% and 35.3% in rich women. In rural women 11.5% cesarean section was observed as compared with twenty five point six percent in women of urban areas. Concluded a higher possibility of cesarean section in women who are highly educated, rich and living in urban areas [36].

Ana Pilar Betran et.al in their research presented the cesarean section trends and trends for previous twenty four years. From data of 150 countries, 18.6% of total births happen by cesarean section fluctuating between 6 percent and 27.2 percent in under developed to developed countries respectively. Latin America and Caribbean has the highest cesarean section i.e. 4.5% and Africa has the least 7.3%. Also trends shows that the global average cesarean section rates increased by 12.4% between 1990 and 2014 with an average annual increase of 4.4% [37].

Jen-Hsing Wang devised a study based on predicting the normal spontaneous delivery through deep learning by analyzing data of fifty six women at Antai Tian-Sheng Memorial hospital between 2017 and 2018 from which thirty eight women experienced normal delivery and eighteen delivered through cesarean section. Data was gathered including features like the height, age, weight of fetus and weight of women. A machine learning algorithm (multilayer perceptron (MLP) model) was used that contained three layers (input, hidden and output) using Keras an open source neural network library and obtained 90% accuracy for estimating the route of delivery [38].

Audrey Gilbert et.al devised a study to assess that whether level of education of mother influence the women to plan elective repeat Cesarean section rather going into vaginal birth after Cesarean. An increase in elective repeat Cesarean deliveries were recorded in women with higher education. From these 12.6% had a high school degree, 38.3% had college level degree and 49.1% with university degree [39].

MS. Michal LIPSCHUETZ in his study evaluated the possibility of using machine learning methods to forecast a successful vaginal birth. Analyzed data of 12 year period collected from tertiary center using gradient boosting model. One model was formed to offer a personalized risk score using available features and a second model was formed that reevaluates the score. From cohort of 9888 parturients,7473 attempted a trial of labour with accuracy of 88% and are under the curve 0.745 which increased to .793 on adding features available [40].

Myriam de Loenzien et.al proposed a study aiming to update the general trends and comparing the fetomaternal outcome of Rural vs urban areas. Used data from the Multiple Indictors Clusters Survey MICS and conducted a bivariate study using logistic regression. On controlling the significant factors results shows that cesarean section rates are almost double as compared to rural areas. Maternal age over 35 years have also a strong positive correlation with cesarean section [41].

K.Butchi Raju et.al in his study title “Classification of cesarean data using machine learning models” uses different classifiers to predict cesarean section. Study system comprises of three phases. Study is distributed into three stages at first stage data is acquired, secondly applies different algorithms and then measures the performance of different classifiers with confusion matrix values and accuracies. Used Decision tree, Gaussian process, Bernoulli NB, Ada Boost, Support vector machines SVM, K Nearest Neighbor, XG Boost and Gradient classifier for classification. Data set consist of 961 pregnant women with characteristics of delivery i.e. age of woman, Parity, gestational age, heart status and blood pressure. He applied above said classifiers and computed accuracies with KNeighbor classifier giving maximum accuracy score of 95%, Decision tree, Gaussian process, and XGB classifier with an accuracy of 92% each. Classification patterns may be used for medical diagnosis, prediction and treatment [42].

Ayesha Sana et.al published her research in international journal of machine learning and computing, collected data from 15 different hospitals of Sargodha. Used almost 50 features that can affect type of birth. Pre-pregnancy features includes body weight index, Age of woman, Education level, hypertension and diabetes. Several social features including low education, dieting, fear of pain etc also effect birth type. Decision tree classifier are used to classify between normal and cesarean births with an accuracy of 80%, Artificial Neural Network can classify with an accuracy of 92% [43].

Stephen d.Robson et.al in his research predicted cesarean section in an Australian birth cohort in 2004. Features used were maternal age, obesity, previous cesarean section and other social factors. Data was acquired by face to face interviewing of patients. They used Logistic regression algorithm and accuracy obtained was 95% [44].

Mehmat Sinan Beksak et.al used classification techniques to predict route of delivery i.e. Cesarean vs vaginal birth. They used maternal age, gravida, parity, gestational age, Labour induction type, presentation of baby and maternal disorders as features or predictors to estimate the type of birth. They used artificial neural network algorithm for classification and obtained accuracy of 91.8% [45].

Jen-Hsing Wang et.al in their research paper published in IEEE conference 2019. Used maternal age, maternal height, maternal weight and weight of newborn. Collected data by their self at Antai TianSheng Memorial hospital and predicted natural spontaneous delivery using Multilayer Perceptron (MLP) and acquired an accuracy of 90% [46].

Tom M.Mitchel uses Decision tree, Neural network, Inductive logic programming to predict an emergency cesarean section using different predictors like age, pregnancy number, Anemia, Diabetes, previous pre mature birth etc. [47].

3 CHAPTER: ANALYSIS OF DATASET

3.1 Data Acquisition and Dataset Overview

I have received data from clinical study/ Dissertation of Dr. Uzma Almas; title "Comparison of indoor vs outdoor induction of labour in full-term uncomplicated pregnancies" Pakistan Institute of Medical Sciences (PIMS) Islamabad. Data was collected through OPD and Emergency while strictly following the inclusion and exclusion criteria defined. Patients were informed about the study and its possible outcomes. Data set consist of 412 pregnant women with singleton pregnancy of cephalic presentation and full term gestational age group of 18-40 years were included in this study. Pregnant women with multiple pregnancies and other medical conditions like diabetes, cardiac diseases, hypertension etc. were not included in this study. From total of 412 women 206 were kept in as outdoor patient and 206 women as indoor patient.

1st group was admitted in ward after admission and 2nd group was kept in emergency for observation. All women were followed till delivery and fetomaternal outcomes i.e. Cesarean Section, Meconium Aspiration Syndrome, Apgar score <7 at 5 minutes and NICU admission were noted. Here every feature is important and attributed as below.

@Attribute 'Age' {18,……………40}; years

@Attribute 'Parity' {1,2,3,4,5};

@Attribute 'BMI' {24,………33};

@Attribute 'Education' {0,1,2,3}; {0 = illiterate, 1 = Primary, 2 = Middle, 3 = Matric}

@Attribute 'Living' {0,1}; {0 = Rural, 1 = Urban}

@Attribute 'Gestational Age' {37,……….,41}; Weeks

@Attribute 'Cesarean' {0,1}; {0 = No, 1 = Yes}

@Attribute 'Low Apgar' {0,1}; {0 = No, 1 = Yes}

@Attribute 'MAS' {0,1}; {0 = No, 1 = Yes}

@Attribute 'NICU admission' {0,1};{0 = No, 1 = Yes}

3.2 Brief Description of Features

3.2.1 Outdoor vs Indoor

Overall data of 406 pregnant women is divided into two equally numbered groups of 206 patients in group A which are kept in as outdoor patient and 206 patients in group B which retained in emergency after admission. Objective is to compare outcome of patients between these two groups.

3.2.2 Age of women

Age range is between 18 and 40 years with mean age of 29.88 ±5.42 years. Age of group A is 30.77±79 and group B is 29.68±5.71 years.

3.2.3 Parity

Parity is that how many times pregnant woman has already given birth to a baby; with pregnancy age of 24 weeks or more. This number is counted either the fetus was born alive or stillborn. Range of parity in this data is 1-5 and mean parity is 3.22±1.19.

3.2.4 Body Mass Index

Body mass index (BMI) is calculated using height and weight. Mean BMI is 28.42±2.47 kg/m^2. Distribution of patients according to BMI is shown in table.

3.2.5 Gestational Age

Gestational age is the period of pregnancy. It is measured in weeks. As in this study full term pregnancy patients are included so the range of gestational age is 37-41 weeks.

3.2.6 Place of Living. Rural/Urban

Place of living is an another factor/feature which is used in this study that effect the fetomaternal outcomes as Social, economic (rich/poor) factor and living style urban/rural affects fetomaternal outcomes [24], [25], [26].

3.2.7 Education Level

Last feature used in this study is educational level i.e. illiterate, primary, middle, matric and graduate. Increased rate of elective repeat Cesarean section are associated with higher education level [27], [28].

Following table shows the fetomaternal outcomes stratification with respect to features used.

Table 1: Stratification of Features used

Feature	Group	Total Cases	Sub Group	Cesarean	MAS	APGAR	NICU
Age of Women	Group A	206	18-30(50.9%)	23	3	1	1
			31-40(49.03%)	21	3	3	2
	Group B	206	18-30(45.63%)	18	12	6	6
			31-40(54.37%)	49	23	9	17
Parity	Group A	206	1-3(60.19%)	34	5	2	2
			4-5(39.81%)	10	1	2	1
	Group B	206	1-3(59.22%)	38	17	13	17
			4-5(40.78%)	29	18	2	6
BMI	Group A	206	<=27(38.83%)	24	3	0	0
			>27(61.17%)	20	3	4	3
	Group B	206	<=27(35.44%)	22	5	1	8
			>27(64.56%)	45	30	14	15
GA	Group A	206	37-39(68.93%)	26	4	2	1
			40-41(31.07%)	18	2	2	2
	Group B	206	37-39(66.99%)	58	23	13	15
			40-41(33.01%)	9	12	2	8
Living	Group A	206	Rural(59.71%)	39	4	4	3
			Urban(40.29%)	5	2	0	0
	Group B	206	Rural(63.11%)	34	27	11	13
			Urban(36.89%)	33	8	4	10
Education	Group A	206	Illiterate (8.74%)	1	1	0	0
			Primary (11.17%)	2	1	0	0
			Middle (40.78%)	20	1	0	0
			Matric (39.32%)	21	3	4	3
	Group B	206	Illiterate (9.22%)	3	4	0	1
			Primary (14.08%)	10	10	1	1
			Middle (33.01%)	23	6	12	8
			Matric (43.69%)	31	15	0	13

3.3 Fetomaternal Outcomes

Success is associated with fetomaternal outcomes which are as under.

3.3.1 Cesarean Section

Cesarean section also known as C-section is a surgical procedure used to deliver a baby through incision in the abdomen and uterus. Cesarean section have turn out to be gradually common in both developing and developed countries. WHO recommends that cesarean section should be 10% to 15% [30]. But due to elective cesarean deliveries this number has increased rapidly, so there is a need to find the root cause and solution to control this [12]. Because there is no proof which shows the benefits of cesarean deliveries, recently governments have shown serious concerns in rising number of cesarean deliveries and negative consequences on mother and child health [30].

In my data set cesarean section was recorded in 111 patients out of 412 from which 44 patients 21.36% were from group A outdoor and 67 patients 32.52% were from group B.

3.3.2 Apgar score

Apgar score is a method by which we are able to summarize the health condition of new born baby. Apgar stands for appearance, pulse, grimace, activity and respiration. This score is calculated after 5 minutes of child birth or delivery. Each factor scores on a level of 0-2 and total of 0-10. More the score tells the baby is stable and fit. Usually it is calculated after 5 minutes of birth and a score of seven or greater is considered good. Apgar score <7 at 5 minutes was recorded in 04 (1.94%) in Outdoor labour induction and 15 (7.28%) in Indoor induction.

3.3.3 Meconium Aspiration Syndrome

It is difficulty in breathing or suffering in respiratory system in the newborn and it occurs in those who has respired a dark green material called meconium into his/ her lungs at the time of delivery. It can lead to cause of severe illness or death of fetal and usually occurs between 5% and 10% of births. It happens due to when baby is unstressed during labour. Symptoms are bluish skin color, breathing problem, limpness and dark green staining of the amniotic fluid. Meconium aspiration syndrome in outdoor patients was recorded 06 (2.91%) and 35 (16.99%) in indoor induction.

3.3.4 NICU Admission

Stands for neonatal intensive care unit. It is a department in hospital which offers care to sick or premature babies around the clock. After birth to assess the neonatal requires NICU admission temperature, heart rate, breathing and color are observed that these are with in normal limits. If mother has risk factors in pregnancy like diabetes, high blood pressure or medical history of using drugs then possible that neonatal require NICU. NICU admission in outdoor patients was recorded 03 (1.46%) versus 23 (11.17%) in Indoor. There may be six possible reasons for neonatal NICU admission.

1. Prematurity: Babies born earlier i.e. before 37 weeks of pregnancy.
2. Respiratory Distress Syndrome: Most common respiratory problem because of immature lungs.
3. Sepsis: It is an infection commonly cause death in neonatal.
4. Hypoglycemia: It is because of low blood pressure and seen in premature babies.
5. Perinatal depression: Difficulties in the course of delivery, can cause reduced blood flow and oxygen to the baby.
6. Maternal chorioamnionitis: It is because of infection in placenta or umbilical cord.

4 CHAPTER: Methodology

Machine learning is a part of Artificial Intelligence that enables the system automatically learn and improve from past practice or historic data. Key objective of machine learning is to allow computers to learn automatically. Process of learning starts from the data available to look patterns in data and makes better and better decisions in future predictions. Machine learning techniques can be used to induce knowledge from data. These techniques are used for medical diagnosis, prediction and treatment. In this study different ML algorithms are applied for classification of outdoor vs indoor labour induction success. Machine learning algorithms are grouped as supervised and unsupervised learning algorithms.

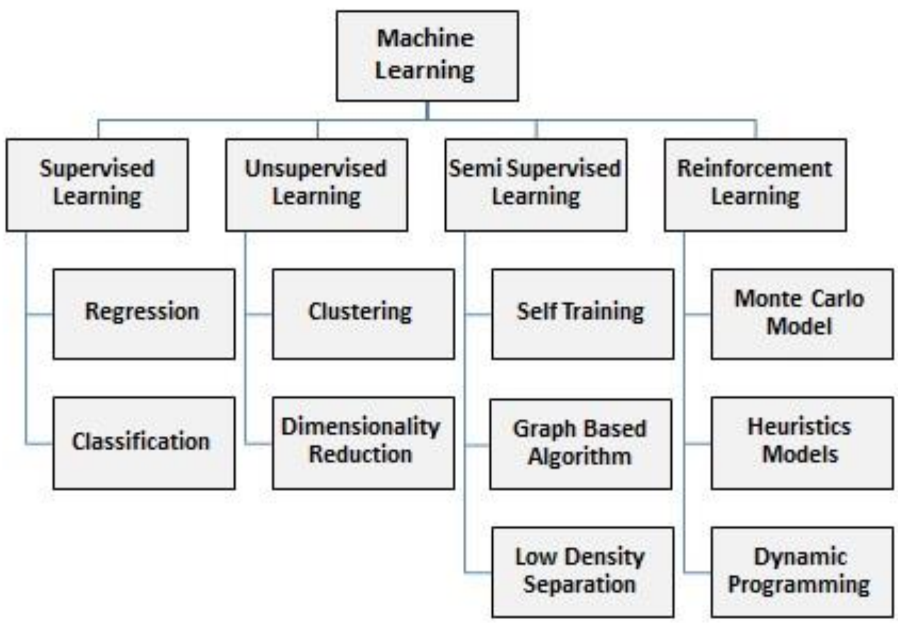


Figure 1: Types of Machine Learning algorithms.

4.1 Types of Machine Learning Algorithms

4.1.1 Supervised Machine Learning Algorithms

These algorithms can be applied to data having labeled examples to forecast upcoming happenings. These starts from training the algorithm from training data set, the learning algorithm produces an inferred function to make predictions about the output values. Then after adequate training system is able for new inputs to estimate targets/ outputs. Learning algorithm also compares its output with the correct intended output and find errors in order to modify the model accordingly. Support Vector Machines SVM, linear regression, logistic regression, Naive Bayes, linear discriminant analysis LDA, decision trees, k-nearest neighbor algorithm KNN, Neural Networks (Multilayer perceptron), Similarity learning are most widely used supervised learning algorithms.

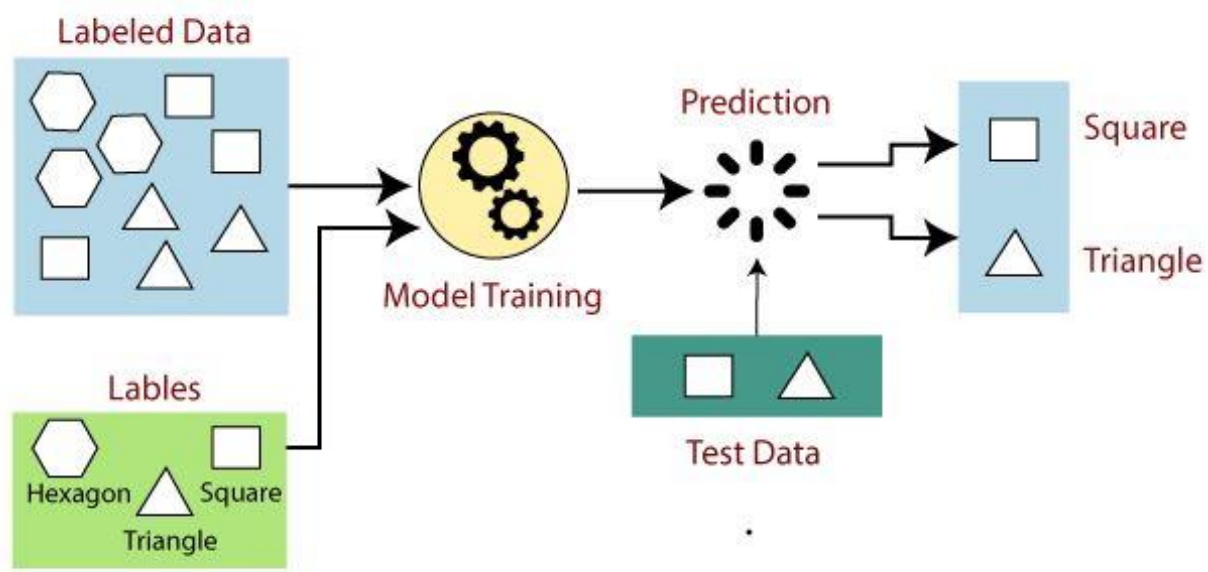


Figure 2: Supervised Machine Learning [48].

4.1.2 Unsupervised Machine Leaning Algorithms

These learning algorithms are used when data or information used is neither classified nor labeled. This system does not figure out the right output, but it classifies the data and can draw inferences from dataset to describe hidden patterns from unlabeled data. Clustering techniques are used in unsupervised machine learning algorithms.

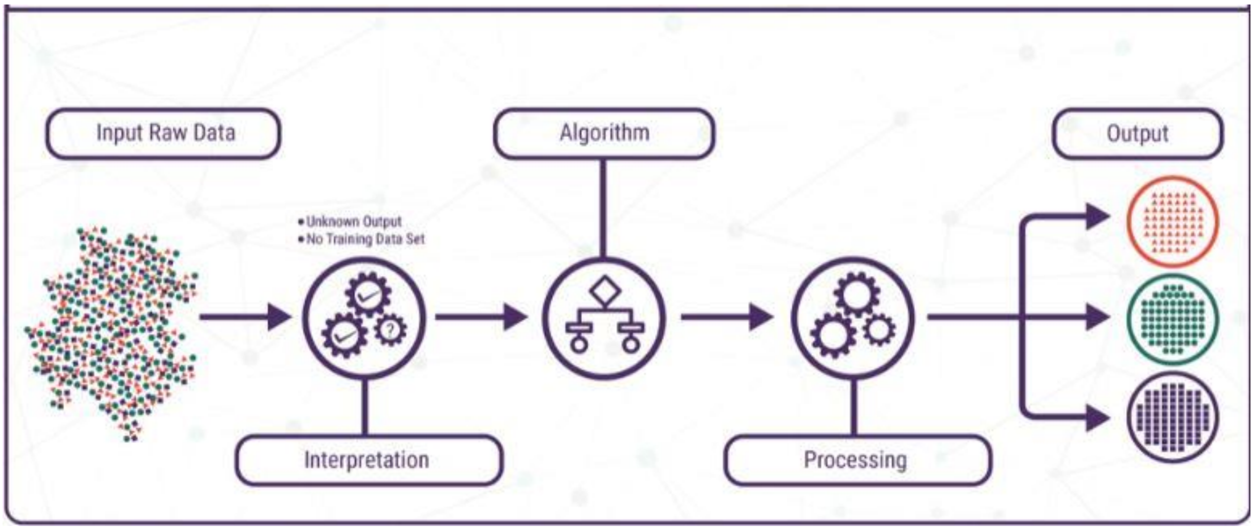


Figure 3: Unsupervised Machine Learning [49].

4.1.3 Semi Supervised Machine Learning Algorithms

This algorithm falls between somewhere in between supervised and unsupervised machine learning algorithms because these use both supervised and unsupervised. Usually these are used for acquiring labeled data and other resource to train. Acquiring unlabeled data generally does not require additional resources.

4.1.4 Reinforcement Machine Learning Algorithms

These algorithms are used in games in which the agent receives a delayed reward in the next time to step to evaluate its previous action. Main difference between reinforcement machine leaning algorithm and others is that reinforcement does not assume knowledge of an exact mathematical model.

In this study, I am using labeled data means fetomaternal outcomes i.e. Cesarean section, Apgar score, Meconium Aspiration Syndrome (MAS), and NICU admission are known to us. So as outputs are available the best algorithms that can be used are of supervised learning. Hence applied different classifiers and results are described in following section.

4.2 Correlation Matrix:

Correlation matrix shows relation between two variables. A correlation matrix is used to summarize the large data and each cell in the table shows the correlation between two variables. Higher the correlation value suggest stronger correlation between two variables and also indicate that linear regression estimation will be unreliable. Missing values in data are assigned using techniques but in our dataset there are no missing values.

The line of 1.00s on diagonal shows that each variable is always perfectly correlated with itself.

Table 2: Correlation Matrix of Outdoor Dataset

	Age	Parity	BMI	Education	Living	GA	CS	Apgar	MAS	NICU
Age	1									
Parity	0.01	1.00								
BMI	0.02	-0.11	1.00							
Education	0.03	-0.10	-0.08	1.00						
Living	0.05	0.00	0.05	-0.06	1.00					
GA	0.27	-0.05	-0.04	-0.05	-0.05	1.00				
CS	0.00	-0.15	-0.23	0.16	-0.31	0.05	1.00			
Apgar	0.08	0.00	0.07	0.14	-0.12	0.06	-0.07	1.00		
MAS	0.01	-0.08	-0.05	-0.02	-0.02	0.03	0.05	-0.02	1.00	
NICU	0.07	-0.06	0.03	0.12	-0.10	0.10	-0.06	0.86	-0.02	1.00

Correlation matrix for data set of Indoor patients is show below in the table.

Table 3: Correlation Matrix of Indoor Datset

	Age	**Parity**	**BMI**	**Education**	**Living**	**GA**	**CS**	**Apgar**	**MAS**	**NICU**
Age	1.00									
Parity	0.39	1.00								
BMI	0.01	0.02	1.00							
Education	0.21	-0.12	0.07	1.00						
Living	0.03	0.05	-0.26	0.08	1.00					
GA	0.17	0.00	-0.27	0.00	0.00	1.00				
CS	0.14	0.06	-0.02	0.08	0.18	0.09	1.00			
Apgar	0.05	0.05	0.16	0.18	-0.06	0.19	0.08	1.00		
Mas	0.12	0.03	0.17	-0.09	-0.13	0.10	0.27	-0.08	1.00	
Nicu	0.11	-0.06	0.09	0.12	0.05	0.10	-0.02	0.67	-0.12	1.00

4.3 Analysis of Dataset

Complete analysis of Outdoor and Indoor patients is shown in following tables.

Table 4: Outdoor

	Age	Parity	BMI	Education	Living	GA	CS	Low apgar	MAS	NICU
Mean	30.77	3.23	28.36	2.11	0.40	38.96	0.21	0.02	0.03	0.01
Standard Error	0.33	0.08	0.17	0.06	0.03	0.09	0.03	0.01	0.01	0.01
Median	30	3	29	2	0	39	0	0	0	0
Mode	36	3	29	2	0	39	0	0	0	0
Standard Deviation	4.79	1.17	2.44	0.92	0.49	1.24	0.41	0.14	0.17	0.12
Variance	22.95	1.37	5.95	0.85	0.24	1.54	0.17	0.02	0.03	0.01
Kurtosis	-0.92	-0.68	-0.82	0.04	-1.86	-0.80	0.02	47.70	30.12	65.28
Skewness	-0.26	-0.15	0.19	-0.90	0.40	-0.06	1.41	7.02	5.64	8.16
Range	18	4	9	3	1	4	1	1	1	1
Minimum	20	1	24	0	0	37	0	0	0	0
Maximum	38	5	33	3	1	41	1	1	1	1

Table 5: Indoor

	Age	*Parity*	*BMI*	*Education*	*Living*	*GA*	*CS*	*APGAR*	*MAS*	*NICU*
Mean	29.68	3.22	28.60	2.11	0.37	39.06	0.33	0.07	0.17	0.11
Standard Error	0.40	0.09	0.18	0.07	0.03	0.09	0.03	0.02	0.03	0.02
Median	31	3	29	2	0	39	0	0	0	0
Mode	36	3	29	3	0	39	0	0	0	0
Standard Deviation	5.71	1.25	2.52	0.97	0.48	1.26	0.47	0.26	0.38	0.32
Sample Variance	32.58	1.56	6.37	0.94	0.23	1.58	0.22	0.07	0.14	0.10
Kurtosis	-1.35	-0.84	-0.87	-0.32	-1.72	-0.72	1.45	9.06	1.15	4.21
Skewness	-0.28	-0.19	0.01	-0.84	0.55	-0.17	0.75	3.31	1.77	2.48
Range	18	4	9	3	1	4	1	1	1	1
Minimum	20	1	24	0	0	37	0	0	0	0
Maximum	38	5	33	3	1	41	1	1	1	1

4.4 Performance Metrics for Classification Problems

To evaluate performance of different classifiers various performance metrics are used as listed below.

4.4.1 Confusion Matrix

A confusion matrix is a table with two dimension "Actual" and "Predicted", containing True Positive TP, True Negative TN, False Positive FP, False Negative FN. It is an easy method to measure the performance of a classifier when predicting two or more classes.

- True Positives is the case when actual and expected class data is 1.
- True Negatives is the case when actual and expected class data is 0.
- False Positives is the case when actual class is 0 and expected class is 1.
- False Negatives is the case when actual class is 1 and expected class is 0.

4.4.2 Classification Accuracy

Accuracy is explained as the total number of true estimates made as a ratio of all estimates made. It is the most common method to check performance of classification algorithm and can be calculated using following formulae [50].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

4.4.3 Area under the Curve (AUC) and ROC

AUC and ROC (Receiver Operating Characteristic) are performance metrics for classification of algorithms. ROC is a possibility curve and AUC measure the separability. In short it will tell us the capability of classifier to separate the output classes means more the area under the curve better the model. It is plotted against TPR (Sensitivity or Recall) and FPR (Specificity) on y and x axis respectively at various threshold values. Following is graph of AUC and ROC.

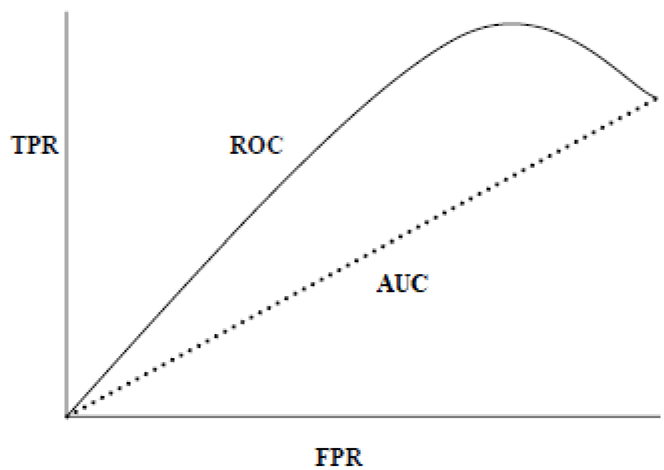


Figure 4: AUC and ROC curve [50]

Recall/ Sensitivity and Specificity can be calculated from following formulae [50].

$$Recall = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

5 CHAPTER: Implementation of Algorithms

5.1 Support Vector Machines

Support Vector Machines SVM is an algorithm that analyzes data for classification and regression. SVM sorts data into categories. It initially trains itself and task of an SVM is to determine which category new data belongs too. Compared to logistic regression and neural networks an SVM sometimes gives a cleaner way of nonlinear function. A support vector machine constructs a hyper plane that reasonably classify the best hyperplane that represent the largest margin between the classes called maximum margin hyperplane. SVM has further many types of classifier like linear SVM, Quadratic SVM and Cubic SVM.

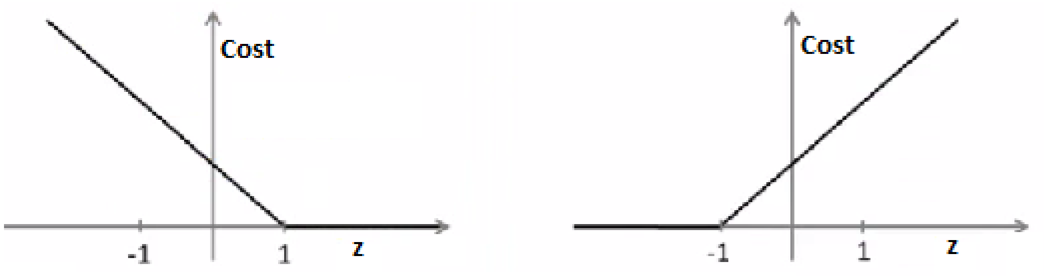
Overall equation of SVM is [51].

$$\min_{\theta} C \sum_{i=1}^{m} \left[y^{i}\, cost_1\left(\theta^{T} x^{i}\right) + \left(1 - y^{i}\right) cost_0\left(\theta^{T} x^{i}\right) \right] + \frac{1}{2} \sum_{i=i}^{n} \theta_j^2$$

$h_\theta(x)$ does not give us a possibility, but instead we get a direct prediction of 0 or 1

- So if θ^T x ≥0 ----> h_θ (x) = 1
- Else ---> h_θ (x) = 0

Sometimes SVM is referred as large margin classifiers and SVM hypothesis looks like [51].



If y = 1, we want $\theta^T x \geq 1$ (not just ≥ 0)

If y = 0, we want $\theta^T x \leq -1$ (not just <0)

Left is $cost_1$ and right is $cost_0$

Large Margin classification Mathematics: If we have two vectors u and v [51].

$$U = \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} \quad V = \begin{bmatrix} V_1 \\ V_2 \end{bmatrix}$$

Euclidean length of vector u [51]. So

$$\|\boldsymbol{U}\| = \sqrt{\left(\boldsymbol{U}_1^2 + \boldsymbol{U}_2^2\right)} = \boldsymbol{Real\ Number}$$

$$\boldsymbol{u^T v} = \boldsymbol{p} * \|\boldsymbol{u}\|$$

P is the magnitude of the projection of vector *v* onto vector u [51]

$$\boldsymbol{u^T\, v = p} * \|\boldsymbol{u}\|$$

$$\boldsymbol{u^T\, v = u_1 v_1 + u_2 v_2}$$

$$\boldsymbol{p} * \|\boldsymbol{u}\| = \boldsymbol{u_1 v_1 + u_2 v_2}$$

For SVM Decision Boundary [51]:

$$\min_{\theta} \frac{1}{2} \sum_{j=1}^{n} \theta_j^2$$

$$\text{s.t.} \quad \theta^T x^{(i)} \geq 1 \quad \text{if} \quad y^{(i)} = 1$$

$$\theta^T x^{(i)} \leq -1 \quad \text{if} \quad y^{(i)} = 0$$

Kernel Function in SVM:

Different mathematical functions are used by SVM algorithms that are defined as kernel function. Kernel function takes data as input and transform it into required form. Different types of kernels are Linear, nonlinear, polynomial, radial basis function and sigmoid function. These kernels are used for sequence data, text, images, graphs etc.

Linear kernel is used for large data vectors and classifies text data. It also performs well in regression problems [51].

$$K(x, y) = 1 + xy + xy \min(x, y) - \frac{x + y}{2} \min(x, y)^2 + \frac{1}{3} \min(x, y)^3$$

Polynomial kernel function equation is as under [51].

$$K\left(X_i, Y_j\right) = \left(X_i . X_j + 1\right)^d$$

Where d is the degree of polynomial.

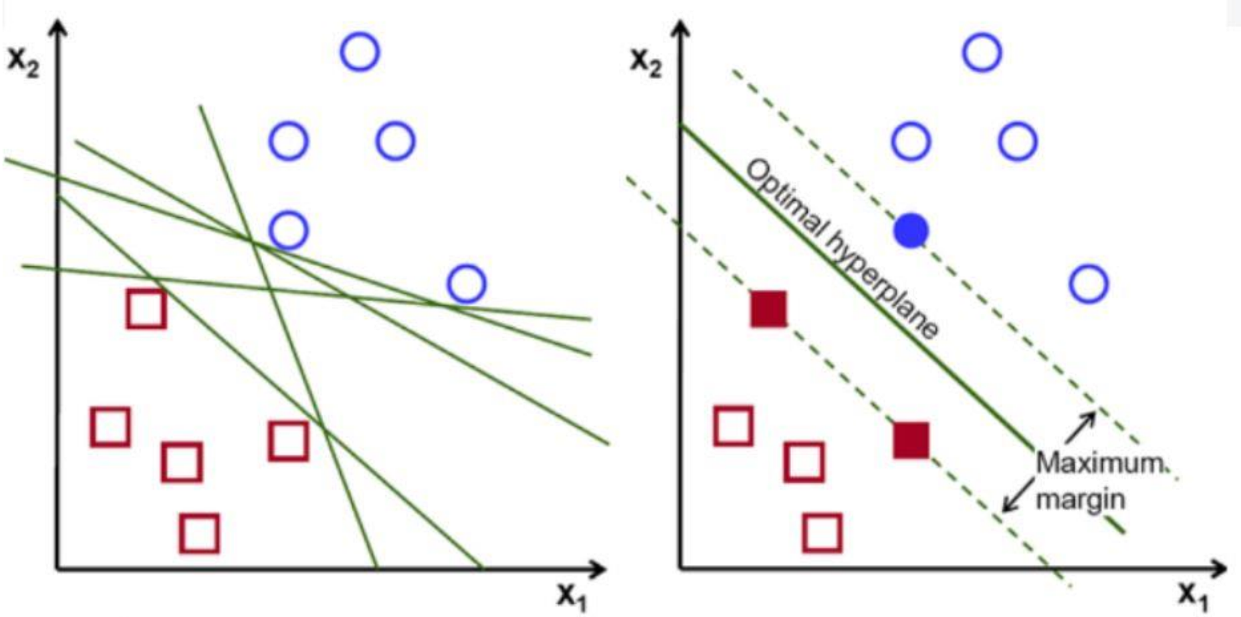
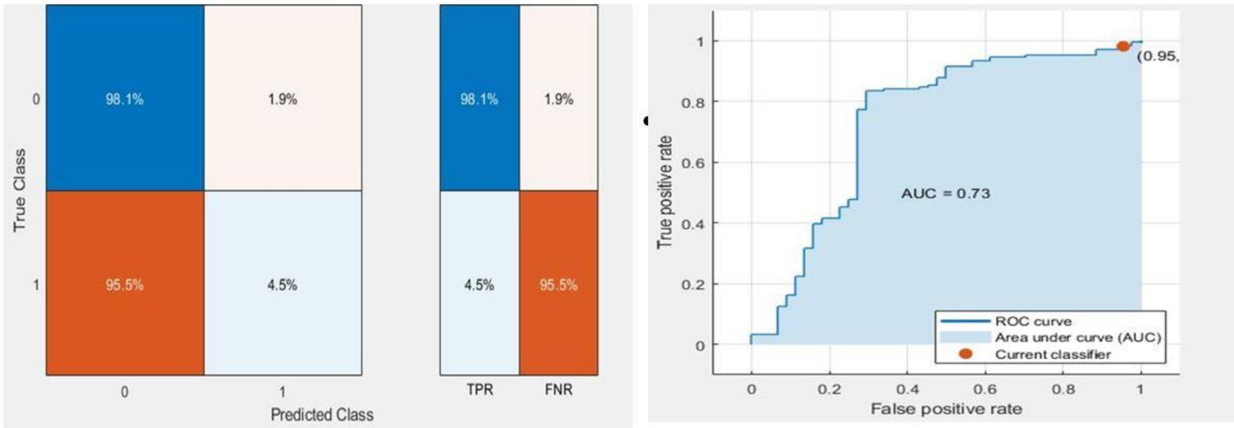


Figure 5: SVM Classification [52]

5.1.1 Classification of outdoor patients using Linear SVM

In our dataset, we have six predictors i.e. Age, Parity, Body Mass Index BMI, Education level, Living style and Gestational period. Using these we are going to predict four fetomaternal outcomes i.e. Cesarean section, Apgar score, MAS and NCIU admission. As out of these four outcomes, I will train SVM for just one outcome, Cesarean section. Because first and most important outcome is cesarean section and other outcomes occur in second phase; after delivery (C.s or Normal). Moreover other outcomes depend on the mode of delivery. So for their prediction C.S will be used as predictor or feature.

Now I have applied linear SVM classifier using MATLAB software on the data set having six features as input and one cesarean section as output. Linear SVM classifier has an accuracy of 78.2% with total miscalculation cost of 45 at training speed of .9312 sec with linear Kernel function when PCA is disabled. On calculating confusion matrix True Positive Rate TPR is .96 and False negative Rate FNR is .95 and area under the curve AUC is .73. As shown in figure.



Confusion Matix ROC Curve

Figure 6: Outdoor induction using Linear SVM

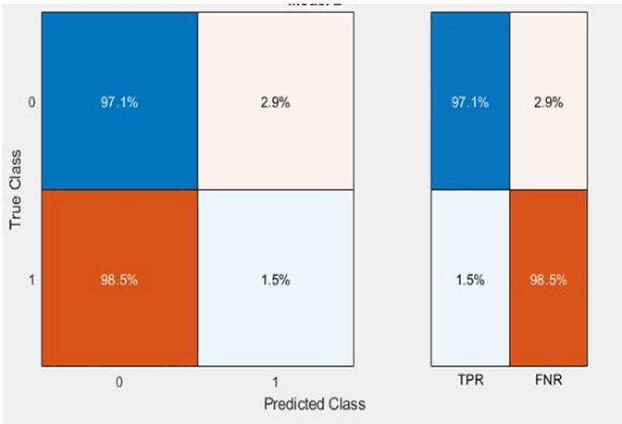
For other outcomes I have applied linear SVM taking cesarean section as input, now I have seven inputs as features/ predictors and three outputs as Apgar score, Meconium Aspiration Syndrome and NICU admission. Following table shows the accuracy, miscalculation, Area under the curve, FPR and TPR.

Table 6: Fetomaternal Outcomes of outdoor data using Linear SVM

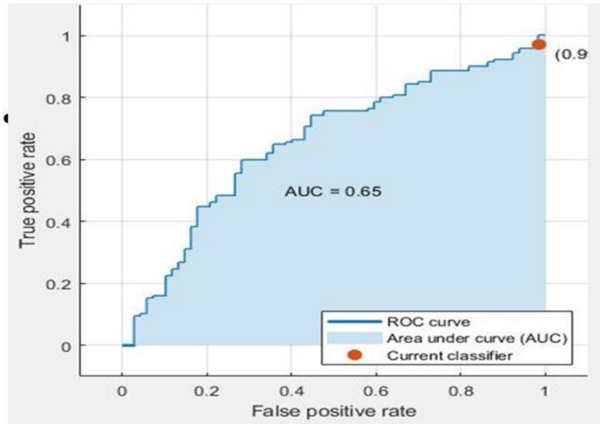
Fetomaternal outcomes of Outdoor data using Linear SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**98.1**	**4**	**1.6**	**0.9**	**1**	**1**
MAS	**97.1**	**6**	**0.788**	**0.21**	**1**	**1**
NICU	**98.5**	**3**	**0.77**	**0.76**	**1**	**1**

5.1.2 Classification of indoor patients using Linear SVM

For indoor patients I have applied linear SVM classifier on data of indoor patients of 206 pregnant women and found an accuracy of 66% with total miscalculation cost of 70 at training speed .82 sec with linear kernel function when PCA is disabled. Calculated confusion matrix and found TPR is .97 and FNR is .98 and area under the curve is .68, as shown in figure.



Confusion Matix



ROC Curve

Figure 7: Indoor induction using Linear SVM

After prediction of Cesarean section classified other three fetomaternal outcomes and results are shown in table.

Table 7: Fetomaternal Outcomes of indoor data using Linear SVM

Fetomaternal outcomes of Indoor data using Linear SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**92.7**	**15**	**0.84**	**0.59**	**1**	**1**
MAS	**83**	**35**	**0.75**	**0.65**	**0.94**	**0.99**
NICU	**88.8**	**23**	**0.81**	**0.49**	**1**	**1**

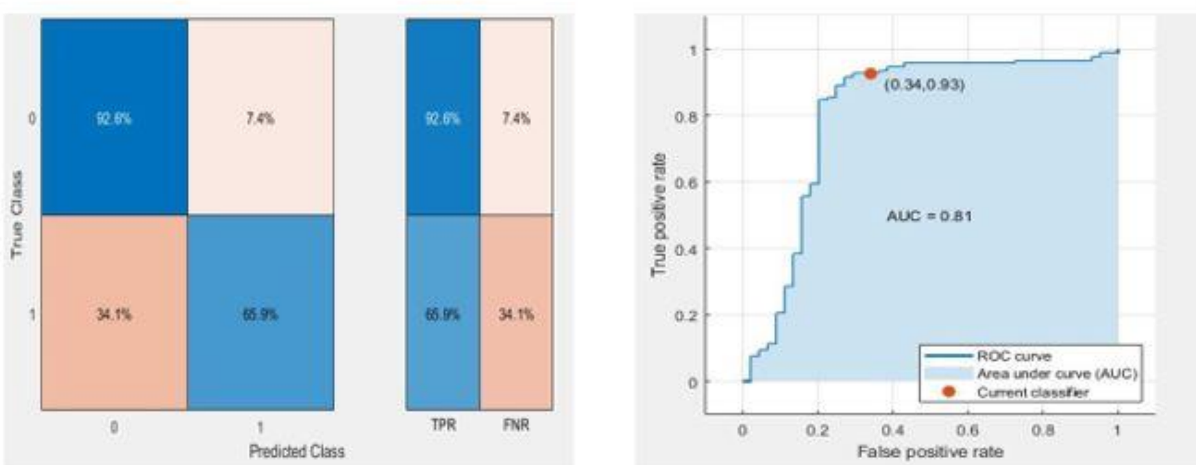
Here it clearly shown that this classifier is not a good choice because its accuracy is low and it misclassifies data of cesarean section and is more inclined towards normal delivery prediction. It is because data is not linearly distinguishable. So I will apply quadratic SVM.

5.2 Quadratic SVM Algorithm

Beauty of SVM is that if data is linearly separable, a unique minimum value exists. In ideal case, SVM will construct a hyper plane which will separate the cases into two classes. It is possible that in some case model will not classify correctly. In this case SVM will find the hyper plane that maximizes the margin and minimizes misclassification. In situation when data is not linearly separable, SVM handles this by using non-linear or quadratic kernel function to map the data into different space where a linear hyper plane cannot separate.

5.2.1 Classification of outdoor patients using quadratic SVM Algorithm

Used quadratic SVM classifier on data of outdoor patients to classify the success of induction labour. For quadratic SVM prediction classifiers using features; found an accuracy of 86.9% with total miscalculation cost of 27 with quadratic kernel function when PCA function is disable. Calculating confusion matrix TPR is .93 and FNR is .34. Area under the curve in ROC plot is .81. As shown in figure.



Confusion Matrix **ROC Curve**

Figure 8: Outdoor Induction using Quadratic SVM

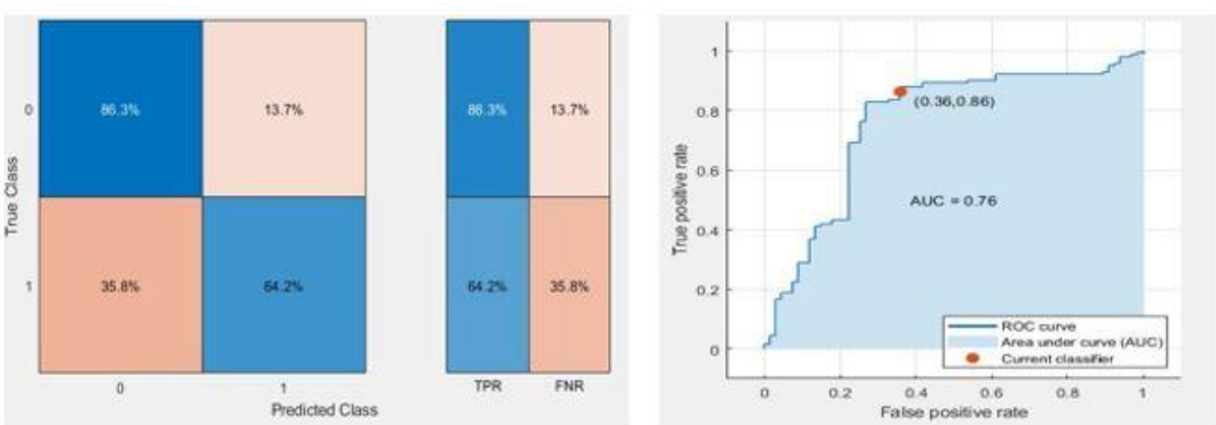
As describe earlier for remaining fetomaternal outcomes cesarean section is used as input for their estimation. Accuracies, confusion matrix ROC curves and all other outputs are shown below.

Table 8: Fetomaternal Outcomes of Outdoor data using Quadratic SVM

Fetomaternal outcomes of Outdoor data using Quadratic SVM						
Outcome	Accuracy %	Miscalculation	Training Speed	AUC	FPR	TPR
APGAR	96.1	8	0.87	0.91	0.5	0.97
MAS	95.1	10	0.79	0.22	1	0.98
NICU	98.1	4	0.72	0.84	0.33	0.99

5.3 Classification of indoor patients using quadratic SVM Algorithms.

For indoor patients on applying quadratic SVM algorithm for cesarean section found an accruing of 79.1%, Area under the curve .76, TPR .86, FNR .36 using quadratic kernel function when PCA is disable. Confusion Matrix and ROC curve is shown below in figure.



Confusion Matrix　　　　ROC Curve

Figure 9: Indoor Induction using Quadratic SVM

For other fetomaternal outcomes; accuracies and AUC are calculated and shown in table below.

Table 9: Fetomaternal Outcomes of Indoor data using Quadratic SVM

Fetomaternal outcomes of Indoor data using Quadratic SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**93.7**	**13**	**0.8**	**0.87**	**0.33**	**0.96**
MAS	**89.3**	**22**	**0.7**	**0.75**	**0.49**	**0.97**
NICU	**93.7**	**13**	**0.77**	**0.84**	**0.22**	**0.96**

5.4 Cubic SVM Algorithm

Cubic SVM finds a hyper plane in multidimensional space, which separate classes in best possible patterns. For Cubic SVM a cubic kernel function is used. Cubic SVM provides higher accuracy in recognizing outcomes correctly.

5.4.1 Classification of outdoor patients using Cubic SVM Algorithm

Trained the cubic SVM algorithm and found accuracy of 87.4%, area under the curve .80, TPR .94, and FNR .36, using cubic kernel function when PCA is disable. Confusion Matrix and ROC curve are shown below.

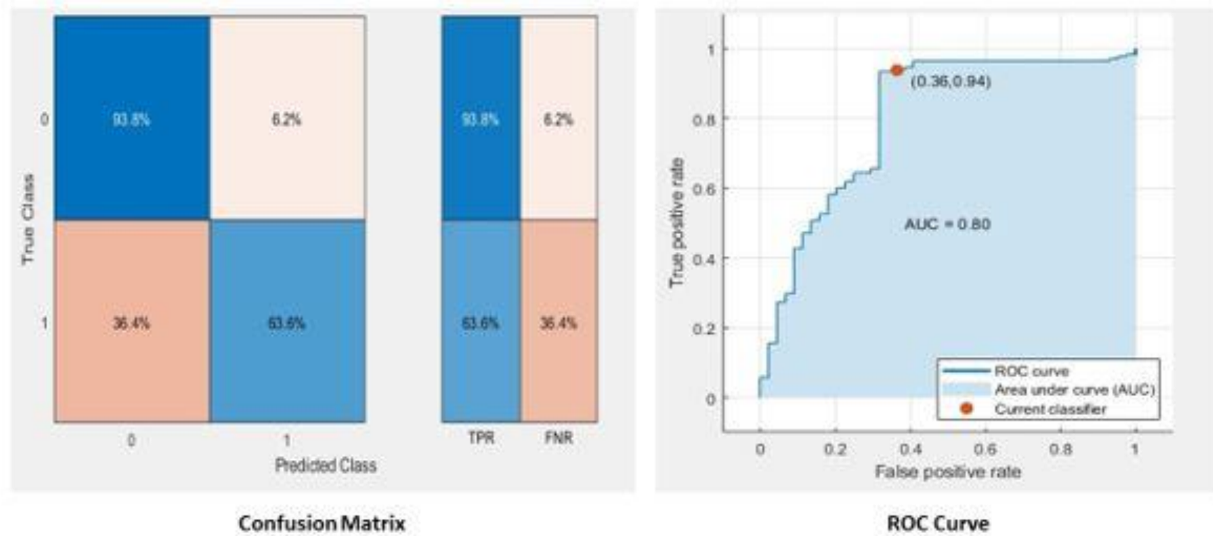


Figure 10: Outdoor Induction using Cubic SVM

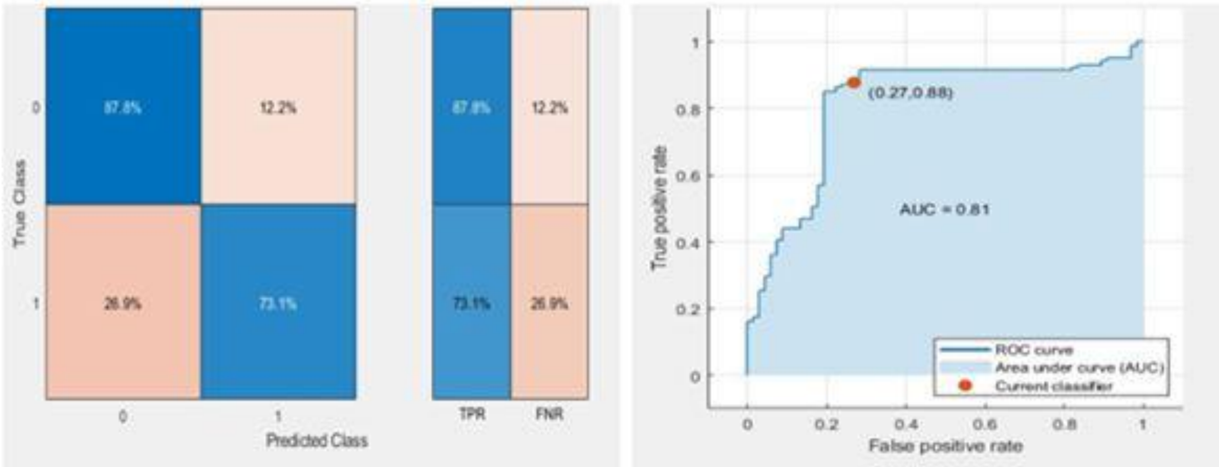
Rest of the results of other fetomaternal outcomes are shown in table below.

Table 10: Fetomaternal Outcomes of Outdoor data using Cubic SVM

Fetomaternal outcomes of Outdoor data using Cubic SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**95.1**	**10**	**0.7**	**0.9**	**0.5**	**0.96**
MAS	**95.1**	**10**	**0.74**	**0.26**	**1**	**0.98**
NICU	**97.6**	**5**	**0.82**	**0.88**	**0.33**	**0.98**

5.4.2 Classification of indoor patients using Cubic SVM Algorithm

Applying cubic SVM Algorithm on data of indoor patients and found accuracy 83%, AUC .81, TPR is .88 and FNR is .27 using cubic kernel function. Confusion Matrix and ROC curve are shown below.



Confusion Matrix **ROC Curve**

Figure 11: Indoor induction using Cubic SVM

For Apgar score, MAS and NICU admission details are given below.

Table 11: Fetomaternal Outcomes of Indoor data using Cubic SVM

Fetomaternal outcomes of Indoor data using Cubic SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**94.2**	**12**	**0.82**	**0.85**	**0.4**	**0.97**
MAS	**91.7**	**17**	**0.77**	**0.86**	**0.29**	**0.96**
NICU	**90.8**	**19**	**0.77**	**0.81**	**0.3**	**0.93**

5.5 K nearest neighbor

KNN is used for classification and regression problems. Its input consists of k training examples and output depends as it is used for classification or regression. It is also called lazy learning algorithm because this algorithm depends on distance between the points so if training data is normalized its accuracy increases. Drawback of this classifier occurs when the class distribution is skewed.

KNN uses feature similarity to predict the values of new data points which calculate the mean again for which new data points are assigned based on distance in training data. KNN uses following steps.

- First step is to acquire data set for training and testing.
- At next step value of K is assigned which is nearest data points and it can be an integer.
- Next step is to calculate distance between points with any method namely Euclidean, Manhattan or Hamming distance.
- Based on distance, sort in ascending order.
- Next it will assign a class to the test point.
- End.

Euclidean Distance can be calculated with following equation [51].

$$\boldsymbol{d(x, x') = \sqrt{(x_1 - x'_1)^2 + \cdots + (x_n - x'_n)^2}}$$

Input x gets assigned to the class with the largest probability [51].

$$\boldsymbol{P(y = j|X = x) = \frac{1}{K} \sum_{i \epsilon A} I\ (y^i = j)}$$

Decision to decide value of K must be such that to get most suitable fit for data set. When k is small classifier becomes more blind, it gives a most suitable fit which have low bias but high variance and decision boundary will be more irregular. A higher value of K will have a smoother boundary, high bias and low variance.

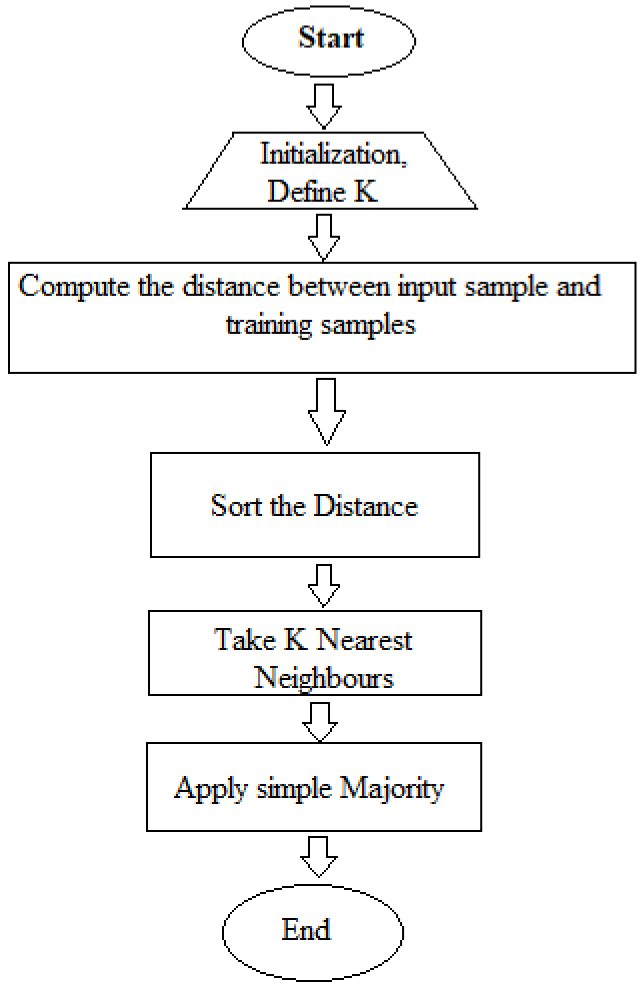
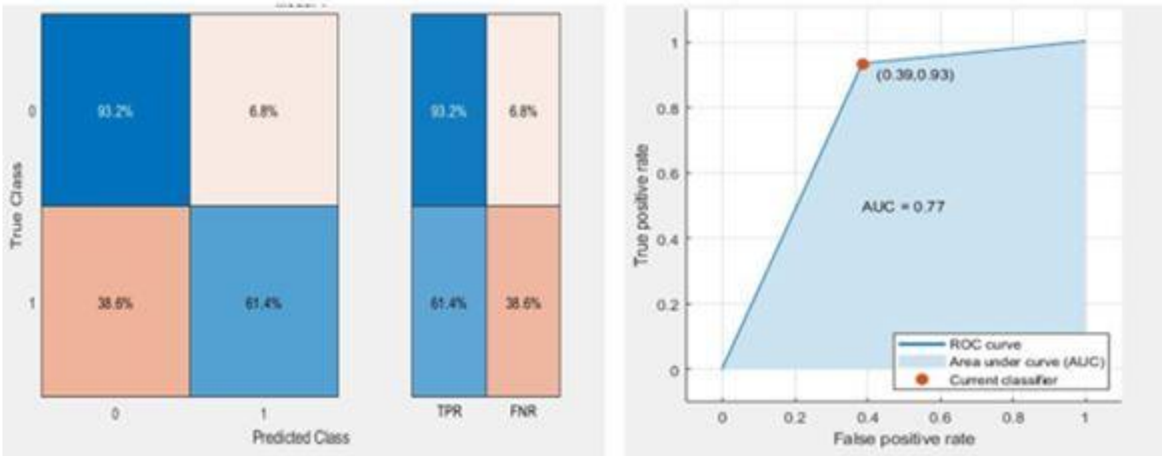


Figure 12: KNN flowchart

5.5.1 Classification of outdoor patients using KNN

Above said algorithm is applied on data of outdoor patients and acquired an accuracy of 86.4%, miscalculation cost of 28 with training speed of 1.87 sec. other results are shown in figure.



Confusion Matrix **ROC Curve**

Figure 13: Outdoor induction using KNN:

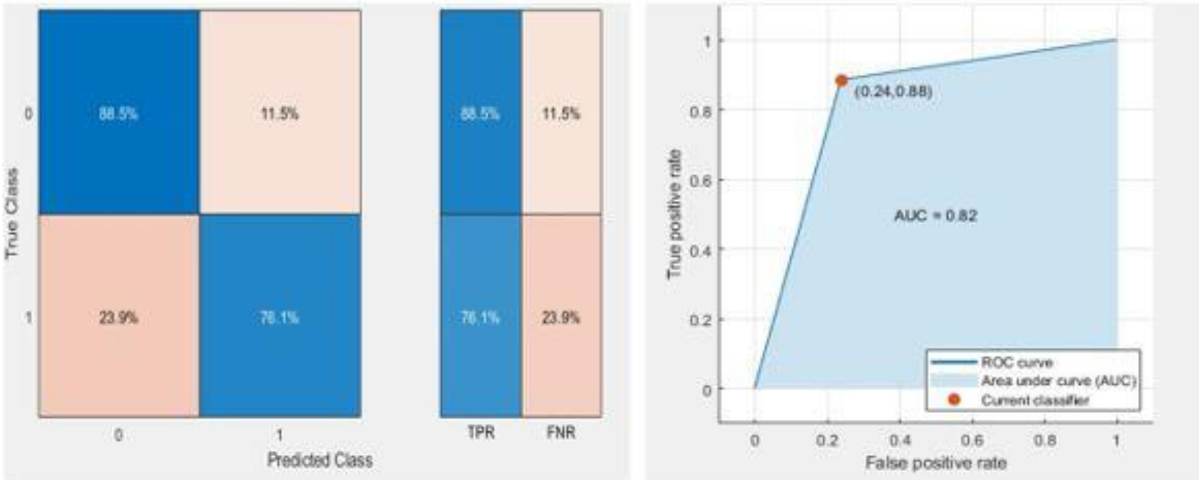
For other outcomes see the table:

Table 12: Fetomaternal Outcomes of Outdoor using KNN

Fetomaternal outcomes of Outdoor data using KNN Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**96.1**	**8**	**1.22**	**0.74**	**0.5**	**0.97**
MAS	**96.1**	**8**	**0.72**	**0.49**	**1**	**0.99**
NICU	**97.6**	**5**	**0.72**	**0.82**	**0.33**	**0.98**

5.5.2 Classification of indoor patients using KNN

Above said algorithm is applied on data of indoor patients and acquired an accuracy of 84.5%, miscalculation cost of 32 with training speed of 1.07 sec. other results are shown in figure below.



Confusion Matrix ROC Curve

Figure 14: Indoor induction using KNN

Other outcomes are listed below in table

Table 13: Fetomaternal Outcomes of Indoor using KNN

Fetomaternal outcomes of Indoor data using KNN Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**94.2**	**12**	**0.83**	**0.78**	**0.4**	**0.97**
MAS	**89.3**	**22**	**0.79**	**0.83**	**0.26**	**0.92**
NICU	**93.2**	**14**	**0.79**	**0.83**	**0.3**	**0.96**

5.6 Decision Tree Algorithm

Decision tree Algorithm is a type of supervised learning algorithm which are used for regression and classification and uses true representation to solve problems. Leaf and node corresponds to a class label and attributes are represented on the internal node of the true. In start whole data is considered as root. A decision tree is a flowchart-like structure in which each internal node represents a “test” on an attribute, branch represent the outcome of test and each leaf represent the class label. From root to leaf path is called classification rule.

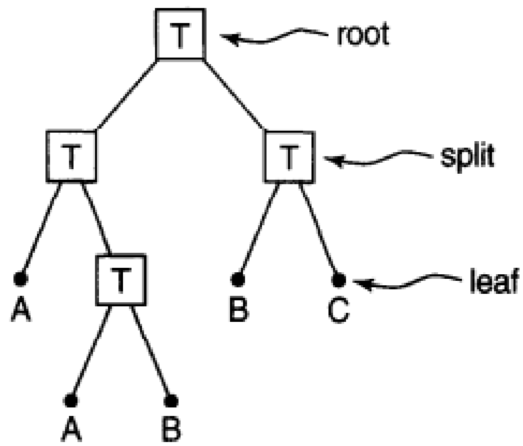


Figure 15: Decision Tree flowchart [53].

Each box is a node at which tests (T) are applied to split the data into successively smaller groups. A, B, C are labels on leaves referred as class labels. Applying decision Tree in Indoor vs outdoor.

5.6.1 Classification of Outdoor Patients data using Decision Tree Algorithm

Decision Tree algorithm is applied on data of outdoor patients and acquired an accuracy of 85.9%, miscalculation cost of 29 with training speed of .84 sec. Other results are shown in figure below.

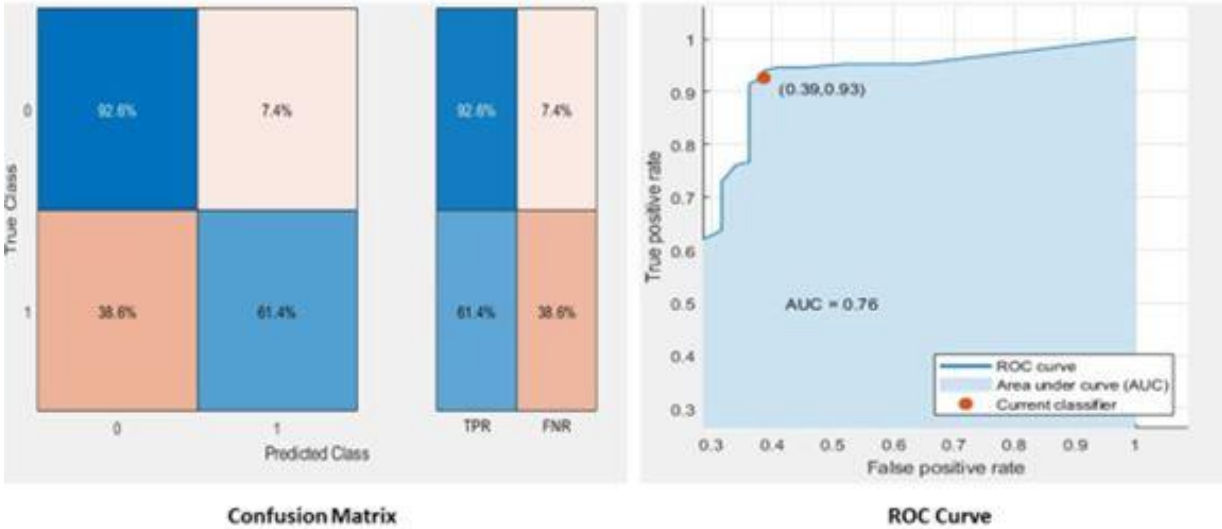


Figure 16: Outdoor induction using Decision Tree

Fetomaternal outcomes (Apgar score, MAS and NICU admission) results are given below.

Table 14: Fetomaternal Outcomes of Outdoor using Decision Tree

Fetomaternal outcomes of Outdoor data using Decision Tree Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**98.1**	**4**	**0.76**	**0.57**	**1**	**1**
MAS	**94.2**	**12**	**0.77**	**0.52**	**1**	**0.97**
NICU	**99**	**2**	**0.76**	**0.6**	**0.67**	**1**

5.6.2 Classification of Indoor Patients data using Decision Tree Algorithm

Decision Tree algorithm is applied on data of Indoor patients and acquired an accuracy of 81.6%, miscalculation cost of 38 with training speed of .81 sec. Results are shown in figure

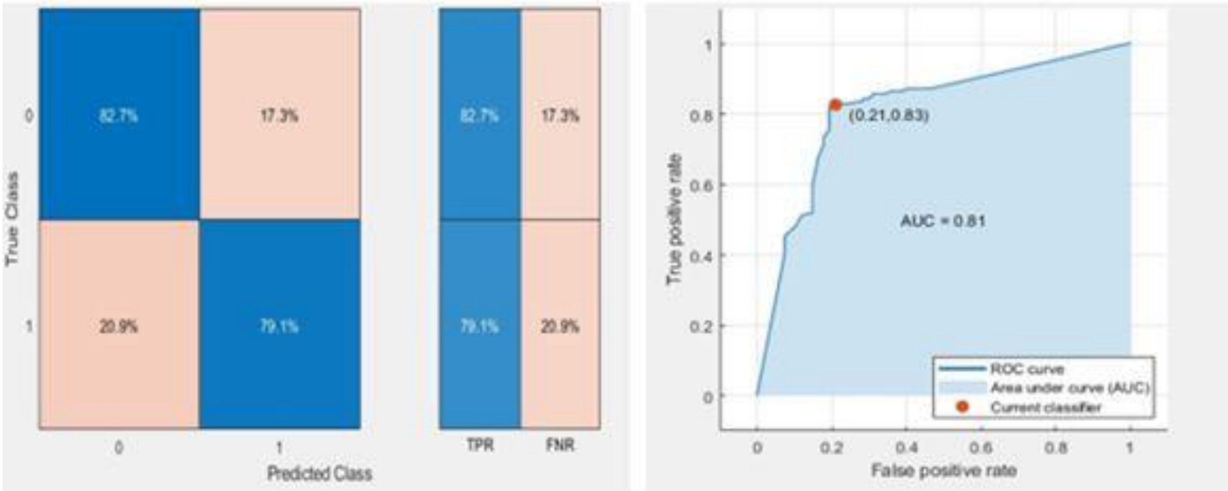


Figure 17: Indoor induction using Decision Tree

Other fetomaternal outcomes with their outputs are given below.

Table 15: Fetomaternal Outcomes of Indoor using Decision Tree

Fetomaternal outcomes of Indoor data using Decision Tree Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**94.7**	**11**	**0.81**	**0.79**	**0.47**	**0.98**
MAS	**86.4**	**28**	**0.85**	**0.79**	**0.37**	**0.91**
NICU	**89.3**	**22**	**0.8**	**0.85**	**0.39**	**0.93**

5.7 Ensemble bagged Tree Algorithm

Ensemble methods combine different classifiers to achieve better performance than a single tree classifier. Its works as several work learners join together to form a strong learner, increasing the accuracy. Bagged is used when it is required to reduce the variance of decision tree. Idea behind bagged classifier is to create several subsets of data set by choosing randomly with replacement from training sample. Then each collection of subset is used for training of respective decision tree ending up with ensemble of several algorithms. Hence performance is increased than using a single tree algorithm.

Bagging means Bootstrap aggregation, an ensemble method is used to improve the classification accuracy. Decision trees are derived from building the base classifiers $C_1, C_2, \ldots\ldots\ldots C_n$ with replacement from dataset D. Then final model is derived from the combination of base classifiers with the majority votes. Process of Bagging is shown in following flow chart.

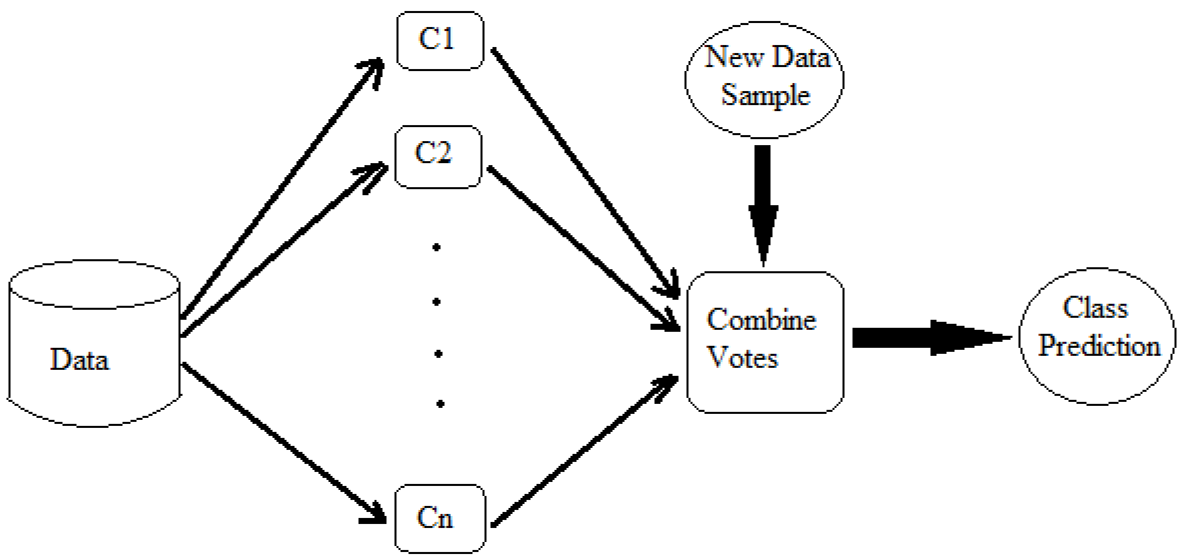
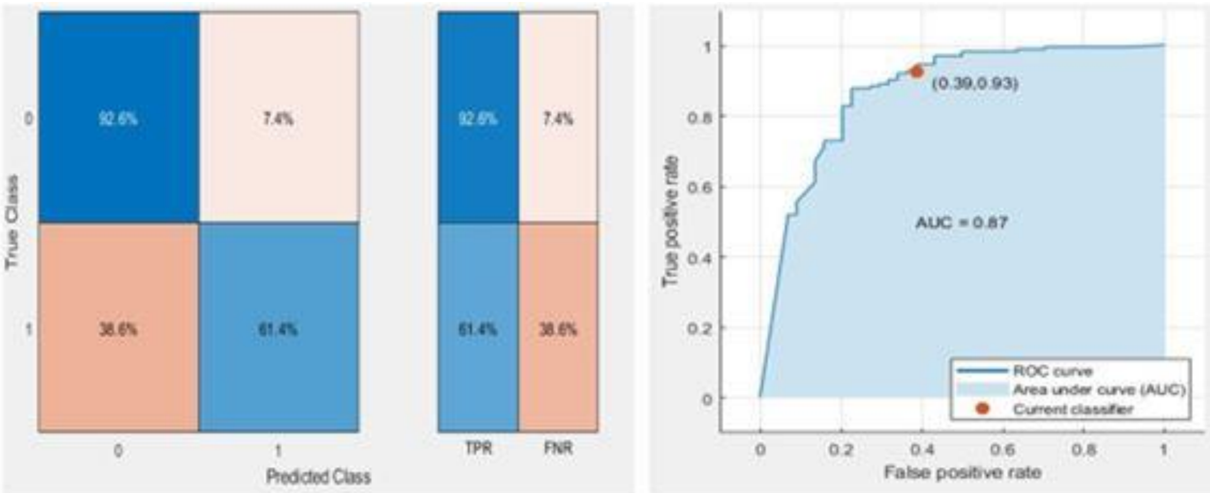


Figure 18: Bagging Process [54].

5.7.1 Classification of outdoor patients using ensemble Bagged Tree

Last but not the least algorithm that I have applied for comparison of outdoor and indoor induction labour success is Ensemble bagged Tree algorithm. Firstly applied this algorithm on outdoor patient's data to train the classifier for prediction of cesarean section in future using previous data. Here the accuracy computed is 85.9% and miscalculation cost is 29 and area under the curve is .87. We can see that accuracy of Decision Tree algorithm and Ensemble Bagged Tree for outdoor patients is same. Confusion matrix and ROC curve are shown in figure.



Confusion Matrix **ROC Curve**

Figure 19: Outdoor induction using Ensemble Bagged Tree

Other outcomes that are APGAR score <7 at 5 minutes, Meconium Aspiration Syndrome and NICU admission using Ensemble Bagged Tree classifier are predicted using seven features including cesarean section are shown in table below.

Table 16: Fetomaternal Outcomes of Outdoor using Bagged Tree

Fetomaternal outcomes of Outdoor data using Ensemble Bagged Tree Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**98.1**	**4**	**3.3**	**0.8**	**0.75**	**1**
MAS	**96.6**	**7**	**1.65**	**0.36**	**1**	**0.99**
NICU	**98.1**	**4**	**2.2**	**0.87**	**1**	**1**

5.7.2 Classification of indoor patients using Ensemble Bagged Tree

At the end I have applied Ensemble Bagged Tree algorithm on dataset of indoor patients and recorded the accuracy 87.9%, miscalculation cost 25 and area under the curve AUC .93. Further details can be seen in figure below.

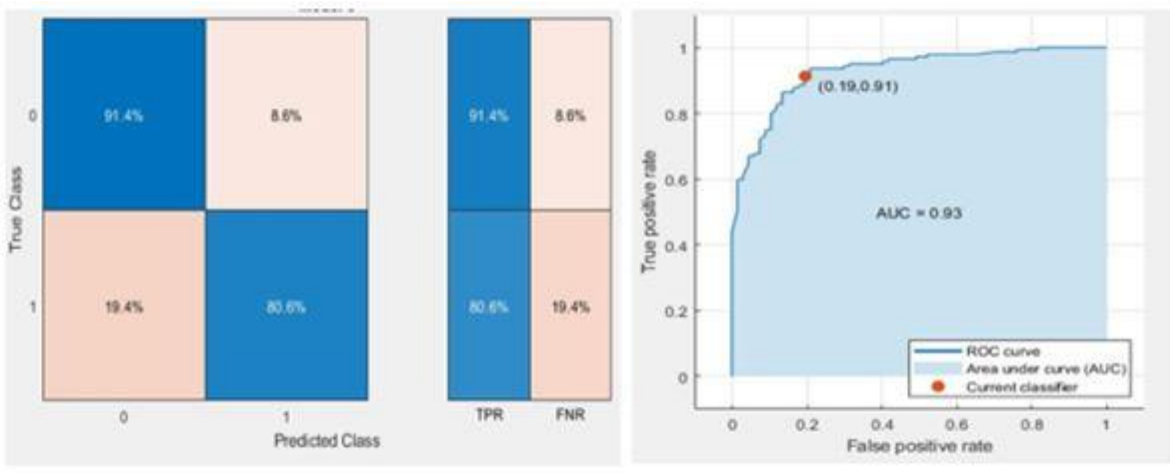


Figure 20: Indoor induction using Ensemble Bagged Tree

Outputs of other outcomes are shown in table below.

Table 17: Fetomaternal Outcomes of Indoor using Bagged Tree

Fetomaternal outcomes of Indoor data using Ensemble Bagged Tree Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**96.1**	**8**	**1.69**	**0.86**	**0.4**	**0.99**
MAS	**89.3**	**22**	**2.246**	**0.91**	**0.43**	**0.96**
NICU	**94.2**	**12**	**1.7**	**0.85**	**0.35**	**0.98**

6 CHAPTER: Results and Discussion

6.1 Results

Using evaluation metric for accuracy score of this model, because this is balance data set so there is no need to use the F1 score. In this study, application of machine learning techniques are successfully used in medical domain. Knowledge engineering and machine learning are used to determine the pattern for medical diagnosis, prediction and treatment.

From the data set of total 412 pregnant women, outdoor patients with cesarean deliveries are 44 and 67 in women with indoor induction, APGAR score <7 at 5 minutes is recorded in 4 vs 15, meconium aspiration syndrome 6 vs 35 and NICU admission 3 vs 23 respectively.

Machine learning algorithms are applied on the data set for training and estimation purposes for future predictions of cesarean section, MAS, Apgar score and NICU admission. Different attributes of data set assigned with values feasible to be used in machine learning models. Used several classifiers and found accuracies of each. Ensemble Bagged Tree has the best accuracy of 87.9% in Indoor patients while 85.9% in Outdoor patients for cesarean section. Linear SVM has the least accuracy of all with 78.2% for outdoor patients and 66% for indoor data. Other classification algorithms have reasonably good accuracies for cesarean section prediction ranging from 79.1% to 87.4% as shown figure.

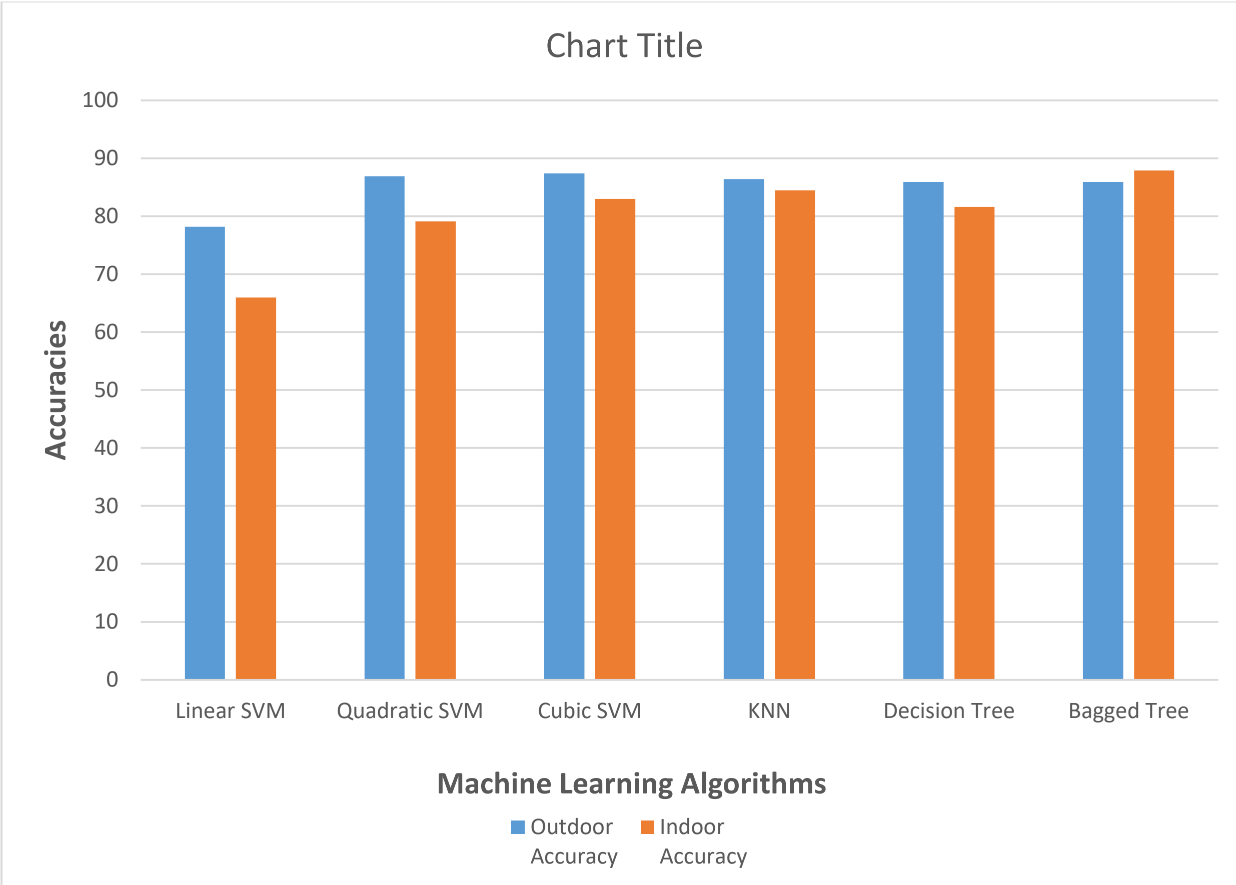


Figure 21: Accuracies of classifiers

For remaining outcomes all above said classifiers are applied and found accuracies of Apgar score, meconium aspiration syndrome and NICU admission which are too high shown in table below but there are concerns; discussed in next part

Table 18: Outdoor vs Indoor Outcomes

Comparison of Outdoor and Indoor Outcomes						
Algorithm	**APGAR Accuracy**		**MAS Accuracy**		**NICU Accuracy**	
	Outdoor	**Indoor**	**Outdoor**	**Indoor**	**Outdoor**	**Indoor**
Linear SVM	**98.1**	**92.7**	**97.1**	**83**	**98.5**	**88**
Quadratic SVM	**96.1**	**93.7**	**95.1**	**89.3**	**98.1**	**93.7**
Cubic SVM	**95.1**	**94.2**	**95.1**	**91.7**	**97.6**	**90.8**
KNN	**96.1**	**94.2**	**96.1**	**89.3**	**97.6**	**93.2**
Decision Tree	**98.1**	**94.7**	**94.2**	**86.4**	**99**	**89.3**
Bagged Tree	**98.1**	**96.1**	**96.6**	**89.3**	**98.1**	**94.2**

6.2 Discussion:

This study is the first to examine the comparison between outdoor and indoor labour induction in a sense that there is no such previous technical study implemented on the data set of pregnant women to predict four fetomaternal outcomes. All previous studies are inclined towards prediction of just one outcome; cesarean section.

Following figure shows the comparison of outdoor and indoor labour induction numbers that are recorded after the admission in wards and emergency respectively. It clearly shows that outcome numbers of outdoor induction is low as compared to indoor induction. So outdoor labour induction is better in terms of fetomaternal outcomes.

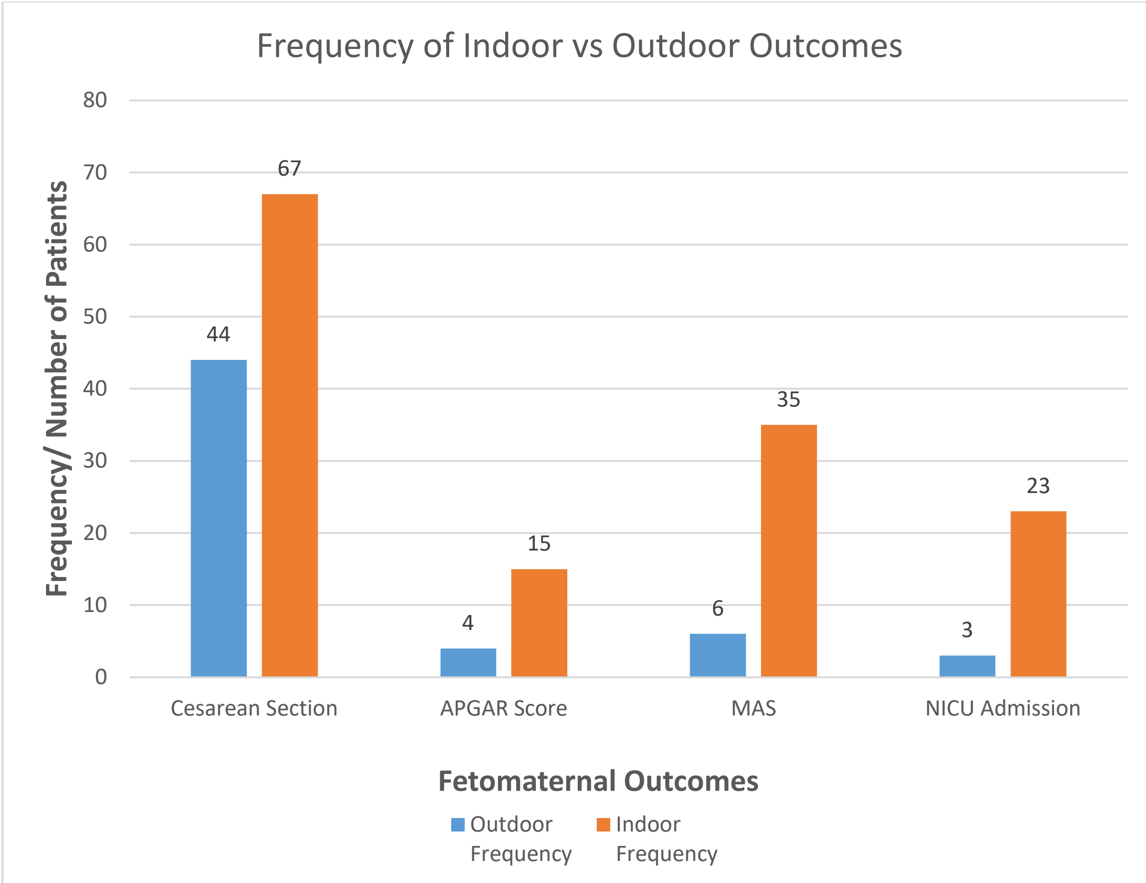


Figure 22: Frequency of Outcomes

Here the accuracies of cesarean section is high for outdoor and indoor patients data. So these classifiers can be used for future prediction. For other outcomes miscalculation cost (TPR and FPR) is very high because for these outcomes; positive numbers are less and correlation with features/ predictors is too low. Accuracies are just high because maximum of data for these outcomes is negative or 0. So it is needed that increase in dataset size and especially include other features like baby weight, premature birth and other complexities of medical conditions should be added to the data to predict the outcomes related to the newborn health.

6.3 Benefits of study

Following benefits can be achieved from this study.

- We came to know that Outdoor induction is better in terms of fetomaternal outcomes as compared to indoor induction.
- With machine learning algorithms; we can predict the future outcomes for the benefits of patients and doctors for consultation.
- Burden on indoor induction can be decreased, resulting the hospitals can provide care to indoor patients using limited resources in developing countries.
- Cesarean section rates can be decreased which are very high and WHO recommends to be 10%-15%. Also governments of developing and developed countries are too much concerned with high rate of cesarean section.
- As simple features are used a patient can directly put her features for prediction and can do needful measures to manage accordingly.

6.4 Conclusion

- Induction of labour in home like environment (outdoor) is better in terms of fetomaternal outcomes versus indoor induction in emergency of hospital and has benefits psychologically and financially too.
- Quadratic SVM, Cubic SVM, KNN, Decision Tree and Ensemble Bagged Tree algorithms can be used to predict future outcomes of cesarean section as there accuracies are relatively good.

- For predictions of other outcomes (Apgar, Meconium aspiration syndrome and NICU admission) more data needs to be acquired adding other features like baby weight, CTG record etc. which are associated with the health of newborn baby.

6.5 Future Work

- To obtain an optimal prediction model, continual testing is required.
- New features should be added to improve prediction accuracy. In most of the cases inventing most suitable features can improve the prediction.
- Development of new machine learning algorithms which can learn and be trained more accurately with higher accuracies.
- Also we can enlarge size of the dataset so the algorithm can be trained precisely and accurately.
- Add features related of health of newborn as baby weight, premature birth, CTG record and complexities associated with baby as well as to mother like diabetes, blood pressure, cardiac or any other chronic disease.
- An android application may be launched in future so that outcomes related to neonatal health can be predicted with higher precision where they can easily enter their features and can predict success/ outcomes.

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