Classification of Indoor vs Outdoor induction labour success

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ISLAMABAD

AUGUST, 2024

THESIS ACCEPTANCE CERTIFICATE

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DEDICATION

I would like to dedicate this to my Parents and Siblings whose wonderful and amazing support led me here to this remarkable achievement.

ACKNOWLEDGEMENTS

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents and family members who raised me when I was not capable of walking and continued to support me throughout in every department of my life.

I would also like to express special thanks to my supervisor Dr. Mohsin Islam Tiwana for his help throughout my thesis.

Finally, I would like to express my gratitude to all the individuals who have rendered valuable assistance to my study.

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.

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

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CHAPTER1: INDUCTION OF LABOUR

1.1 Objective and Motivation

The aim of this study was to compare fetal outcomes between indoor and outdoor induction of labor in a local population. Research also benefits patients, doctors, and hospitals. Tertiary care hospitals in developing countries are often under-resourced and unable to meet the needs of many patients. Therefore, managing low-risk patients through outdoor induction can reduce hospitalization and improve the care of indoor patients.

1.2 Introduction

In recent decades, the number of women getting pregnant to have a baby has increased. One in four women in developed countries experiences induced labor. In developing countries, rates are lower but in some cases similar to developed countries. Induction of labor should only be performed if there are clear indications and the benefits of the outcome outweigh the risks.

Childbirth is a physical intervention that expels the placenta, membranes, umbilical cord, and fetus (i.e., products of pregnancy) from the uterus. This is achieved through biochemical changes in the connective tissue and dilatation and effacement of the cervix, which determine the frequency, duration and intensity of rhythmic contractions. There are various indicators to evaluate work. The onset of labor is defined by mild but painful uterine contractions, which cause the cervix to efface and dilate.

If the cervix does not dilate during uterine contractions, the cervix is insufficient, and uterine contractions cannot meet the need for labor if there is no significant change in the cervix. Pregnancy is divided into four long periods: early pregnancy (from week 37 to the end of 38 weeks), full pregnancy (from week 39 to the end of 40 weeks), and late pregnancy (from the beginning to week 41).). late (week 41) and late (beginning of week 42 and beyond) [2]. Studies have shown that babies' health improves later in pregnancy [3]. Forming a company usually involves several processes. This is not only an intervention but also poses challenges for clinicians and mothers [4].

Studies have shown that the best results are achieved at the end of the pregnancy period. However, the pregnancy must be terminated to prevent complications that can put mother and child at risk. Drugs commonly used to induce vaginal labor include prostaglandin E2 and misoprostol. By comparing fetal outcomes in inpatients and outpatients and recording cesarean delivery, 5-minute Apgar score <7, meconium alcohol stains, and NICU admission, we concluded that cesarean delivery rates were higher in hospitalized patients.

Outside of clinical studies, few studies have used deep learning and machine learning algorithms to predict future outcomes using previous indoor and outdoor patient data. In this study, we used ANN, Random Forest classifier, kernel support vector machine, logistic regression, and gradient boosting classifier to predict fetal outcomes in indoor and outdoor patients. The results were compared, and based on these machine learning algorithms, conclusions could be drawn about the classification of indoor and outdoor induction success rates. Results are presented in terms of precision, confusion matrix, TPR, and FPR.

What is Induction of Labour?

Induction of labor is a process that provides artificial stimulation through uterine contractions rather than natural childbirth. This feminization procedure is the most widely used and commonly used in the United States [6]. From 1990 to 2004, the incidence of induced labor nearly doubled from 9.5% to 21%. Because there are better cervical ripening agents out there. Doctors and patients want a convenient way to determine the exact time of delivery and signs of labor [7]. A reason for the increased induction rate is also patient or physician concern about the risk of immediate or subsequent neonatal death [8].

1.3 Indications

Detection should be tested after deployment. Moreover, the successful outcome of vaginal birth outweighs the potential risks of fetal and maternal disorders. These issues should be communicated to the mother before induction of labor begins. Induction of labor is observed in most subsequent pregnancies. The gestation period is at least 41 weeks. This inclusion indicates a reduced probability of perinatal death. Other indications include premature rupture of the membranes, [j], [h] fetal growth restriction, health conditions of the mother (kidney disease, high blood pressure, lung disease or kidney disease), stillbirth, premature separation of the placenta from the uterus, chorioamnionitis, etc.

In cases where there are no maternal or medical signs, labor may be induced for social or geographical reasons[a]. There were only a few studies describing the included indications. Two randomized clinical trials [c] [d] did not suggest widespread risks to mothers or newborns, but were not large enough to draw conclusions. Another study suggested that elective induction of labor in nulliparous women is not recommended because it increases the number of cesarean sections. . Case-control studies are inconclusive that elective induction of labor does not predict delivery by cesarean section. Additionally, an analysis of the initial trial concluded that elective induction of labor had no benefit and was unlikely to be used during pregnancy[e]. According to the American College of Obstetricians and Gynecologists, “Logistical factors, including distance from the hospital, psychological factors, and speed of delivery, can affect delivery” [13].

Predicting a successful induction

The most common factor used to predict your odds is cervical status. Therefore, the cervix should be checked before attempting induction of labor. There are several scoring systems used to evaluate cervical spine status, including the Bishop system, Burnett system, Modified Friedman system, etc.

Other indicators associated with successful induction of labor include postpartum, female body mass index, baby weight and height, and multiple births. These factors or predictors of success also exist in vaginal birth.

1.3.1 Bishop score

The Bishop score is commonly used in clinical practice. This system consists of four cervical spine characteristics: Status, persistence, spread and growth. Additionally, System Scoring is a scoring system that can be used to evaluate the need for onboarding.

If a nulliparous woman undergoes elective induction of labor, her chances of having a surgical delivery double. Because most studies included randomized trials, a Bishop score of 5 or less on admission suggests that cervical insufficiency increases the risk of cesarean delivery. If your Bishop score is higher, ≥5 or ≥8 (definition varies), vaginal delivery is more likely to occur, regardless of whether labor is induced or spontaneous.

On the other hand, if the Bishop score is lower than expected, vaginal birth after induction will fail. As mentioned above, the rate of sexual intercourse is relatively high among nulliparous women undergoing labor induction.

The best tool for predicting the likelihood that an induction of labor will lead to a vaginal birth is the Bishop score. This view is based on a systematic review of controlled studies showing that the Bishop score predicts outcome better than ultrasound quantification of cervical length and that the most important factor in the Bishop score is dilatation.

2 CHAPTER: LITERATURE REVIEW

As discussed in the introduction, there are few clinical studies (approximately three) comparing fetal outcomes in indoor and outdoor patients, but no studies yet predict future outcomes using machine learning or other technical algorithms leveraging historical data and patient characteristics estimation study. The novelty of this study is that it classifies the success of outdoor detection and that of indoor detection. Previous studies/surveys tended to be better predictors of cesarean section.

According to the World Health Organization (WHO), the number of women undergoing induced labor (artificial induction of labor) has increased exponentially in recent decades. In developed countries, one quarter of births involve labor. Rates in developing countries are lower but in some cases similar to those in developed countries [11]. Induction of labor should only be performed if there are clear indications and the benefits of the outcome outweigh the risks. Induction of labor should be performed with caution due to the risk of uterine rupture and fetal distress associated with this method. In addition, induced labor should be performed in a facility that can perform cesarean section [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].

In their study, Marjo Riitta Jarvelin et al examined policy indicators for employment induction and employment induction. We also compared the outcomes of induced labor and spontaneous labor. According to the study results, labor induction was most often performed in lower-level specialties (29.4%), regional areas (23.6%), and specialty medical centers (17.7%). Labor induction practices are not the same in all hospitals. Feedback from individual agents and staffing practices can influence your onboarding policies. Liberal induction policies have also led to an increase in operative deliveries [32].

Hye-in Kim et al. reviewed observational studies describing the benefits and risks of induction of labor at 39 weeks or longer in singleton pregnancies and found no significant results for either maternal (cesarean section rate) or fetal outcomes compared with induced labor and induced labor. . . The cesarean section rate was 17.7% in the natural delivery group and 12.3% in the induced delivery group. Similar rates were found for other neonatal outcomes, leading to the conclusion that scheduling induction of labor 7 days before the due date may be acceptable [33].

Philippa Middleton et al designed a study to investigate improvements in birth outcomes due to induction of labor at term or after birth. Because beyond these conditions, the risk of neonatal or fetal death increases. This study examines the impact of work incentive policies during and after this period compared to work policies that were essentially voluntary. It included 30 randomized controlled trials (enrolling 12,749 women) conducted in several countries. It was concluded that because the absolute risk of death is low, it may be useful to advise women about choosing planned induction of labor or monitoring subsequent pregnancies without induction [34].

In a systematic review and analysis of induced labor, Ekaterina Mishanina MBBS et al examined whether induced labor was associated with a higher or lower risk of cesarean section compared to pregnancies. The risk of cesarean delivery was found to be 12% lower during the delivery period than during the management period. Fetal deaths and intensive care unit admissions also decreased. It has been reported that labor induction has no effect on maternal mortality [35].

In the Pakistan Demographic and Health Survey, Sarwat Mumtaz et al described the increasing trends and differences in cesarean section rates in Pakistan. A comparison of socioeconomic inequalities in cesarean section rates showed that illiterate women (7.5%) had a lower cesarean section rate than highly educated women (40.3%), poor women had a cesarean section rate of 5.5%, and rich women had a lower cesarean section rate. The incision rate was 35.3%. %. The cesarean section rate for women in rural areas is 11.5%, while the cesarean section rate for women in urban areas is 25.6%. Studies have shown that women who are more educated, wealthier, and live in urban areas are more likely to have a cesarean section [36].

Ana Pilar Betran et al presented in a study trends and trends in cesarean section over the past 24 years. Data from 150 countries show that 18.6% of births occur by caesarean section, ranging from 6% to 27.2% in underdeveloped to developed countries. Latin America and the Caribbean have the highest cesarean section rate at 4.5%, while Africa has the lowest at 7.3%. Additionally, from 1990 to 2014, the global average cesarean section rate increased by 12.4%, with an average annual increase of 4.4% [37].

Jane Hsing Wang conducted a study to predict normal natural childbirth based on deep learning by analyzing data from 56 women, 38 of whom had live births and 18 of whom were born by cesarean section, at Antai Tiansheng Memorial Hospital from 2017 to 2018. Data collected included characteristics such as height, age, fetal weight, and female weight. A machine learning algorithm (Multilayer Perceptron (MLP) model) consisting of three layers (input layer, hidden layer, and output layer) is used to estimate the transmission path using Keras, an open source neural network library [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

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. The data set for this study included 448 pregnant women with singleton pregnancies with cephalic presentation, with gestational age ranging from 18 to 40 years. The study did not include pregnant women with multiple pregnancies or other medical conditions such as diabetes, heart disease or high blood pressure. Of the total 448 women, 224 were outpatients and 224 were inpatients.

The first group was admitted to the ward after hospitalization, and the second group was admitted for emergency observation. All women were followed up until delivery and fetal outcomes, namely cesarean section, meconium aspiration syndrome, Apgar score <7 at 5 minutes, and NICU admission. Each feature is important here and is described 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

A total of 448 pregnant women were divided into two groups of 224 patients each. Group A consisted of outpatients, and Group B consisted of 224 emergency patients after hospitalization. The goal was to compare patient outcomes 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 29.42±2.14 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

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].

3.2.8 Diabetes

Last feature is used in this case study is diabetes of pregnant women, Normally in some cases Gestational Diabetes start from starting weeks of pregnancy, 0 indicates diabetes not effected women health & 1 indicates its changes women health. [29].

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

Table 1 Analysis of Dataset

Feature	Group	Total Cases	Sub Group	Cesarean	MAS	APGAR	NICU
Age of Women	Group A	224	18-30	29	7	6	4
			31-40	22	4	5	7
	Group B	224	18-30	25	11	13	12
			31-40	54	26	15	25
Parity	Group A	224	1-3	34	7	9	8
			4-5	17	4	2	3
	Group B	224	1-3	43	20	18	19
			4-5	36	17	10	18
BMI	Group A	224	<=27	28	7	9	10
			>27	23	4	2	3
	Group B	224	<=27	30	15	10	18
			>27	49	23	18	19
GA	Group A	224	37-39	30	6	9	9
			40-41	24	5	3	4
	Group B	224	37-39	61	23	18	20
			40-41	18	14	10	17
Diabetes	Group A	224	18-30	26	10	8	9
			31-40	25	1	3	4
	Group B	224	18-30	58	22	15	25
			31-40	21	15	13	12
Living	Group A	224	Rural	39	5	10	11
			Urban	12	6	1	2
	Group B	224	Rural	34	27	1	13
			Urban	33	8	4	10
Education	Group A	224	Illiterate	5	2	3	7
			Primary	10	3	3	1
			Middle	17	1	5	1
			Matric	19	5	0	4
	Group B	224	Illiterate	13	15	5	10
			Primary	20	7	6	8
			Middle	17	3	7	5
			Matric	29	12	10	14

3.3 Fetomaternal Outcomes

Success is associated with fetomaternal outcomes which are as under.

3.3.1 Cesarean Section

A cesarean section, also called a C section, is a surgery to deliver a baby through an incision in the abdomen and uterus. Caesarean section is becoming increasingly common in both developing and developed countries. WHO recommends the caesarean section rate to be 10-15% [30]. However, this number is rapidly increasing due to elective cesarean section, and there is a need to find the root cause and solution to overcome this [12]. Because there is no evidence on the benefits of cesarean section, the government has recently expressed serious concern about the increase in the number of cesarean sections and its negative impact on maternal 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

The Apgar score is a way to summarize a newborn's health. Apgar refers to appearance, pulse, fat, activity and respiration. Your score is calculated five minutes after your baby is born or delivered. Each element is scored from 0 to 2, with a total score of 0 to 10. The higher the score, the more stable and healthy the child is. Generally, a score of 7 or higher, calculated within 5 minutes after birth, 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

Neonatal dyspnea, or dyspnea, occurs in people who inhale a dark green substance called meconium into their lungs during birth. This can cause significant morbidity or stillbirth and typically occurs in 5 to 10% of newborns. This is because it makes the baby comfortable during childbirth. Symptoms include bluish skin, difficulty breathing, lameness, and dark green amniotic fluid.

3.3.4 NICU Admission

Abbreviation for Neonatal Intensive Care Unit. A hospital department that provides 24-hour care for sick or premature infants. After birth, the newborn should be admitted to the neonatal intensive care unit and monitored to ensure that body temperature, heart rate, breathing, and color are within normal ranges. If the mother has risk factors during pregnancy, such as diabetes, high blood pressure, or a history of substance abuse, the newborn may need a neonatal intensive care unit (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.

4 CHAPTER: METHODOLOGY

Machine learning is a branch of artificial intelligence that allows systems to automatically learn and improve from past practices or historical data. The core goal of machine learning is to enable computers to learn automatically. The learning process begins with available data to identify patterns in the data and make better decisions in future predictions. Machine learning techniques can be used to extract knowledge from data. These techniques are used for clinical diagnosis, prognosis, and treatment. In this study, we applied various machine learning algorithms to classify successful outdoor and indoor labor inductions. Machine learning algorithms are divided into supervised learning algorithms and unsupervised learning algorithms.

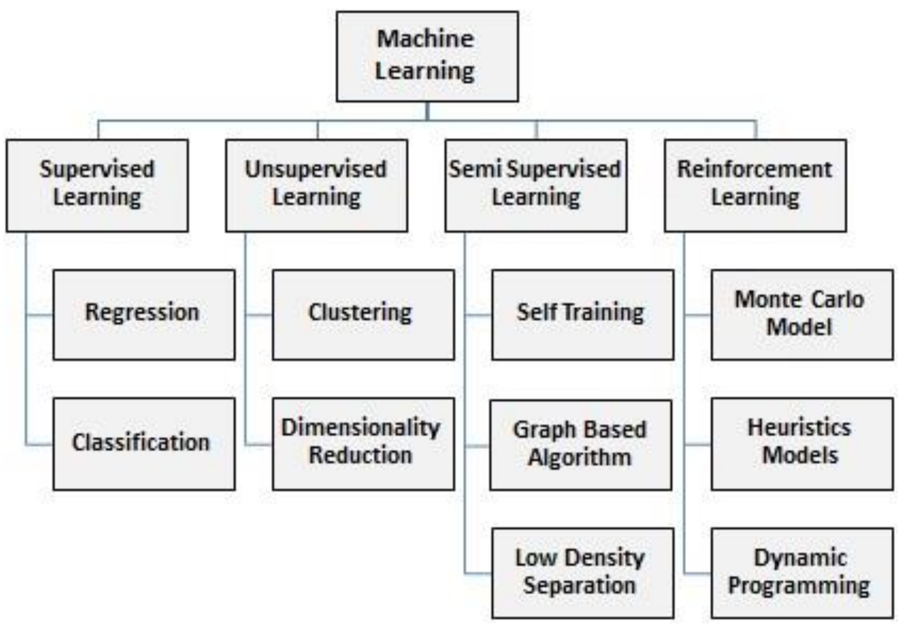


Figure 1: Types of Machine Learning algorithms.

4.1 Types of Machine Learning Algorithms

4.1.1 Supervised Machine Learning Algorithms

These algorithms can be applied to data containing labeled instances to predict future events. First, we train the algorithm from the training data set, and the learning algorithm generates a prediction function that predicts the output values. A properly trained system can estimate the target/production of new inputs.. The learning algorithm also compares its results with the correct desired result and looks for errors in order to modify the model accordingly. Support Vector Machine SVM, Linear Regression, Logistic Regression, Naive Bayes, Linear Discriminant Analysis LDA, Decision Tree, K-Nearest Neighbor Algorithm KNN, Neural Network (Multilayer Perceptron), Similarity Learning These are the most commonly used learning algorithms.

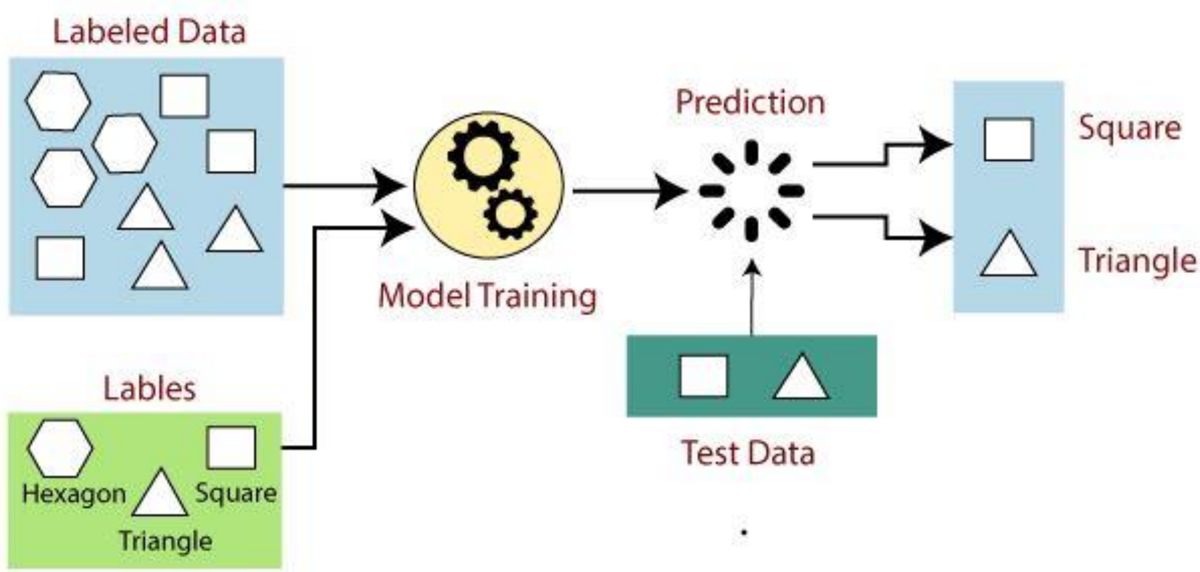


Figure 2: Supervised Machine Learning [48].

4.1.2 Unsupervised Machine Leaning Algorithms

These learning algorithms are used when the data or information used is not classified or labeled. Although the system does not detect the exact output, it can classify the data and make inferences from the data set to explain hidden patterns in the unlabeled data. Clustering techniques are used in unsupervised machine learning algorithms.

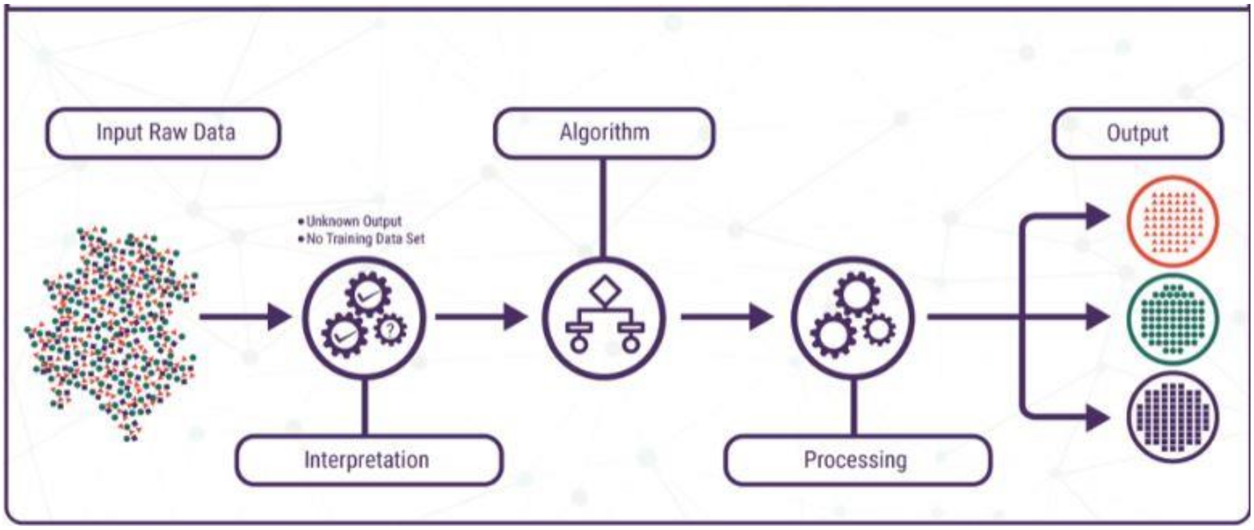


Figure 3: Unsupervised Machine Learning [49].

4.1.3 Semi Supervised Machine Learning Algorithms

This algorithm falls between supervised and unsupervised machine learning algorithms as it uses both supervised and unsupervised algorithms. It is typically used to retrieve labeled data and other resources for training. Obtaining unlabeled data typically does not require additional resources.

4.1.4 Reinforcement Machine Learning Algorithms

4.2 These algorithms are used in games where agents receive delayed rewards until the next previous action is evaluated. The main difference between the reinforcement machine gradient algorithm and other algorithms is that reinforcement does not require knowledge of an exact mathematical model.

This study uses labeled data: fetal outcomes of cesarean section, Apgar score, meconium aspiration syndrome (MAS), and neonatal intensive care unit (NICU) admission. Therefore, if the results are available, the best algorithm to use is supervised learning. Therefore, various classifications were applied and the results are discussed in the following sections.

4.3 Correlation Matrix:

A correlation matrix shows the relationship between two variables. Correlation matrices are used to summarize big data, with each cell in the table showing the correlation between two variables. High correlation values indicate a strong correlation between the two variables and indicate that the linear regression estimates may be unreliable. This technique is used to impute missing values in the data, but there are no missing values in the data set.

The 1.00 line on the diagonal indicates that each variable is always perfectly related to 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

4.4 Analysis of Dataset

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

Table 4: Outdoor Data Analysis

	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

4.5 Performance Metrics for Classification Problems

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

4.5.1 Confusion Matrix

The confusion matrix is a table with two dimensions, “actual” and “predicted,” containing TP true positives, TN true negatives, FP false positives, and FN false negatives. This is a simple way to measure the performance of a classifier predicting two or more classes.
A true positive occurs when both the actual class data and the expected class data are 1.

If both actual and expected class data are 0, the actual is negative.

• A false positive occurs when the actual class is 0 and the expected class is 1.

• If the actual class is 1 and the expected class is 0, a false negative occurs.

4.5.2 Classification Accuracy

Precision is defined as the ratio of the total number of true estimates to all estimates. This is the most common way to evaluate the performance of a classification algorithm and can be calculated using the following formula [50].

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

4.5.3 Area under the Curve (AUC) and ROC

AUC and Receiver Operating Characteristics (ROC) are performance metrics for classification algorithms. ROC is a probability curve and AUC measures separation. Simply put, the ability of a classifier to separate output classes means that the area under the curve is better than the model. This is plotted on the y and x axes for sensitivity or recovery (TPR) and specificity (FPR) at different thresholds, respectively. Below are the AUC and ROC graphs.

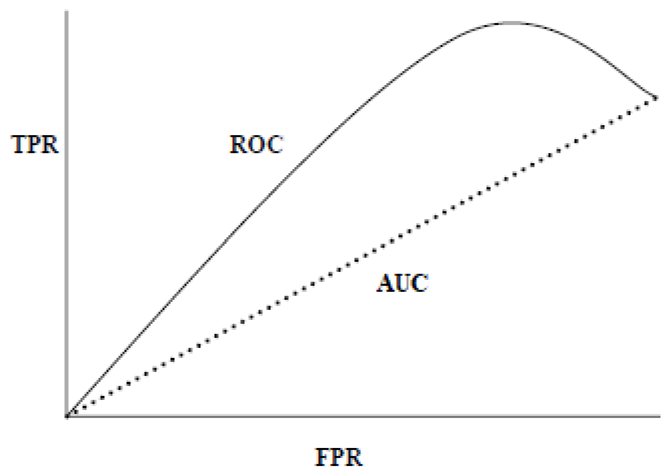


Figure 4: AUC and ROC curve [50]

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

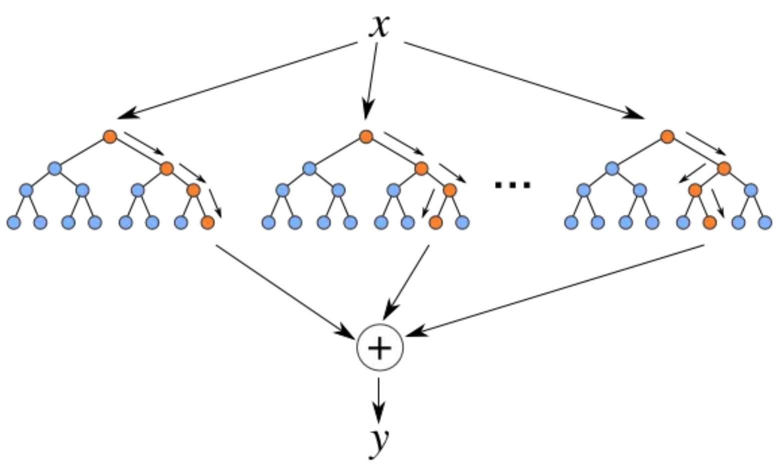
$$Recall = \frac{TP}{TP + FN}$$

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

5 CHAPTER: IMPLEMENTATION OF ALGORITHMS

5.1 Random Forest Algorithm

It is a supervised learning model. It uses labeled data to “learn” how to classify unlabeled data. The random forest algorithm consists of different decision trees, each tree having the same number of nodes but using different data to decide on different directions. Combines decisions from multiple decision trees to find an answer that represents the average of all decision trees.



These equation decide the no of decision trees branches

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2$$

We also use the entropy to determine the number of nodes

$$Entropy = \sum_{i=1}^{C} -p_i * \log_2(p_i)$$

Entropy uses the probability of a particular outcome to determine how nodes branch. Unlike the Gini index, it is more mathematically intensive because it uses a logarithmic function for its calculations.

5.1.1 Classification of outdoor patients using Random Forest

There are six predictor variables in the data set: age, parity, diabetes body mass index (BMI), education level, lifestyle, and gestational age. Using this data, we will predict four fetal outcomes: cesarean delivery, Apgar score, MAS, and NCIU admission. Of these four outcomes, we will train the Random Forest on a single outcome (cesarean section). Since the first and most important outcome is cesarean section, other outcomes occur in the second stage. After delivery (C.s or regular). Additionally, different results depend on the delivery method. Therefore, CS is used as a predictor or characteristic to predict it.

Now we have applied a random forest classifier to the dataset using MATLAB software with seven features as input and C-section as output. With PCA enabled, the Random Forest classifier has an accuracy of 93.3%, a total computational error cost of 45, and a training speed of 0.9312 seconds.

When calculating the confusion matrix, the true positive rate TPR is 0.96, the false negative rate FNR is 0.95, and the area under the curve AUC is 0.73. It's like the picture.

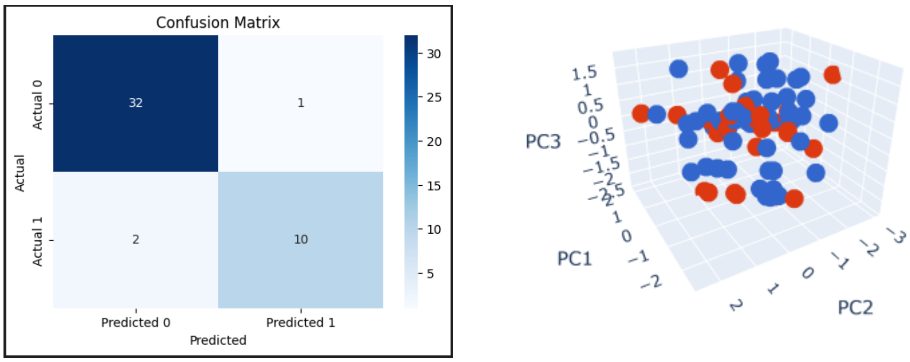


Figure 5: Confusion Matrix of Outdoor Data using Random Forest

For other outcomes, we applied Random Forest, C-section as input and now have 8 features/predictors and 3 outcomes: Apgar score, meconium aspiration syndrome, and NICU admission. The following table shows precision, calculation error, area under the curve, FPR, and TPR.

Table 6 : Random forest Algorithm Accuracies of Outdoor Data

Fetomaternal outcomes of Outdoor data using Random Forest						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**98.2**	**1**	**1.6**	**0.9**	**1**	**1**
MAS	**97.7**	**1**	**0.788**	**0.21**	**1**	**1**
NICU	**98.7**	**1**	**0.77**	**0.76**	**1**	**1**

5.1.2 Classification of indoor patients using Random Forest

For indoor patients, we applied Random Forest Classifier to indoor patient data of 224 pregnant women and found an accuracy of 88.8% with a training speed of 82 seconds and a miscalculation cost of 70 when PCA was activated. As a result of calculating the confusion matrix, TPR was 0.97, FNR was 0.98, and area under the curve was 0.68., as shown in figure.

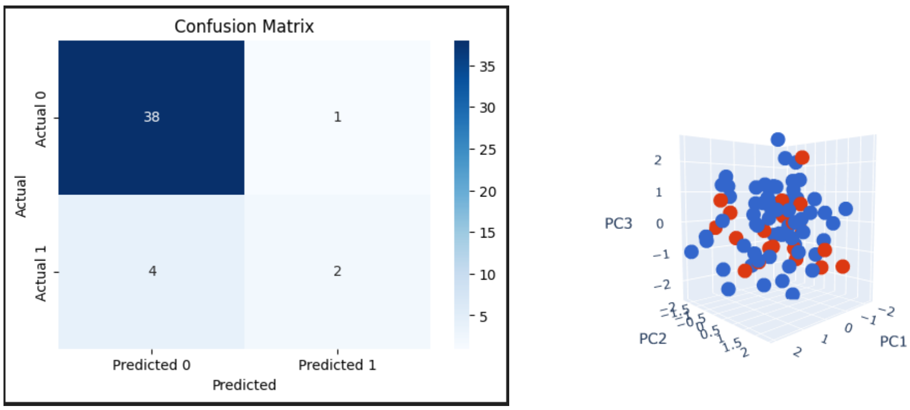


Figure 6: Confusion Matrix of Indoor Data using Random Forest

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

Table 7 : Random forest Algorithm Accuracies of Indoor Data

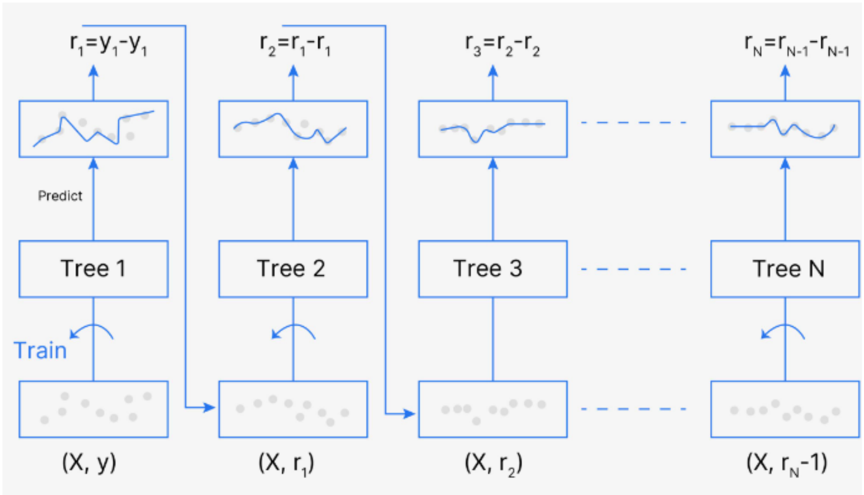
Fetomaternal outcomes of Indoor data using Random Forest						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.9**	**1**	**0.84**	**0.59**	**1**	**1**
MAS	**93.3**	**3**	**0.75**	**0.65**	**0.94**	**0.99**
NICU	**94.2**	**3**	**0.81**	**0.49**	**1**	**1**

5.2 Gradient Boosting Algorithm

Gradient boosting is one of the most widely used machine learning algorithms for tabular data sets. It is powerful enough to detect non-linear relationships between model targets and features, is useful for missing values, outliers, and high cardinality, and can handle categorical values without special treatment of features. You can generate a simple gradient boost tree using some popular libraries like XGBoost or LightGBM without knowing the details of the algorithm, but you still want to know when you start tuning hyperparameters, customizing loss functions, etc. Get better model quality.

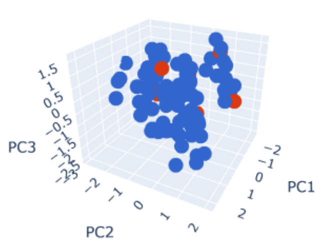
$$\boldsymbol{d(x, x') = \sqrt{(x_1 - x'_1)^2 + \cdots + (x_n - x'_n)^2}}$$

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



5.2.1 Classification of outdoor patients using Gradient boosting

Above said algorithm is applied on data of outdoor patients and acquired an accuracy of 94.3%, miscalculation cost of 28 with training speed of 1.87 sec. other results are shown in figure.



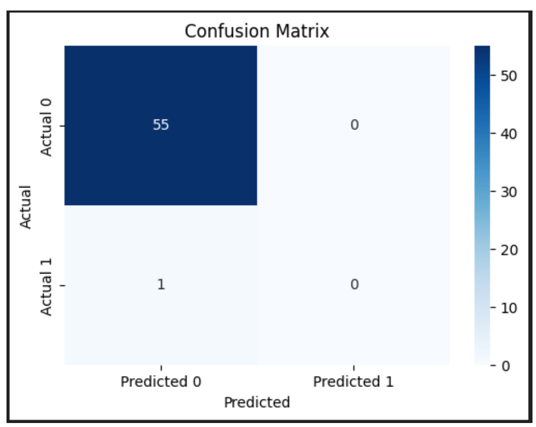


Figure 7: Confusion Matrix of Outdoor Data using Gradient Boosting

Table 8: Gradient Boosting Algorithm Accuracies of Outdoor Data

Fetomaternal outcomes of Outdoor data using Gradient boosting Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.7**	**8**	**1.22**	**0.74**	**0.5**	**0.97**
MAS	**97.7**	**8**	**0.72**	**0.49**	**1**	**0.99**
NICU	**98.1**	**5**	**0.72**	**0.82**	**0.33**	**0.98**

5.2.2 Classification of Indoor patients using Gradient boosting

Above said algorithm is applied on data of outdoor patients and acquired an accuracy of 88.8%, miscalculation cost of 28 with training speed of 1.87 sec. other results are shown in figure.

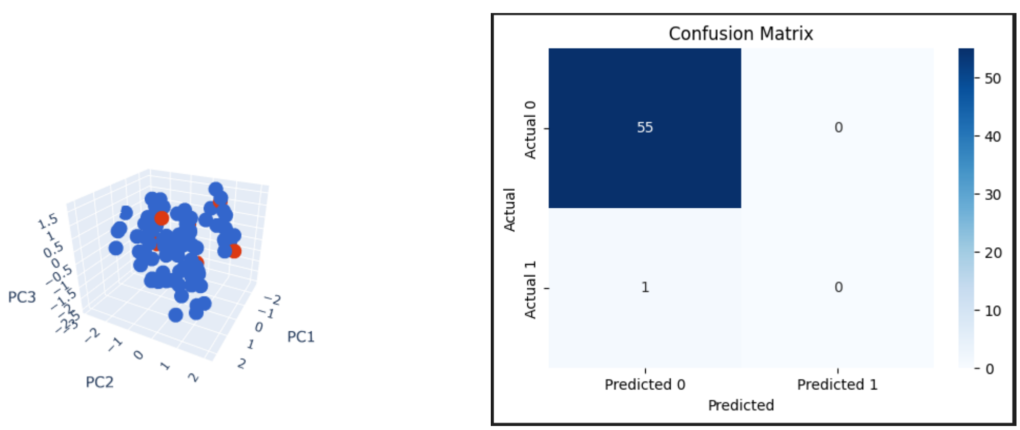


Figure 8: Confusion Matrix of Indoor Data using Gradient Boosting

For other outcomes see the table:

Table 9 : Gradient Boosting Algorithm Accuracies of Indoor Data

Fetomaternal outcomes of Indoor data using Gradient boosting Classifier						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**93.3**	**3**	**1.22**	**0.74**	**0.5**	**0.93**
MAS	**91.8**	**4**	**0.72**	**0.49**	**1**	**0.95**
NICU	**95.5**	**2**	**0.72**	**0.82**	**0.35**	**0.94**

5.3 Kernel SVM Algorithm

Kernel SVM finds a hyperplane in a multidimensional space that separates classes into the best possible pattern. Kernel SVM uses cubic kernel functions. Cubic SVM provides high precision to accurately identify results.

5.3.1 Classification of outdoor patients using Kernel SVM Algorithm

Trained the cubic SVM algorithm and found accuracy of 90.3%, area under the curve .80, TPR .94, and FNR .36, using cubic kernel function when PCA is enabled. Confusion Matrix and ROC curve are shown below.

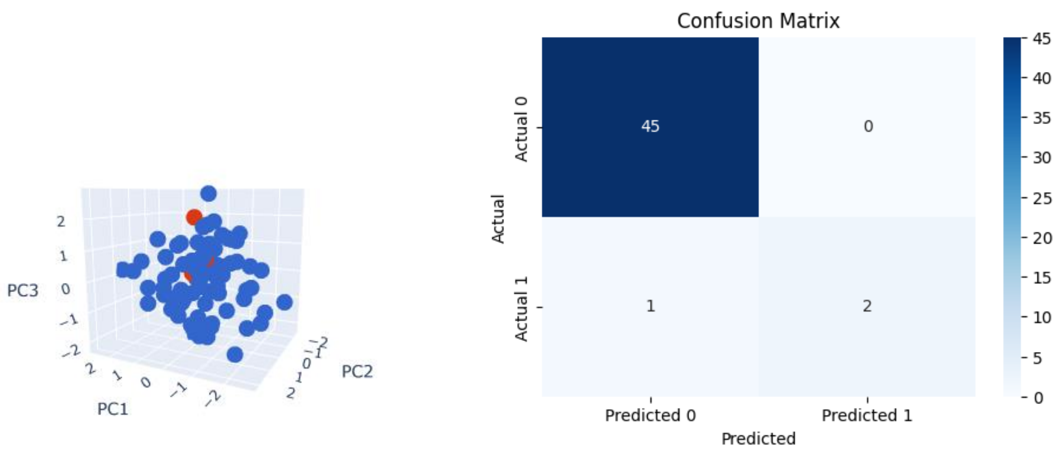


Figure 9: Confusion Matrix of Indoor Data using Kernel SVM

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

Table 10 : Kernel SVM Algorithm Accuracies of Indoor Data

Fetomaternal outcomes of Outdoor data using kernel SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.6**	**5**	**0.7**	**0.9**	**0.5**	**0.96**
MAS	**97.7**	**4**	**0.74**	**0.26**	**1**	**0.98**
NICU	**98.06**	**2**	**0.82**	**0.88**	**0.33**	**0.98**

5.3.2 Classification of indoor patients using Kernel SVM Algorithm

Applying kernel SVM Algorithm on data of indoor patients and found accuracy 82.2%, AUC .81, TPR is .88 and FNR is .27 using kernel function. Confusion Matrix and ROC curve are shown below.

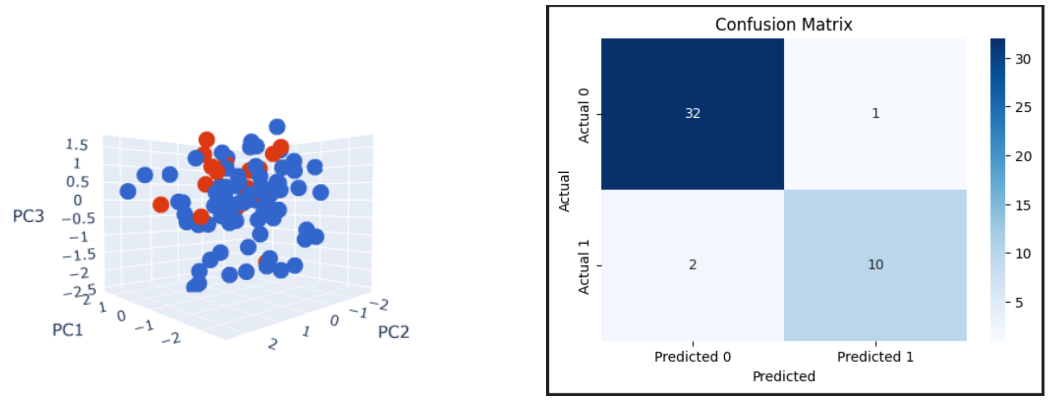


Figure 10: Confusion Matrix of Indoor Data using Kernel SVM

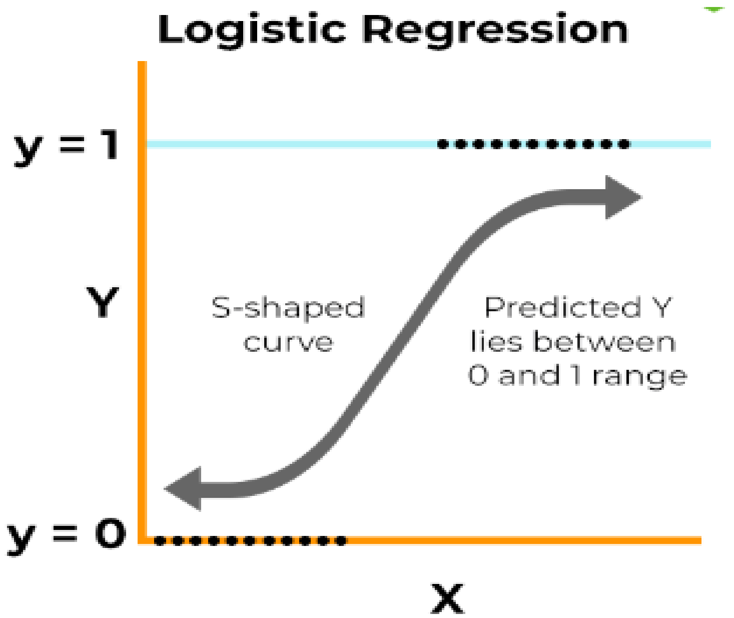
For Apgar score, MAS and NICU admission details are given below.

Table 11 : Kernel SVM Algorithm Accuracies of Indoor Data

Fetomaternal outcomes of Indoor data using kernel SVM						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**94.2**	**5**	**0.82**	**0.85**	**0.4**	**0.97**
MAS	**91.1**	**7**	**0.77**	**0.86**	**0.29**	**0.96**
NICU	**95.5**	**3**	**0.77**	**0.81**	**0.3**	**0.93**

5.4 Logistic Regressor Algorithm

Logistic regression is defined as a supervised machine learning algorithm that performs binary classification tasks by predicting the probability of an outcome, event, or observation. This article explains the basic principles, mathematical equations and assumptions, types, and best practices of logistic regression.



5.5 Classification of outdoor patients using Logistic Regressor Algorithm

Trained the Logistic Regressor algorithm and found accuracy of 84.4%, area under the curve .80, TPR .94, and FNR .36, using cubic kernel function when PCA is enabled. Confusion Matrix are shown below.

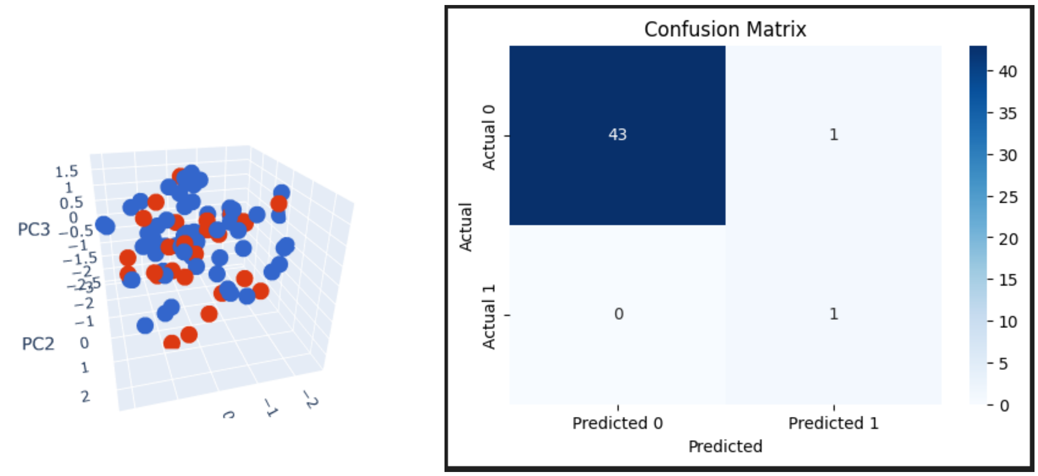


Figure 11: Confusion Matrix of Outdoor Data using Logistic Regressor

Table 12 : Logistic Regressor Algorithm Accuracies of Outdoor Data

Fetomaternal outcomes of Outdoor data using Logistic Regressor						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.8**	**3**	**0.75**	**0.9**	**0.5**	**0.96**
MAS	**95.6**	**2**	**0.82**	**0.26**	**1**	**0.98**
NICU	**97.7**	**4**	**0.86**	**0.88**	**0.33**	**0.98**

5.6 Classification of Indoor patients using Logistic Regressor Algorithm

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

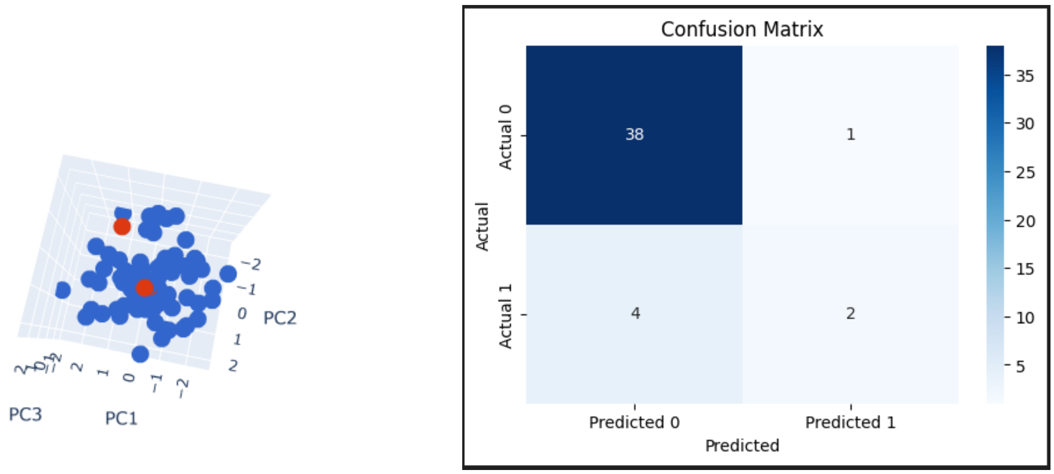


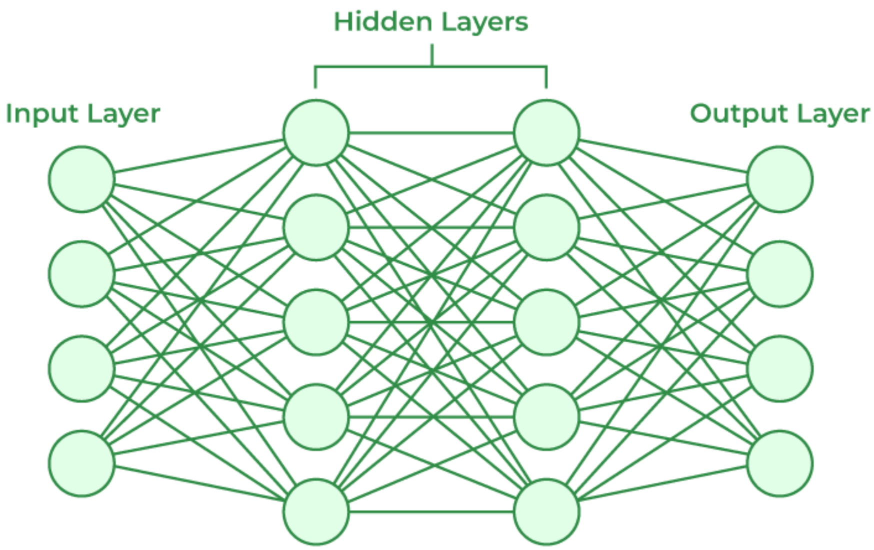
Figure 12: Confusion Matrix of Indoor Data using Logistic Regressor

Table 13 : Logistic Regressor Algorithm Accuracies of Indoor Data

Fetomaternal outcomes of Indoor data using Logistic Regressor						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**95.2**	**2**	**0.75**	**0.9**	**0.5**	**0.96**
MAS	**93.3**	**5**	**0.82**	**0.26**	**1**	**0.98**
NICU	**95.5**	**4**	**0.86**	**0.88**	**0.33**	**0.98**

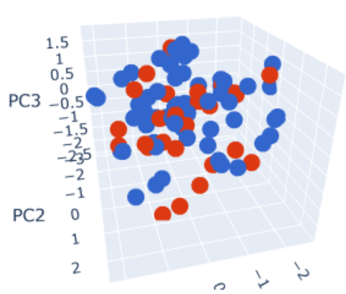
5.7 Artificial Neural Network Algorithm

Artificial neural networks (ANNs) work by simulating interconnected neurons that process input data across multiple layers and adjust connections based on feedback to increase accuracy. The ability to learn complex patterns and relationships from large data sets is useful for tasks such as image and speech recognition, natural language processing, and predictive analytics. It has been widely adopted in various fields due to its flexibility and efficiency in handling diverse and complex data-driven problems.



5.8 Classification of Outdoor patients using ANN Algorithm

Trained the ANN algorithm and found accuracy of 88.8%, area under the curve .80, TPR .94, and FNR .36, using ANN when PCA is enabled. Confusion Matrix are shown below.



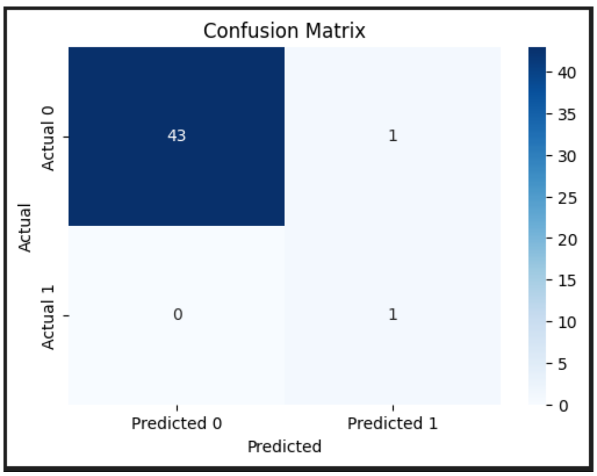


Figure 13: Confusion Matrix of Outdoor Data using ANN

Table 14 : ANN Algorithm Accuracies of Outdoor Data

Fetomaternal outcomes of Outdoor data using ANN						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.7**	**3**	**0.75**	**0.9**	**0.5**	**0.96**
MAS	**97.7**	**2**	**0.82**	**0.26**	**1**	**0.98**
NICU	**97.7**	**4**	**0.86**	**0.88**	**0.33**	**0.98**

5.9 Classification of Indoor patients using ANN Algorithm

Trained the ANN algorithm and found accuracy of 80%, area under the curve .80, TPR .94, and FNR .36, using ANN function when PCA is enabled. Confusion Matrix are shown below.

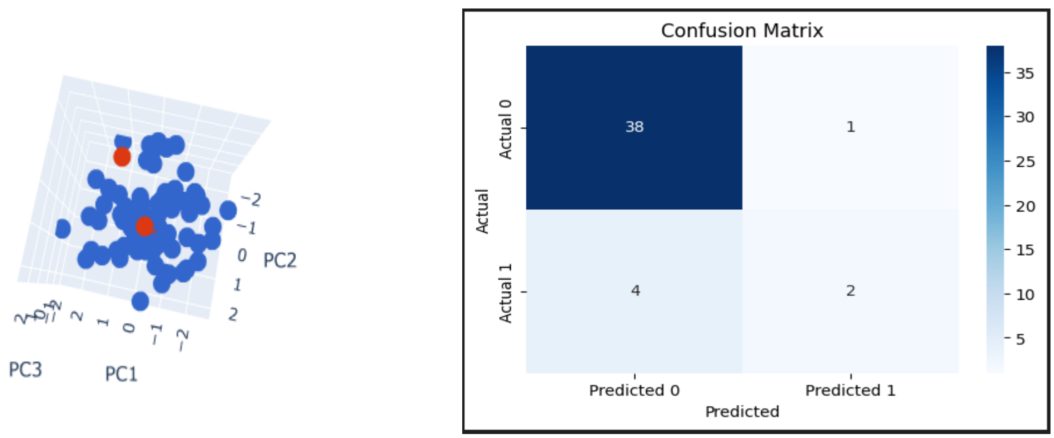


Figure 14: Confusion Matrix of Indoor Data using ANN

Table 15 : ANN Algorithm Accuracies of Indoor Data

Fetomaternal outcomes of Indoor data using ANN						
Outcome	**Accuracy %**	**Miscalculation**	**Training Speed**	**AUC**	**FPR**	**TPR**
APGAR	**97.9**	**2**	**0.75**	**0.9**	**0.5**	**0.96**
MAS	**93.3**	**5**	**0.82**	**0.26**	**1**	**0.98**
NICU	**94.2**	**4**	**0.86**	**0.88**	**0.33**	**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 448 pregnant women, outdoor patients with cesarean deliveries are 51 and 79 in women with indoor induction, APGAR score <7 at 5 minutes is recorded in 11 vs 28, meconium aspiration syndrome 11 vs 37 and NICU admission 13 vs 37 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. Random forest algorithm has the best accuracy of 88.87% in Indoor patients while 93.3% in Outdoor patients for cesarean section. Other classification algorithms have reasonably good accuracies for cesarean section prediction ranging from 77.1% to 88.8% as shown figure.

Figure 15: Accuracies comparison of Cesarean Outcome

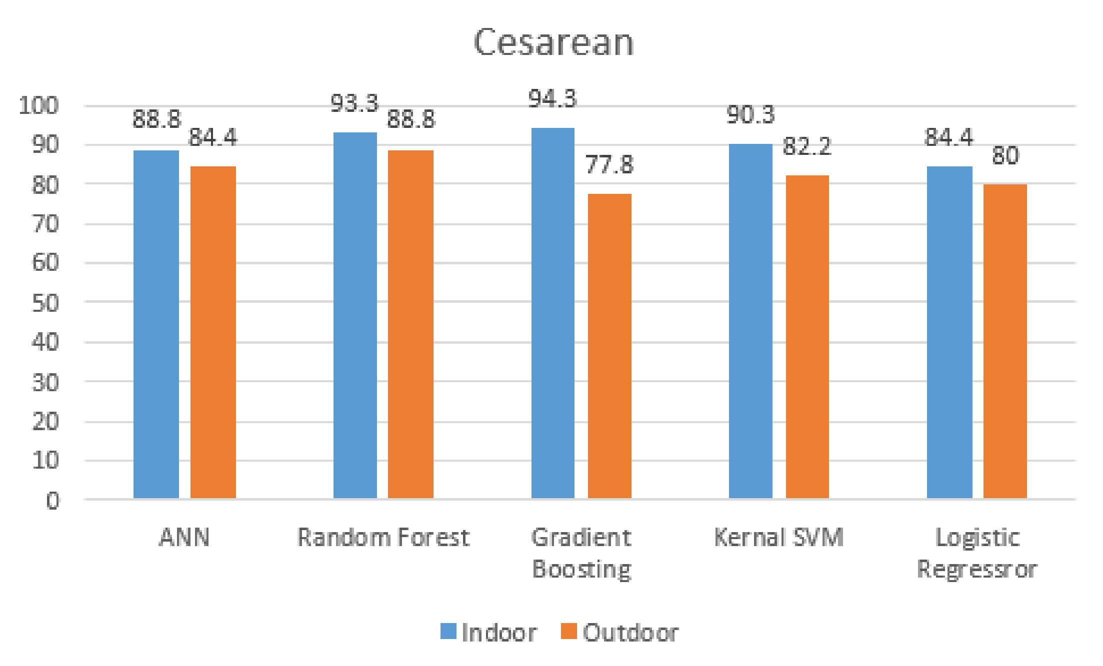


Figure 16: Accuracies comparison of APGAR Outcome

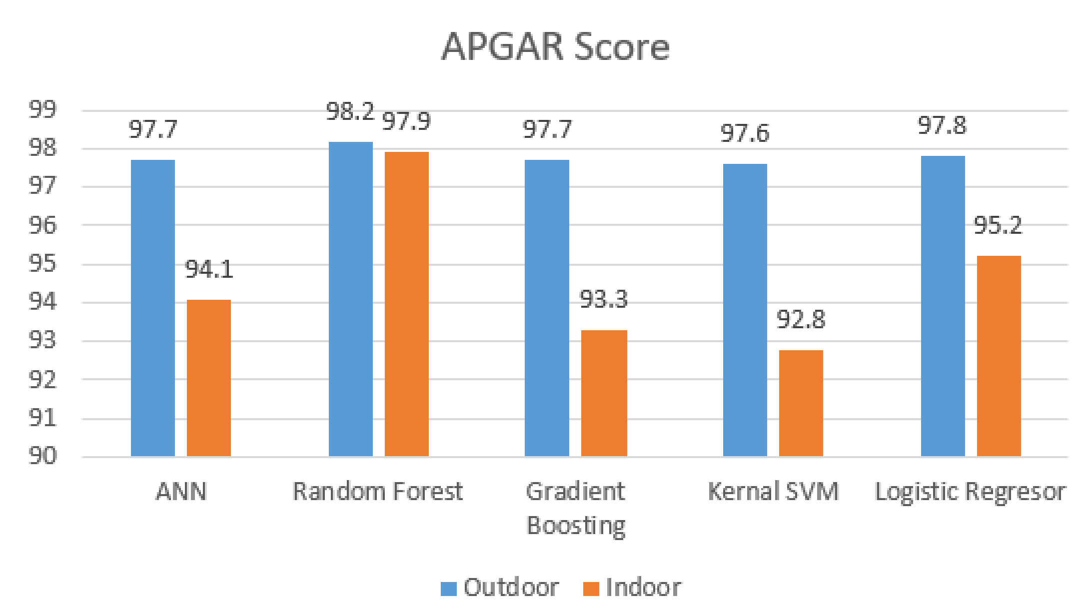


Figure 17: Accuracies comparison of NICU Outcome

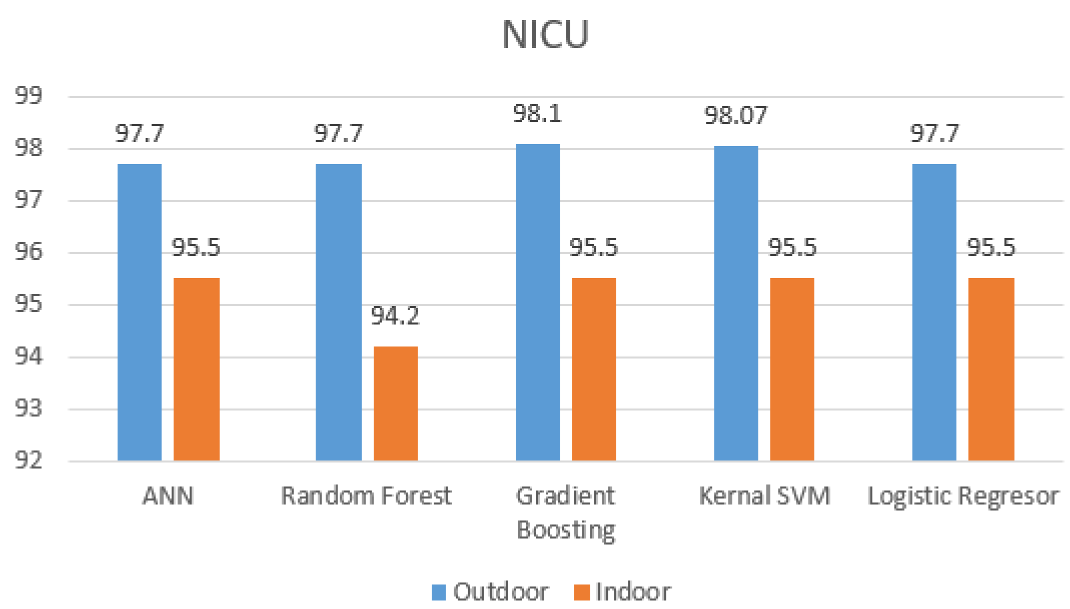


Figure 18: Accuracies comparison of MAS Outcome

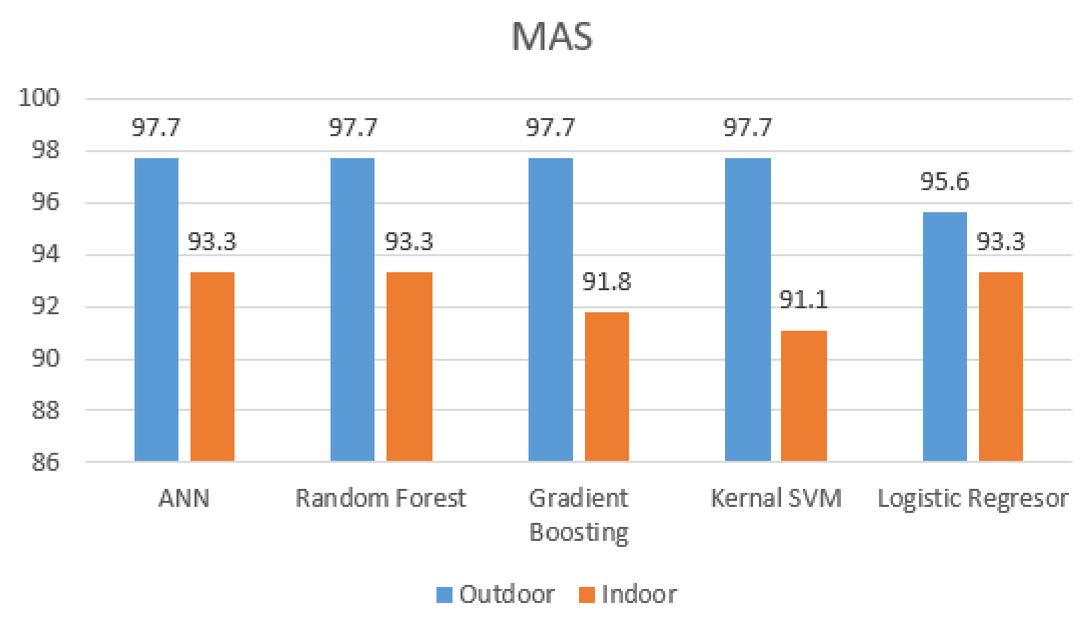


Table 16 : Accuracies Comparison of fetomaternal Outcome

Comparison of Outdoor and Indoor Outcomes						
Algorithm	**APGAR Accuracy**		**MAS Accuracy**		**NICU Accuracy**	
	Outdoor	**Indoor**	**Outdoor**	**Indoor**	**Outdoor**	**Indoor**
ANN	**97.7**	**94.1**	**97.7**	**93.3**	**97.7**	**95.5**
Random Forest	**98.2**	**97.9**	**97.7**	**93.3**	**97.7**	**94.2**
Gradient Boosting	**97.7**	**93.3**	**97.7**	**91.8**	**98.1**	**95.5**
Kernal SVM	**97.6**	**94.2**	**97.7**	**91.1**	**98.07**	**95.5**
Logistic Regressror	**97.8**	**95.2**	**95.6**	**93.3**	**97.7**	**95.5**

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.

6.3 Benefits of 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.
- ANN, Random forest, Kernel SVM, Logistic Regressor 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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