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A MODEL TOWARDS PREDICTING SAFE MODE CHILD BIRTH USING MACHINE LEARNING: CASE OF ADARE GENERAL HOSPITAL HAWASSA

Research Paper BY

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SPECIAL THANKS GOES TO INFOLINK UNIVERSITY COLLEGE FOR SUPPORTING THIS RESEARCH

ABBREVIATIONS

APH	Antepartum Hemorrhage
AUC	Area Under Curve
B/P	Blood Pressure
BPP	Biophysical Profile
CS	Caesarean Section
CSV	Comma Separated Value
DT	Decision Tree
FN	False Negative
FP	False Positive
GA	Gestational Age
GLM	Generalized Linear Models
KNN	K-nearest Neighbors
ML	Machine learning
NB	Naive Bayes
OA	Occiput Anterior
PA	Posterior Anterior
Px	Pregnancies
RF	Random Forest
ROC	Receiver Operating Characteristics
SC	Stacking Classification
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
WEKA	Waikato Environment for Knowledge Analysis
WHO	World Health Organization
ARFF	Attribute Relation File Format
ROC	Receiver Operating Characteristics

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ABSTRACT

For both mother and child to be safe, the method of birthing is a key factor. The physician is responsible for choosing mode of delivery. Making decisions quickly becomes extremely difficult for the doctor during childbirth. Furthermore, humans may make incorrect decisions regarding the safe mode of childbirth delivery. This study was aimed to develop a model towards predicting safe mode child birth using machine learning. In this study, safe mode child birth predictive model is developed by using stack learning classifier for Adare General Hospital Hawassa. Nineteen features and five methods were applied to 7020 datasets to construct the stacking model. The data set was collected from Adare General Hospital Hawassa. An experimental study was conducted to develop a model towards predicting safe mode child birth by using stack classifier. The algorithm used were Decision tree (DT), k-nearest neighbors (KNN), random forest (RF), support vector machine (SVM) and Naive Bayes (NB). Stack model has accuracy of 98.45% and 98.79% using percentage split 66% and 80% respectively and 98.23% accuracy using 10-fold cross validation test options. The result obtained using stacking had higher accuracy compared to others individual algorithms.

Key words: cesarean section, normal delivery, mode of delivery, childbirth machine learning, stack classifier, prediction, data mining

CHAPTER ONE

1. INTRODUCTION

Background of the study

In a woman's life, childbirth is both a profound emotional experience and a typical physiological process(Kotaska, 2015). One or more babies leave the womb at the end of pregnancy either naturally or by a cesarean section, but choose the incorrect delivery method can result in various short- and long-term health problems for both mother and child.(Islam et al., 2021). Every day, almost 800 women worldwide pass away from issues related to pregnancy or childbirth(Ababa & Thupayagale-, 2016). In Ethiopia mortality rate of woman caused by childbirth delivery was, 67 per 1,000 live births in 2016. Similarly, infant mortality rate 48 per 1,000 live births in 2016 (Geleto et al., 2020). Pregnant women can give birth to their children either naturally or surgically(Ayano & Guto, 2018).

Caesarian section (CS) is the delivery of the pregnancy outcome through an incision through the maternal abdomen and uterus. It was named after the belief that Julius Caesar was born through CS(Shi et al., 2016).A Caesarean section (CS) is a surgical procedure intended to avoid or treat potentially fatal complications for either the mother or the fetus(Gebremedhin, 2014). The delivery protocol states that a caesarean section is carried out when a safe vaginal delivery is either not possible or would put the mother or fetus at unnecessary risk (Ababa & Thupayagale-, 2016). According to current WHO guidelines, CS is crucial for lowering maternal and perinatal mortality and morbidity(Gebreegziabher Hailu et al., 2020). It is currently estimated that approximately 20 million cesarean section (CS) deliveries occur worldwide each year.(Ayano & Guto, 2018)

The global rate of caesarean section (CS) is increasing gradually. Ethiopia is also experiencing increasing rate of CS (Tenaw et al., 2019).CS has been recommended for the mothers whose labor progress is poor due to either maternal or fetal factors(Hailegebreal et al., 2021).

Unnecessary CS increases maternal mortality. According to the World Health Organization (WHO), unnecessary CS raises the risk of maternal and neonatal mortality. (National & Pillars, n.d.,2018). Caesarean section without a proper medical indication may increase the risk of adverse maternal and perinatal outcomes(Gebremedhin, 2014). The majority of women with prior CS should have preferred vaginal delivery but did not. The CS creates lots of complications to a child and mother. Children delivered by CS are much more likely to allergies, asthma, and diabetes. The risk of diabetes is 20%, and asthma is 79%, considerably more than the normal delivery (Bin Alam et al., 2021).

To avoid or minimize such problems as mentioned above, it is critical for physicians to identify the safe mode of delivery.

ML is being used to analysis the importance of clinical parameters and their combinations for prognosis, such as disease progression prediction, to extract medical knowledge for outcomes research and support, and overall patient management(Magoulas et al., 2017). A machine-learning model can learn the patterns of a large number of patients' health trajectories. This capability can assist physicians in anticipating future events at an expert level, drawing on information that extends far beyond the individual physician's practice experience(Rajkomar et al., 2019). The application of Machine Learning (ML) for prediction and classification in the health care domain is increasing significant.ML techniques make the pattern extractions more convenient. Several studies have been performed to automate the decision-making process in many fields, particularly in medical data analysis.

The research was aimed to build a prediction model to classify subjects either Caesarean Section (CS) or vaginal delivery for Adare General Hospital Hawassa.

Statement of the problem

Every day, almost 800 women worldwide pass away from issues related to pregnancy or childbirth(Gebreegziabher Hailu et al., 2020).According to current WHO guidelines, CS is crucial for lowering maternal and perinatal mortality and morbidity, provided that there is a valid medical justification(Kotaska, 2015). However, in the absence of a clear medical justification, CS does not have any medical benefits; instead, it is associated with social and obstetric maternal factors (age, educational level, income, preference, height, weight, parity, premature rupture of the amniotic membrane, and multiple pregnancies), as well as fetal factors (cephalic, breech presentation, etc.) and fetal factors (breech presentation, etc.)(Ayano & Guto, 2018). There is growing concern around the world about the dramatically rising rates of caesarean section due to birth attendant failure to attempt a vaginal birth after a previous caesarean delivery(Abebe et al., 2016). Despite the World Health Organization's (WHO) recommendation of a maximum of 10-15% acceptable caesarean section rate in the presence of reasonable indications, many countries report rates higher than this due to maternal preference(Rajkomar et al., 2019). An unnecessary CS can result in additional maternal and perinatal morbidity, such as postpartum hemorrhaging, reduced fertility, and placental complications in subsequent pregnancies for mothers(Shi et al., 2016).

When used correctly, C-sections can improve infant and/or maternal outcomes. However, when used incorrectly, the potential harm may outweigh the potential benefit of a C-section. C-sections are more expensive than vaginal births and can put the mother and baby at risk(Abebe et al., 2016). Ethiopia has some of the highest rates of maternal and newborn mortality and morbidity in the world(Shi et al., 2016). In Ethiopia mortality rate of woman caused by childbirth delivery was, 67 per 1,000 live births in 2016. Similarly, infant mortality rate 48 per 1,000 live births in 2016 (Geleto et al., 2020).

The physician in charge is responsible for choosing safe mode of delivery. Choosing the wrong method of delivery can cause different health issues for both mother and baby. Inappropriate choosing of CS expose the child for allergies, asthma, and diabetes(Kowsher et al., 2021). When the health or life of the expected child or mother is at risk choosing normal delivery is not safe mode for the health of both mother and child. During the baby delivery, decision-making within a short time becomes very challenging for the physician. Besides, humans may make wrong decisions selecting the safe mode of childbirth delivery. Choosing a wrong mode of delivery exposes the mother's life at risk and can also be harmful to the newborn baby's health.

Objectives of the Research

General objective

The general objective of the research is to develop a model towards predicting safe mode child birth using machine learning for the case of Adare General Hospital Hawassa.

Specific objectives

The specific objectives of the research:

- To review related literature to understand what other researchers came up with related research areas.
- To explore the possible features of child birth delivery for determining the preferable mode of childbirth.
- To develop a model by using stack ensemble learning classifier.
- To evaluate the performance and efficiency of the developed model

Research Questions

1. Which features are used for prediction of childbirth delivery?
2. How to develop a ML model using ensemble learning for better prediction of childbirth delivery?

Significance of the Study

As the research focus on predicting safe mode of childbirth delivery by using ML algorithm, it reduces human error which occur due to inappropriate mode of childbirth delivery chosen by physician. As a result, this research will help the physician to choose safe mode of childbirth delivery assisted by automated system. Choosing appropriate mode of delivery will help the mother to deliver the child without or with less health complication.

Scope of the Study

The scope of this research will be limited to the specific objective of the study as identifying the possible features for predicting safe mode of childbirth delivery and the research only focus on how stack ensemble learning classifier will perform better prediction than DT, KNN, RF, SVM and NB. For this data set acquired is taken from Adare General Hospital Hawassa. The research was conducted by using weka tool.

Limitation of The Study

This study was aimed to develop a model towards predicting safe mode of child birth using machine learning algorithm for Adare General, Hospital. The study, used secondary data to develop the model and the findings must be interpreted in the light of the following limitations: Firstly, this study was conducted only in one study step up this might be different for another study set up. Secondly, the scope of the study is only restricted for Adare General, Hospital. In this study, nineteen features included in developing a model because of some features were included like economic status, education status, height of mother, behavioral factors (alcohol drinking cigarette smoking).

CHAPTER TWO

2. LITERATURE REVIEW

Conceptual Literature

Mode of Delivery

The mode of delivery is a crucial determinant for ensuring the safety of both mother and child. A vaginal birth refers to the natural method of birth that requires no assistance(Abebe et al., 2016). When the pregnancy conditions require additional support, operative vaginal delivery techniques, forceps and vacuum, are demanded. They are suitable for cord prolapse, exhaustion and certain neurological and heart conditions of the mother (Pereira et al., 2015).

Caesarian section (CS) is the delivery of the pregnancy outcome through an incision through the maternal abdomen and uterus. It was named after the belief that Julius Caesar was born through CS(Shi et al., 2016).A Caesarean section (CS) is a surgical procedure intended to avoid or treat potentially fatal complications for either the mother or the fetus(Gebremedhin, 2014) The current practice for predicting the mode of delivery is generally the opinion of the physician in charge, but choosing the wrong method of delivery can cause different short-term and long-term health issues for both mother and baby (Islam et al., 2021)

Machine learning

Pattern recognition and the idea that computers may learn without being programmed to carry out certain tasks gave rise to machine learning(Panesar, 2019). Hard-coded knowledge bases in systems generally have trouble adapting to changing situations(Luis & Moncayo, 2019). A system with the ability to learn on its own can overcome some challenges. This capability is referred to as machine learning. Machine learning is concerned with the creation of algorithms that adapt to the presentation of new data and the discovery of new information (Kubat, 2017).

There are numerous studies being conducted that use machine learning techniques for medical diagnosis, prediction, and treatment. (Kowsher et al., 2020). ML provides a learning technique that may be used to extract information from enormous data and aids in performing predictive analysis or pattern identification on large data. (Alpaydın, 2019).

To increase patient safety and healthcare quality, ML provides a variety of alerting and decision support capabilities. (Pubrica, 2018).

a). ***Supervised learning***

In supervised learning, the machine (the system) learns with the assistance of labeled training data. The dataset or training data is the foundation on which the algorithm learns to infer. (Russell, 2018). In supervised learning, algorithms are given training data in the form of example inputs and the intended outputs that follow in order to teach them general principles that map inputs to outputs(Morgan, 2016). Training data is the name given to input data, and it is coupled with a known output (Nelli, 2018). The algorithm's development is guided by the training data. A model is developed through a training process in which the model predicts and is corrected when the predictions are incorrect (Alpaydın, 2019). The model is trained until it achieves the desired level of accuracy on the training data(Luis & Moncayo, 2019). Supervised algorithms include logistic regression, support vector machines, naive Bayes, Gaussian Bayes, k-nearest neighbors and some others to predict future events by applying what has been learned in the past to new data using labeled data examples(Panesar, 2019).To identify any faults and remedy them, the learning algorithm can also compare the output with the intended outcome..(Golden, 2020). Supervised learning problems can be used in a variety of ways, including:

Classification

To forecast the outcome based on a training dataset with distinct categories for the output variable. Models are created by feeding in training data in the form of pre-labeled data(Kubat, 2017). Support vector machines, naive Bayes, Gaussian Bayes, k-nearest neighbors (KNN), and logistic regression are classification approaches that determine decision boundaries(Magoulas et al., 2017). Classification examples include labeling someone as ill or healthy based on a group of symptoms (or, in practical terms, diagnosing them)(Rajkomar et al., 2019).

Regression

It is very similar to classification. The only distinction between classification and regression is that regression is the result of a given sample with a real-valued output variable (i.e., the temperature as a value, rather than a classification of hot or cold)Linear regression, polynomial regression, support vector machine (SVM), ensembles, decision trees, and neural networks are examples of regression models(Luis & Moncayo, 2019).

Forecasting, is also the process of making predictions based on historical and current data. This is also referred to as time-series forecasting. (Kubat, 2017).

Decision trees

Decision trees are flowcharts that represent the decision-making process as rules for performing categorization(Ayyadevara, 2018). Decision trees start from a root and contain internal nodes that represent features and branches that represent outcomes. As such, decision trees are a representation of a classification problem(Hartshorn, 2016). Each decision tree is a disjunction of implications (i.e., if-then statements), and the implications are Horn clauses useful for logic programming. A Horn clause is a disjunction of literals(Hartshorn, 2016).

Decision trees have a root and internal nodes that represent features, as well as branches that represent outcomes and it is a representation of a classification problem(Panesar, 2019).

Trees are built and tested from top to bottom. The root is the top node. A branch that doesn't split is stated as a terminal node, decision, or leaf in a way that is clear to read and comprehend. The tree is divided into branches, each of which is evaluated using a cost function(Luis & Moncayo, 2019). It is similar to human decision-making in that priority is determined by feature importance, relationships, and decisions. They are straightforward in that the results can be stated as a set of rules A decision tree's size is decreased during pruning by deleting characteristics that offer little information(Kubat, 2017).

Random Forest Decision Trees

Random forests, which are collections of decision tree learners (thus the name "forest"), are produced by simultaneously training several decision trees(Aksenova, 2018). The purpose of random forests is to prevent overfitting(Panesar, 2019). The accuracy of the results increases with the number of decision trees in the random forest. For decision, each random forest uses a sample of the dataset and a random subset of features(Luis & Moncayo, 2019). Random forest decision trees can be used for classification and regression problems(Hartshorn, 2016).

Support vector machine (SVM)

SVM is a nonprobability binary linear classifier that can be used for both classification and regression problems(Panesar, 2019).

The algorithm finds a hyperplane, or line of best fit, between two classes determined by the support vectors. Support vectors are data points near the hyperplane that, if removed, would change the position of the hyperplane(Ayyadevara, 2018).

The greater the margin value, or the distance between the data points and the hyperplane, the greater the confidence that the data is correctly classified. An optimization procedure that seeks to maximize the margin yields the line of best fit(Hao, 2015). SVM uses something known as kernelling to map data to higher dimensional feature spaces. Data is mapped using the kernel trick in iteratively more dimensions until a hyperplane can be formed to classify it. SVM uses the kernel trick to map data into three dimensions and can define a hyperplane to classify the data. The kernel trick is used to map data in successively more dimensions until a hyperplane can be created to categorize it(Panesar, 2019).As dataset size increases, so too can training time. SVMs are also less capable on noisy data.(Hartshorn, 2016)

Naive Bayes

The Bayesian classifier is based on the Bayesian theorem and is best suited when the input dimensionality is high. Naive Bayes can frequently outperform more complex classification techniques despite how simple it is(Kubat, 2017). This technique can be used to categorize the likelihood that a vector representing a document will be of interest to a user given a particular threshold(Luis & Moncayo, 2019). Using Bayes' theorem, Naive Bayes determines the likelihood that an event will occur given that another event has already occurred. The technique is regarded as naive because it assumes that every variable is independent of every other variable, which is uncommon in real-world situations. (Panesar, 2019). When the input dimensionality is high, the Bayesian classifier is frequently used.

This technique, for instance, can be used to probabilistically categorize whether a vector belongs to one class or another given a certain threshold:

P(B|A) = (P(A|B) * P(B))/P(A)

- P(B|A) = Posterior probability.
- P(A|B) = Likelihood: the probability of data A given that the hypopaper B was true
- P(A) = Class prior probability
- P(B) = Predictor prior probability(Ayyadevara, 2018)

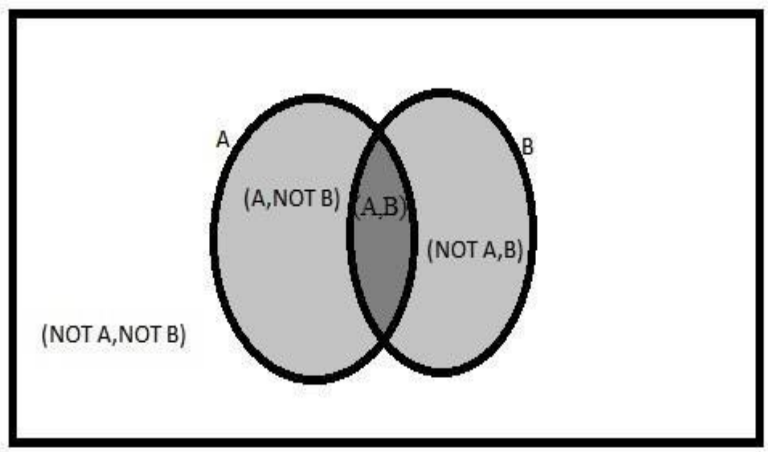

Figure 2. 1 Posterior probability

KNN (k-nearest neighbor)

The KNN method labels an unknown object O with the majority of its k-nearest neighbors' labels. It used in classification and regression problems(Panesar, 2019). NNs don't learn a model; they are a nonparametric method. Instead, KNNs execute classification of a fresh sample based on learning by analogy and store the training dataset as its representation(Russell, 2018). KNNs are viewed as lazy learners because there is no model learning. Every object in N-dimensional space corresponds to a single point. A neighbor is said to be closest if it has the shortest distance in feature space. The Euclidian distance between A = (a1... an) and B = (b1... bn) is used to calculate the distance between an unseen object and its neighbor as follows:

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(a_{i-b_i})^2}$$

The algorithm operates as follows:

1. Determine the separation between any two points.
2. Based on these pairwise distances, identify the closest neighbors.
3. A majority vote on a class designation based on a list of close neighbors(Panesar, 2019).

At the time of the request, the prediction is made. The mean or median of the k-most similar instances is used in regression problems. In classification problems, the class with the highest frequency among the k-most similar instances is chosen(Magoulas et al., 2017). Like most algorithms, the determinant technique is flexible. Additionally, the sum of the absolute differences between real vectors (Hamming distance) and the distance between binary vectors (Hamming distance) are employed.(Ayyadevara, 2018).

KNNs have the drawback of requiring a lot of processing power to categorize an object because the distance between every neighbor in the training dataset must be calculated(Panesar, 2019). High-dimensional data are not particularly well suited for it. A dimension of the n-dimension input space can be thought of as each predictor variable. For example, x1 would be one dimension, x1, x2 would be two dimensions, and so on(Kubat, 2017). The volume of the input space grows exponentially as the dimensionality increases. KNNs are not suitable for data with missing values since it is impossible to determine the distances between vectors on missing data. (Morgan, 2016).

B). Unsupervised learning

The technique of classifying data into related groups is known as unsupervised learning (Golden, 2020). When people refer to self-learning systems, they are actually referring to unsupervised learning. he learning algorithm in unsupervised learning does not receive labels for data, leaving the algorithm to find structure from the input(Ayyadevara, 2018). Since the data is unlabeled, the algorithm's output structure cannot be evaluated for accuracy. Data for both classifications and labels may be missing(Rajkomar et al., 2019). As a result, the model is built through interpretation: discovering hidden structures and making inferences from the input data. This could happen as a result of data organization, rule extraction, or data redundancy reduction.(Kubat, 2017).

C). Reinforcement learning

This is where systems interact with a dynamic environment in which an agent must complete a specific task. Reinforcement learning bridges the gap between machine learning, behavioral psychology, ethics, and information theory(Nelli, 2018).

As the algorithm works its way through the issue, it receives feedback regarding incentives and penalties(Hao, 2015). By learning behaviors that will maximize the reward and using its present state, reinforcement learning enables the agent to choose the optimum course of action. The best course of action (or policy) is often discovered through feedback and trial and error. As a result, the algorithm may decide on the best behaviors for the context(Morgan, 2016). Robotics frequently uses reinforcement learning; an example would be a robotic vacuum that learns to avoid collisions by hitting tables, chairs, and other objects. Today, computer vision techniques are also applied in this situation(Hartshorn, 2016). Correct examples are never given in reinforcement learning, unlike in supervised methods learning, and incorrect decisions are never explicitly corrected(Rajkomar et al., 2019). Performance in the real world is the main focus. Reinforcement learning mimics how people learn and assumes logical conduct when it comes to learning from experience. As a result, it helps us understand how people learn from experience to make wise decisions(Bhattacharjee, 2020). Autonomous vehicles use reinforcement learning. In the actual world, the agent must take into account a variety of environmental factors, such as the present speed, potential road hazards, nearby traffic, available road information, and operator controls(Russell, 2018)

How machine learning algorithm work

The automated process of assuming a function from labeled training data is known as supervised learning. It is possible to understand Y = f(x) as Output = function (Input).

Both inputs and outputs can be thought of as variables and often take the shape of a vector with the notation f denoting the function you are attempting to infer from the input. Machine learning uses algorithms to try to understand how people make decisions(Kubat, 2017). The emphasis is on creating algorithms (or software) that can access data and utilize it to learn for themselves. Tasks requiring classification and prediction benefit greatly from machine learning. Predictive analytics—learning the mapping of Y = f(X) to create predictions of Y for fresh X—is where machine learning is most frequently applied(Russell, 2018)

Training and Test Data

The data used by the learning algorithm to learn possible hypotheses is referred to as training data. From the prepared data, a test set and a training set are chosen. The algorithm is trained on the training dataset before being tested on the test dataset. In many cases, it is a case of experimenting with various machine learning methods(Kubat, 2017)

Empirical Literature

(Pereira et al., 2015), conducted a study to predict types of delivery (normal, cesarean, forceps, and vacuum) by identifying obstetric risk factors through data mining. The purpose of their study was to develop real-time Data Mining (DM) classification models that could predict the type of delivery that would be most suitable with each patient's pregnancy features. The information required is provided by the information systems and technologies used in the perinatal and maternity care unit of the Porto Central Hospital. They used 4236 records of data having 26 features(age, allergies, planned (whether a delivery is planned or not), reason, alertness, gestation (single or multiple pregnancies), grav170 (normal delivery or unexpected events), weight, height, body mass index , blood pressure , number of gestational weeks, marital status, blood type, and a series of medical exams; particular end-of-pregnancy features, including fetal weight, dilatation, consistency, extinction, position, Bishop score, and Hodge plan - cardiotocography, RFC, streptococcus, and rhesus).

In their study, different data mining techniques were applied, such as DT, generalized linear models (GLMs), SVMs, and NB. Among these models, the most satisfactory results for statistical metrics, with the best accuracy and specificity, were achieved using DT. As shown in table 2.1

Table 2. 1 Result of accuracy, sensitivity and specificity for four models

Model	Accuracy	Sensitivity	Specificity
DT	0.8391	0.8828	0.8005
GLM	0.7741	0.8427	0.6755
SVM	0.6206	0.8557	0.2792
NB	0.7469	0.8429	0.6298

(Islam et al., 2021), conducted a study to explore machine learning algorithms and by considering the possible features for predicting the mode of childbirth. On the basis of 6157 birth records, five different machine learning algorithms were investigated to determine the most significant algorithm for prediction. They revealed 32 features (Previous cesarean, complications, Robson group, assisted reproductive technology (art) mode, previous preterm pregnancies, amniocentesis, pre-induction, induction, episiotomy, oxytocin, fetal intrapartum pH, Parity, obstetric risk, comorbidity, number of previous cesarean sections, weight increased during pregnancy, start week of antenatal care, art, previous term pregnancies, amniotic liquid, number of miscarriages in the past, anesthesia, gestational stage, height, weight, BMI, age, cardiotocography, maternal education, substance abuse, smoking, alcohol). They developed a model with stacking classification (SC) producing the highest f1 (97.9%) score.

(Abbas et al., 2018), studied the relationship between caesarean section and maternal age. The objective of this study was to identify the factors that contributed to increased C-section rates and to assist physicians by providing decision support systems based on knowledge derived from machine learning approaches. They found that majority of CS had been stated in age groups younger than 20 years (86%) and older than 36 (96%) years old. The analysis revealed that women who experienced caesarean delivery have more blood pressure compared to women who experienced vaginal delivery. They used 488 records of data set after reduction and cleansing of the data with 23 features, (Hasan et al., 2019) ,studied the contributing factors for caesarean deliveries among married women in Bangladesh and how each factor affects those deliveries. A total of 4422 record of data set is used. They conducted their research by using stepwise logistic regression on married women in Bangladesh. They concluded that location, type of residence, education of respondent and husband, wealth index, age at first birth, working status, number of children, and baby's birth weight were the most significant features of caesarean delivery among Bangladeshi women.

(Tenaw et al., 2019),studied maternal preferences, delivery methods, and related characteristics among women who gave birth in Hawassa City, Southern Ethiopia, public and private hospitals. The study included 300 mothers and was conducted using a systematic sampling procedure. They came to the conclusion that mothers who earn more money each month than the federal poverty level, had had previous pregnancies complicated, and are now pregnant are more likely to deliver their babies via caesarean section.

(Kowsher et al., 2020),studied to produce a computer-aided decision-making process to choose between vaginal birth and a C-section. They applied nine machine learning classifier algorithms across the entire datasets and evaluated how well each technique performed.

They developed a computer-recommended mode of baby delivery using the most convincing method known as "impact learning," which demonstrated an accuracy of 0.89 with an F1 value of 0.88 as shown in table 2.2.

Table 2. 2 Accuracy and F1 score of algorithms

Name	Accuracy	F1 score
Logistic Regression	0.84	0.83
SVM	0.82	0.80
Naive Bayes	0.87	0.87
KNN	0.85	0.82
LDA	0.83	0.82
Decision Tree	0.84	0.83
Random Forest	0.86	0.85
ANN	0.87	0.86
Impact Learning	0.89	0.88

(Kowsher et al., 2021), studied computerized decision-making method for determining the best mode of childbirth. They used a dataset that contained the medical records of 13527 women and 21 features (age, address, admission time and time, ANC number of shrouds, para, the reason of confirmation, amid pregnancy, cesarean, breech conveyance, partograph, blood circulation, AMTSL, birth weight, postnatal administrations and the status of the patient), postnatal delivery administrations, BP, introduction, layer and cervix). They developed quadratic discriminant analysis, which yielded the highest accuracy of 0.98 with an F1 score of 0.98. The use of this model to determine the best labor mode may significantly reduce maternal and infant health risks.

Table 2. 3 Review of related work

Author (Year)	Objectives	Methods	Key Finding
(Pereira et al., 2015)	predicting type of delivery by identification of obstetric risk factors through data mining	SVM NB DT GLM	The result shows that the prediction based on DT and GLM indicate better accuracy
(Abbas et al., 2018)	cause analysis of caesarian sections and application of machine learning methods for classification of birth data	Adaboost LDA KNN RF SVM NB NNET	The result shows that the prediction based on RF indicates better accuracy
(Hasan et al., 2019)	Identifying associated factors and their individual contributions to caesarean delivery	logistic regression	The result shows important predictors of CS delivery
(Islam et al., 2021)	exploring machine learning algorithms for predicting the mode of childbirth.	stacking	The result shows that the prediction model based on stacking indicates better accuracy.

Research Gap

From the review of literature article, it is observed that number of data set is small. As shown in table 2.4 below (Pereira et al., 2015), they used data set contained 4326. (Islam et al., 2021), they used data set contained,6157. (Hasan et al., 2019), they used data set contained 4422. Kowsher et al., 2021), they used data set contained 13527. Abbas et al., 2018), they used data set contained 488. Most of research were conducted by using traditional machine learning algorithm.

Table 2. 4 Findings from literature review

Reference	**Objectives of the Study**	**Total no of Features**	**Total no of dataset**	**Example features**
(Pereira et al., 2015)	To develop real-time Data Mining (DM) classification models that could predict the type of delivery	26	4236	weight, height, body mass index, blood pressure, number of gestational weeks, marital status, blood type, fetal weight, dilatation, consistency, extinction, position, Bishop score
(Islam et al., 2021)	to explore machine learning algorithms and by considering the possible features for predicting the mode of childbirth	32	6157	previous preterm pregnancies, amniocentesis, pre-induction, induction, episiotomy, oxytocin, fetal intrapartum pH, Parity
(Abbas et al., 2018)	to identify the factors that contributed to increased C-section rates	26	488	age, blood pressures, hemoglobin, mode of last delivery, miscarriages, abortions, hypertension, folic acid, diabetes
(Hasan et al., 2019)	to identify contributing factors for caesarean deliveries among married women	Not sated	4422	Not all of the features were explicitly stated
(Kowsher et al., 2021)	to develop computerized decision-making method for determining the best mode of childbirth.	21	13,527	age, address, admission time and time, ANC number of shrouds, para, the reason of confirmation, amid pregnancy, cesarean, breech
(Tenaw et al., 2019)	to identify maternal preferences, delivery methods, and related characteristics	Not sated	300	Not all of the features were explicitly stated

CHAPTER THREE

3. RESEARCH METHODOLOGY

Description of the Study Area

Once the research problem is identified it requires a proper research design and method in order to tackle the problem and reach at a justifying result. As per the research question documented in chapter one, the method followed here is experimentation on data collected from one public hospital located at Hawassa city.

The data source is from dare General Hospital, Hawassa, Ethiopia. The current practice in Adare General Hospital for predicting the mode of delivery is generally the opinion of the physician in charge, but choosing the incorrect method of delivery can result in a variety of short- and long-term health issues for both mother and baby**.** The research problem is finding safe mode of childbirth delivery (cesarean or normal) to minimize maternal mortality rate, child mortality rate and health complication on mother and child during delivery.

The first phase was to explore and prioritize the features necessary for predicting modes of delivery. This phase has been done by experimental research method The results were experimented and analyzed to identify all possible features for predicting safe modes of childbirth. The second phase involved the development of machine learning models using a stack ensemble learning classifier to effectively predict safe mode of delivery using the fewest features possible. The stack ensemble learning classifier model was developed by using five supervised learning algorithms: Decision tree (DT), k-nearest neighbors (KNN), random forest (RF), support vector machine (SVM) and Naive Bayes (NB).

The researcher chose the five algorithms because of the data set is based on classification and regression. As a result, the chosen algorithms had been used for classification and regression and well-known supervised learning algorithm.

The reason stack ensemble learning classifier selected by the researcher is as follows:

- Stack ensemble learning algorithm combines multiple machine learning algorithms through meta learning.
- It has higher predictive accuracy compared to individual's model.
- It is very useful when there is both linear and non-linear type of data in data set.
- It decreases bias, noise and more stable.
- The model is not underfitted or overfitted(Russell, 2018)

Sampling Design

Sample size determination

To develop efficient prediction models, a data set consisting of diverse sets of features relating to pregnant women is used. The data obtained from Adare General Hospital contain 7020 birth records, which occurred in year 2020 and 2021.

Data Analysis Techniques

Data collection

The data used for this work was collected from Gynecology and Obstetrics department in Adare Hospital Hawassa. Gynecology and Obstetrics department in Adare Hospital Hawassa. The data obtained from Adare General Hospital contain 7,020 birth records, which occurred in 2020 and 2021. The dataset had 19 attributes as listed in table 3.1

Table 3. 1 Attributes with description

Attributes	**Types**	**Description**
Age	Numeric	Age of the Pregnant women
Surgical history	Categorical	Previous surgical history
APH	Numeric	Antepartum hemorrhage bleeding occurring before delivery.
GA	Numeric	Gestational age the length of pregnancy
B/P	Numeric	Diastolic pressure of Pregnant women
Lie	Categorical	Fetal lie
FHB	Numeric	Fetal heart beat
Presentation	Categorical	Presentation of the fetus
Position	Categorical	Position of the fetus
Membrane	Categorical	A sac that surrounds the fetus in uterus(womb)
No of Px	Categorical	Number of pregnancies
Amniotic Fluid	Categorical	The liquid that surrounds the fetus
Placenta	Categorical	Temporarily organ forms in the uterus
Placental calcification	Categorical	Aging of the placenta
BPP	Categorical	Biophysical profile
Weight	Numeric	Weight of the fetus
Cervix dilatation	Numeric	the cervix opens (dilates) and thins out (effaces) to allow the baby to move into the birth canal
Contraction	Numeric	uterine contraction
Mode of delivery	Categorical	In which baby is delivered from mother womb (Normal delivery or CS)

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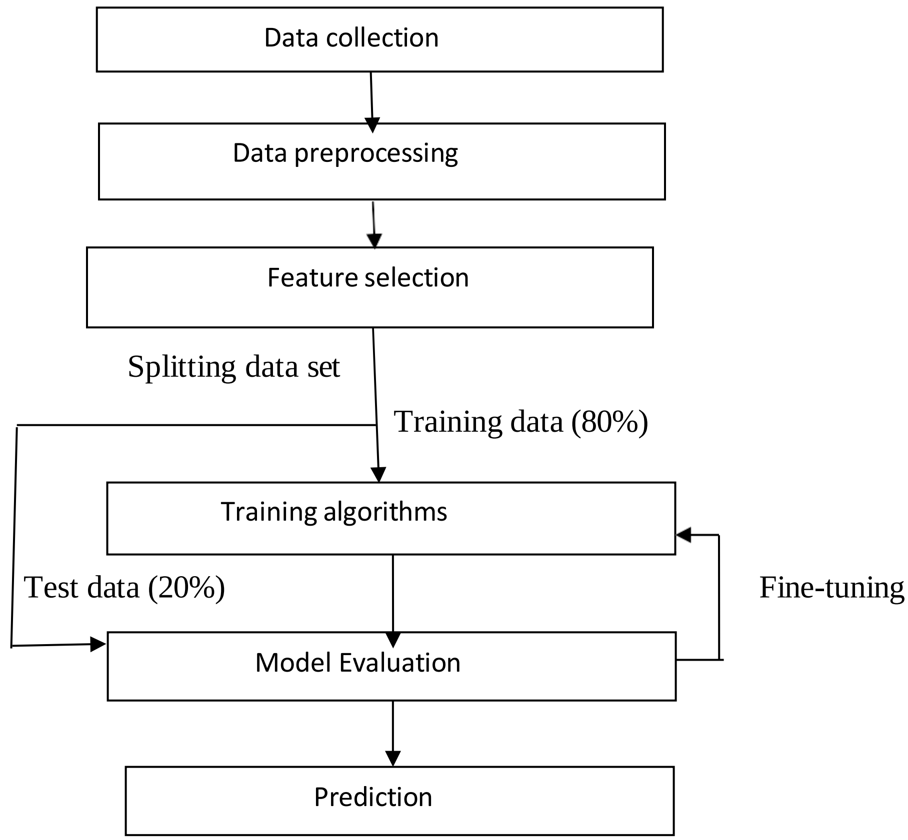

Figure 3. 1 Conceptual framework

Data preparation

Data preparation is the process of constructing a dataset from one or more data sources for use in exploration and modeling. Starting with an initial dataset allows you to become acquainted with the data, gain early insights into it, and gain a good understanding of any potential data quality issues. In the data preparation stage, the researcher use Microsoft excel and by WEKA preprocessor module

Attribute selection

The process of creating a dataset from one or more data sources for use in exploration and modeling is known as data preparation. Starting with a small dataset allows you to become familiar with the data, gain early insights into it, and gain a good understanding of any potential data quality issues. If information is irrelevant or redundant, feature selection might help or the data is noisy and unreliable. The process of identifying and removing as much irrelevant and redundant information as possible is known as attribute selection. In this research the attributes are selected with the help of domain expert and by using Weka tool.

A model takes longer to develop when all the variables are taken into account, and models that contain unnecessary columns may be inaccurate. Thus, it is necessary to ignore those attributes that are not important for analysis with the help of domain experts and weka tool in order to simplify the task of modeling.The following attributes are selected from adare general hospital database: Age, Surgical history, APH, GA, B/P, Lie, Presentation, Membrane, Position, Contraction, Cervix dilation, No of Px, Amniotic Fluid, Placenta, Placental calcification, Weight, BPP and Mode of delivery.

Data cleaning

The results of a data mining analysis are in doubt without clean data. Data cleaning routines "clean" the data by completing missing values, smoothing noisy data, identifying and removing outliers, and resolving inconsistencies. At this stage, the researcher, filled the missing value by using the mean of the numerical distribution using the ReplaceWithMissingValues filter in Weka.

Data transformation

Steps data transformation include the following:

- Smoothing: This removes noise from the data. Binning, regression, and clustering are examples of techniques.
- Attribute construction, the process of creating and adding new attributes from a given set of attributes to aid in the mining process.
- Aggregation, s the application of summary or aggregation operations to data. For example, daily sales data can be aggregated to calculate monthly and annual totals. This step is commonly used when building a data cube for data analysis at various abstraction levels
- Normalization, where the attribute data are scaled so as to fall within a smaller range, such as -1.0 to 1.0, or 0.0 to 1.0.
- Discretization is the process by which the raw values of a numeric attribute (for example, age) are replaced by interval labels.
- Concept hierarchy creation for nominal data, allowing attributes like street to be generalized to ideas at a higher level like city or country. The database schema has several implicit hierarchies for nominal characteristics that can be automatically defined at the level of the schema definition.(Russell, 2018).

To make the analytic process reasonable and affordable, the data must be reduced. One method for reducing the number of values for a particular continuous attribute is to discretize the data, which involves breaking the attribute's range into intervals. Then, actual data values, data cube aggregation, dimension reduction (redundant or irrelevant features are deleted), data compression (data is encoded to minimize size), and numerously reduction (models or samples are used instead of the actual data) can be used to substitute interval labels.

The following data transformation operation has been employed:

- **Defining the class attributes**: The class attribute is mode of delivery. The class attributes are Normal delivery and CS. This attribute is dependent variables that can help to classify the individual into groups. This classification would help to predict the likelihood that a given class is fallen at what condition with related to the independent variables.
- **Defining the Surgical history**: The derived attribute is an independent variable that can classify into two groups. This classification can help to identify in which groups the dependent variable are affected/changes its condition. These independent variables categorized into two groups Yes and No.
- **Defining the lie**: This independent variable also categorized into three different groups. These are Longitudinal, Oblique and Transverse.
- **Defining the Presentation**: This is an independent variable that can classify into two groups. These are Cephalic and Breach.
- **Defining the Position**: This is an independent variable that can classify into four groups. These are OA (Occiput Anterior), PA (Posterior Anterior), Face and Brow.
- **Defining the Amniotic Fluid**: This is an independent variable that can classify into two groups. These are Adequate and Severe.
- **Defining the placenta**: This is an independent variable that can classify into three groups. These are Fundal, Placenta previa and Low lying.
- **Defining the Amniotic BPP**: This is an independent variable that can classify into two groups. These are Reassuring and Non-reassuring.

Data Preparation for Weka Tools

WEKA was developed at the University of Waikato in New Zealand, and the name stands for Waikato Environment for Knowledge Analysis. It runs on almost any platform and has been tested under Linux, Windows, and Macintosh operating systems and even on a personal digital assistant. It provides a uniform interface to many different learning algorithms, along with methods for pre- and post-processing and for evaluating the result of learning schemes on any given dataset(Kubat, 2017). WEKA is a collection of machine learning algorithms for solving real-world data mining problems. A number of data mining methods were implemented and experimented in the WEKA software.

The researcher first has converted the original Microsoft Excel into Comma Separated Value (CSV). Then preprocessing activities are performed and the file is saved into WEKA acceptable comma separated values (CSV) or comma delimited file format. WEKA native data format is known as the ARFF (Attribute Relation File Format). It is basically a CSV (comma separated value) format with some extra headers to specify what type each attribute is (numerical, binary, nominal). The CSV file format is converted into ARFF by using WEKA mining software, to take advantage of easier data manipulation and also compatible interaction with WEKA software.

3.3.7 Model building

Data modeling refers to a group of processes in which multiple sets of data are combined and analyzed to uncover relationships or patterns. The goal of data modeling is to use past data to inform future efforts.

a). Selecting modeling techniques

The first step in model building is selecting the actual modeling techniques that are to be used. The purpose of this research is to develop a predictive model for childbirth classification algorithms has been used for building the model. The analyses were performed by WEKA 3.9.6 software. More than 41 categorization algorithms have been incorporated into WEKA's software. Rule-based classification and Decision tree induction are two different types of classification algorithms. A rule-based classifier classifies data using a collection of IF-THEN rules. Decision trees allow for the extraction of rules. Using sequential covering algorithms, rules can also be produced directly from training data. (Hartshorn, 2016).

The researcher mainly focuses on the classification algorithm J48, Classification is the process of building a model of class from a set of records that contains class labels. The system had to find the rules that predict the class-label, which is the predicted attribute's value, from the predicting attribute's value when learning classification rules. Furthermore, based on the training instances, classes for newly generated instances are discovered(Golden, 2020). J48 is a WEKA data mining tool's open-source java implementation of the C4.5 algorithm. C4.5 is a program that generates a decision tree from labeled input data. The WEKA tool provides a number of options associated with tree pruning. In case of potential over fitting pruning can be used as a tool for précising. In other algorithms the classification is performed recursively till every single node/leaf is pure, that is the classification of the data should be as perfect as possible. This algorithm generates the rules from which particular identity of that data is generated(Panesar, 2019).

b). Generate test design

The most important aspect of model building is that it is an iterative process. To ensure the most accurate and robust predictions, the process of building predictive models necessitates a well-defined training and validation protocol. This type of protocol is also known as supervised learning. The basic idea behind supervised learning is to train your model on a subset of the data, then test and validate it on the remaining data. A model is built when the cycle of training and testing is completed. In this phase, the researcher uses both testing methods i.e., percentage split and 10-fold cross validation, with percentage split the dataset divided into two groups; these are one for model training and one for model testing(Panesar, 2019). By default, in WEKA, 66 percent of the data set's instances are utilized for the training set while the remaining portion is used for the test set. Cross-validation is particularly useful when there is a dearth of data. Cross-validation repeats the training and testing procedure numerous times with various random samples rather than keeping a portion for testing. The 10-fold cross-validation method divides the data at random into 10 parts, with the classes represented in roughly the same proportions as in the full dataset (stratification). The algorithm is trained on the nine remaining parts while holding out each part in turn, and its error rate is then determined using the holdout set. Finally, an overall error estimate is produced by averaging the 10 error estimates. Therefore, the model is built on the training data and its quality estimated on the test set.

Machine Learning Performance Matrix

Confusion matrix

It is a table with two dimensions (Actual and Predicted), and sets of classes in both dimensions. Actual classifications are columns and Predicted ones are Rows as shown table 6

Table 3. 2 Confusion Matrix

		Predicted	
		Negatives (0)	Positives (1)
Actual	Negatives (0)	True negative	False positive
	Positives (1)	False negative	True positive

The Confusion matrix in itself is not a performance measure as such, but almost all of the performance metrics are based on Confusion Matrix and the numbers inside it.

Terms associated with confusion matrix

True Positive (TP)

TP is the cases when the actual class of the data point was 1(True) and the predicted is also 1(True).

True Negative (TN)

TN is the cases when the actual class of the data point was 0(False) and the predicted is also 0(False)

False Positive (FP)

FP is the cases when the actual class of the data point was 0(False) and the predicted is 1(True). False is because the model has predicted incorrectly and positive because the class predicted was a positive one (1).

False Negative (FN)

FN is the cases when the actual class of the data point was 1(True) and the predicted is 0(False). False is because the model has predicted incorrectly and negative because the class predicted was a negative one (0).

Accuracy

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made.

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

Precision

Precision can be defined as the number of correct positive predictions divided by the sum of correct positive predictions and incorrect negative predictions.

Precision=$\frac{TP}{TP+FP}$

Recall or Sensitivity

Recall can be defined as the number of correct positive predictions divided by the sum of correct positive predictions and incorrect positive predictions. It is also called a true positive rate.

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

Specificity

Specificity can be defined as the number of correct negative predictions divided by the sum of correct negative predictions and incorrect negative predictions. It is also called a true negative rate.

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

F1 score

F1 score uses both precision and recall values. It is the harmonic mean of Precision and recall score.

F1 Score= $2 * (\frac{precision * recall}{precision+recall})$

The roc (receiver operating characteristics) curve

The ROC curve is a metric that is used to depict the performance of a binary classification problem. The ROC curve is a probability curve. It is a plot of False positive rate vs True positive rate. The AUC score is the area under the ROC curve. The higher the AUC score better the performance of the classifier(Kubat, 2017).

Dataset

The researcher dataset contains medical information of 7020 pregnant women birth records, which is recorded in year 2020 and 2021 at Adare hospital located in Hawassa, Ethiopia

Pre-processing

Data preprocessing is a very significant step in developing machine learning algorithm.

Missing Value Check: missing values occur when no data value is stored for the variable in an observation. Missing values reduces the accuracy of parameter calculation as well as the accuracy of features. A lot of researchers are using prediction, mean, median, mode method to replace a missing value. But the most promising way of replacing a missing value is the mean imputation method. The researcher carefully inspected for missing values and filled those fields with the mean value of the most similar population. The mean value will be calculated by using the following equation

$$\bar{x} = \frac{1}{n} \Sigma x_k$$

Where, x^{-} denotes the mean and provides the average number of n.

Features Selection: Feature selection includes the identification of features and reduction of the features having no significance or having very small significance on the objective function and high impact features are maintained. The researcher, selected features by using Weka attribute selection module.

Training Selective Algorithms

To compute the safe mode of childbirth delivery, the researcher implemented six machine learning classifiers such as Decision tree (DT), k-nearest neighbors (KNN), random forest (RF), support vector machine (SVM) and Naive Bayes (NB) and stack ensemble learning classifier.

The Decision Tree generates a predictive model by putting logic in the form of a tree structure to interpret the features. Nodes are classified into three types: root nodes, decision nodes, and leaf nodes. The top node is the root node, and decision nodes are made up of decision rules to generate outputs. The leaf nodes are chosen after all decisions have been made(Kowsher et al., 2020).

The Support Vector Machine is useful for both classification and regression problems. SVM separates each data element in the n-dimensional feature space. SVM then constructs a hyperplane that divides elements into their respective classes(Tohka & van Gils, 2021).

The K-Nearest Neighbors algorithm is non-parametric because it makes no explicit assumptions regarding the distribution of the data. In this case, input labeled data serve as a training example. K-NN classifies each object in the output based on the majority poll of its neighbors.(Kowsher et al., 2021).

The Bayes theorem, which naively asserts conditional independence between each pair of features given the value of the class variable, is where the Naive Bayes classifier derives its name. The Naive Bayes technique makes the assumption that the presence or absence of one attribute in a set is independent of the presence or absence of other characteristics in the same set(Bin Alam et al., 2021).

The RF ensemble learning approach builds a large number of decision trees during training period and outputs the class that represents the mean of the classes (for classification) or mean prediction (for regression) of the individual trees(Kowsher et al., 2021).

he best predictions from several classifiers are combined in stacking, an ensemble learning technique, to create a new training set for a meta-classifier. The meta-classifier is fitted based on the results of individual classification models, and the individual base classifiers are trained using the entire training set.(Islam et al., 2021).

CHAPTER FOUR

3. EXPERIMENTS AND RESULTS

This chapter mainly discusses the models to be built and experiments carried out together with their analysis. The experiments were run on a larger dataset in order to address the main objectives of the research study with respect to nineteen attributes. In this study an attempt was made to design a model that enables to predict safe mode of childbirth in Adare General Hospital Hawassa. J48 decision tree, k-nearest neighbors, random forest, support vector machine, Naive Bayes and stack classifier are the algorithms with which predictive model building experiments are conducted. These algorithms split the dataset to learn a model and test its performance on a dataset prepared for a study. In 10-fold cross validation, one option in WEKA for the purpose mentioned; the dataset is split into 10 equal parts. The algorithm is trained on nine–tenth of the dataset and then the classifier is tested on one-tenth. This way, the error of the resultant model will be the average of all the models found during each fold or iteration. For creating predictive model, a total size of 7020 records were used for training and testing. The validations were done using 10-fold cross validation and percentage (%) split test option.

Model Building Using J48 Decision Tree

A decision tree is a predictive machine-learning model that determines the target value (dependent variable) of a new sample based on the available data's attribute values. The internal nodes of a decision tree represent the various attributes; the branches between the nodes indicate the possible values that these attributes can have in the observed samples, and the terminal nodes indicate the dependent variable's final value (classification). A decision tree is a classifier that can be fed previously unobserved records. It will be sent either left or right at each node based on a test. It is possible to generate interesting rules using the decision tree classifier results. In fact, in addition to classification and prediction, decision tree methods are frequently chosen for their ability to generate understandable rules(Hartshorn, 2016). The researcher employs J48 for applying decision tree classification model. There are three experiments that are experimented for decision tree classification in this research. These experiments are analyzed to compare them to each other in terms of different performance matrices values, accuracies, number of leaves, and size of tree generated, ROC curves and execution time. The experiments for decision tree classification that are experimented in this research are as listed below.

Experiment 1: J48 decision tree algorithm with pruned, confidence factor 0.25, default Minimum number of instance (minNumObj) for a leaf of 35 and 66% split test mode. **Experiment 2:** J48 decision tree algorithm with pruned, confidence factor 0.25, default Minimum number of instance (minNumObj) for a leaf of 35 and 80% split test mode. **Experiment 3**: J48 decision tree algorithm with pruned, confidence factor 0.25, default Minimum number of instance (minNumObj) for a leaf of 35 and 10-fold cross validation test mode.

ROC analysis and metrics such as precision, recall and F-measure have been used to understand the performance of the learning algorithm. These experiments were analyzed to compare them in terms of different performance matrices values, accuracies, size of trees, no. of leaves, time taken in sec. in the execution, and ROC. Accuracy is the percentage of predictions that are correct. The precision is the measure of accuracy provided that a specific class has been predicted. The sensitivity is the measure of the ability of a prediction model to select instances of a certain class from a data set. The specificity corresponds to the true negative rate which is commonly used in two class problems.

Table 4. 1 J48 decision tree parameter option of WEKA

S.NO	Performance Measure	1	2	3
1	Testing Mode	66%	80%	10 fold
2	Confidence factor	0.25	0.25	0.25
3	Uprunning	False	False	False
4	minNumObj	2	2	2
5	Size of Tree	52	52	52
6	No. of Leaves	35	35	35
7	Time taken to Build	0.09sec.	0.07sec.	0.08sec
8	Recall	0.98	0.99	0.98
9	Precision	0.98	0.99	0.98
10	F-Measure	0.98	0.99	0.98
11	ROC	0.99	0.99	0.98
12	Correctly Classified	2349	1386	6894
13	Incorrectly Classified	35	17	126
14	Mean Absolute Error	0.03	0.02	0.03
15	Accuracy	98.45%	98.79%	98.20%

As can be observed from this table 4.1, the model has accuracy of 98.45% using 66% split,98.79% using 80% and 98.2% accuracy using 10-fold cross validation test options.

Confusion Matrix for J48 Decision Tree Model

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. A confusion matrix provides a quick understanding of model accuracy and the types of errors the model makes when scoring records. It is the result of a test task for classification models. Moreover, the overall predictive accuracy on unseen instances it is often helpful to see a breakdown of the classifier's performance. The confusion matrix for J48 decision tree presented in table 4.1 depicts that out of the total records provided to the WEKA using 66% split, 2349 (98.45%) records were correctly classified and 35 (1.55%) were incorrectly classified. Using 80% split,1386 (98.79%) records were correctly classified and 17(1.21%) were incorrectly classified. Using 10-fold cross validation test options, 6894 (98.20%) records were correctly classified and 126 (1.80%) were incorrectly classified.

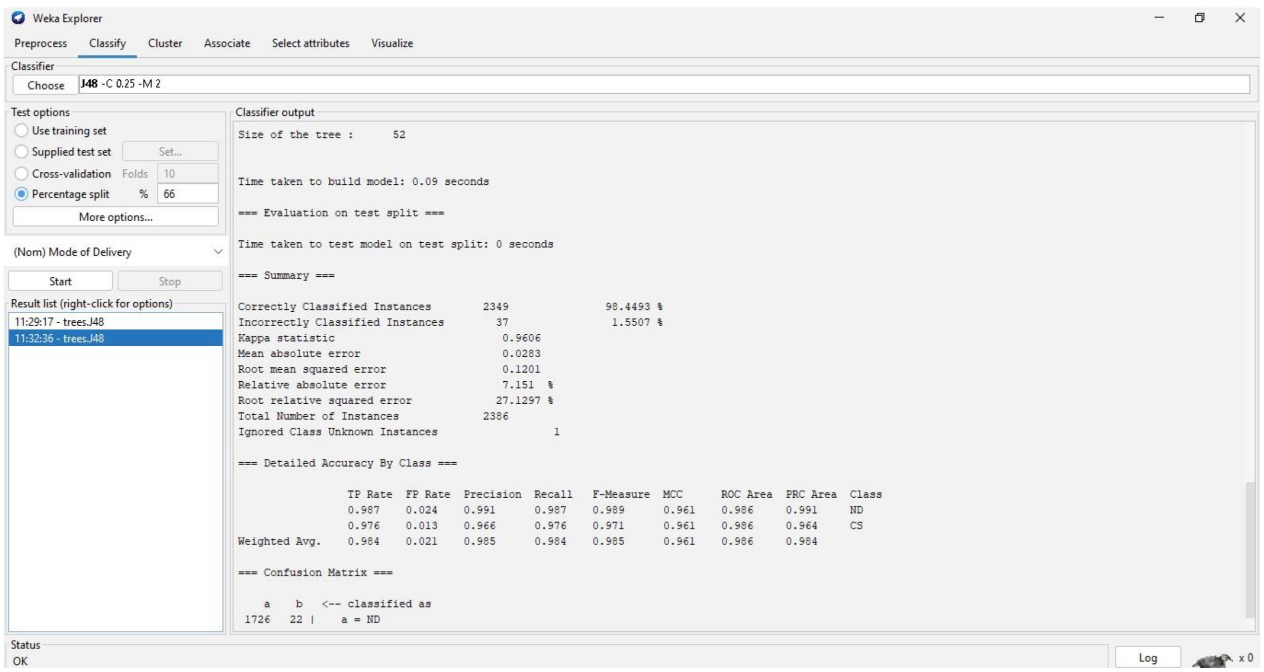

Figure 4. 1 Classifier output based on J48 Decision Tree using 66% split

=== Confusion Matrix ===

Table 4. 2 Confusion matrix of J48 Decision tree using 80% split

	Predicted class		
	a	b	<-- classified as
Actual class	1726	22	A = ND
	12	623	B = CS

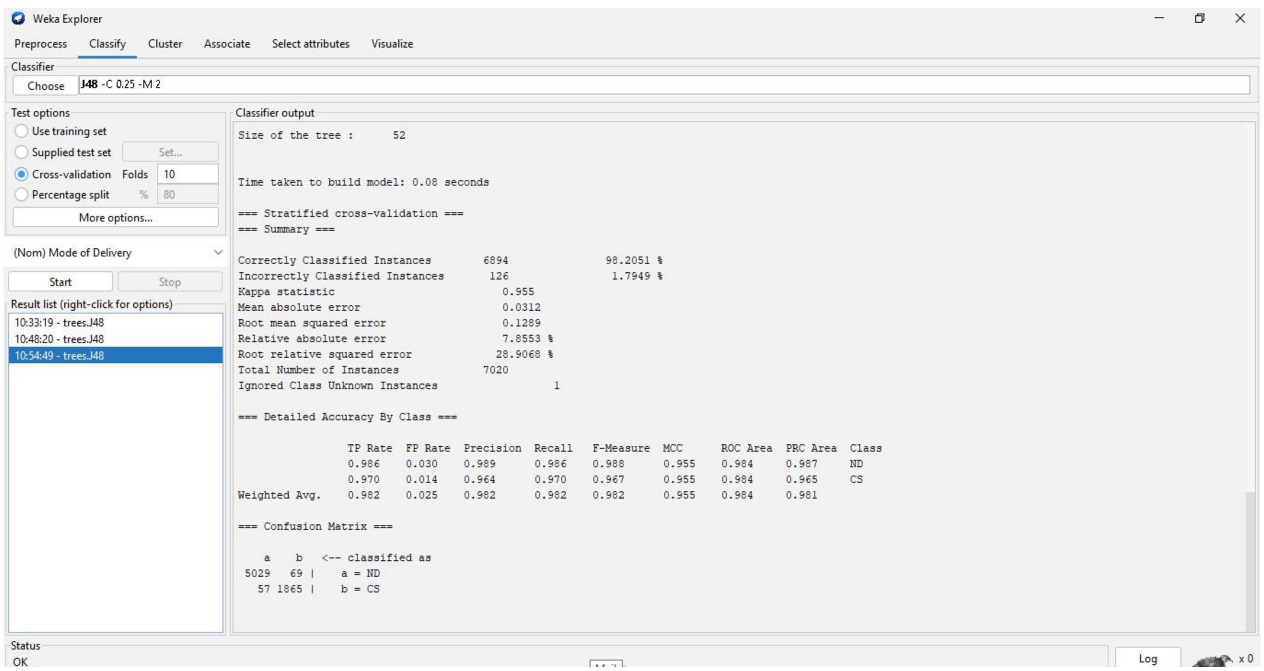

Figure 4. 2 Classifier output based on J48 Decision Tree using 10-fold cross validation test

=== Confusion Matrix ===

Table 4. 3 Confusion matrix of J48 Decision tree using 10-fold cross validation test

	Predicted class		
	a	b	<-- classified as
Actual class	5029	69	A = ND
	57	1865	B = CS

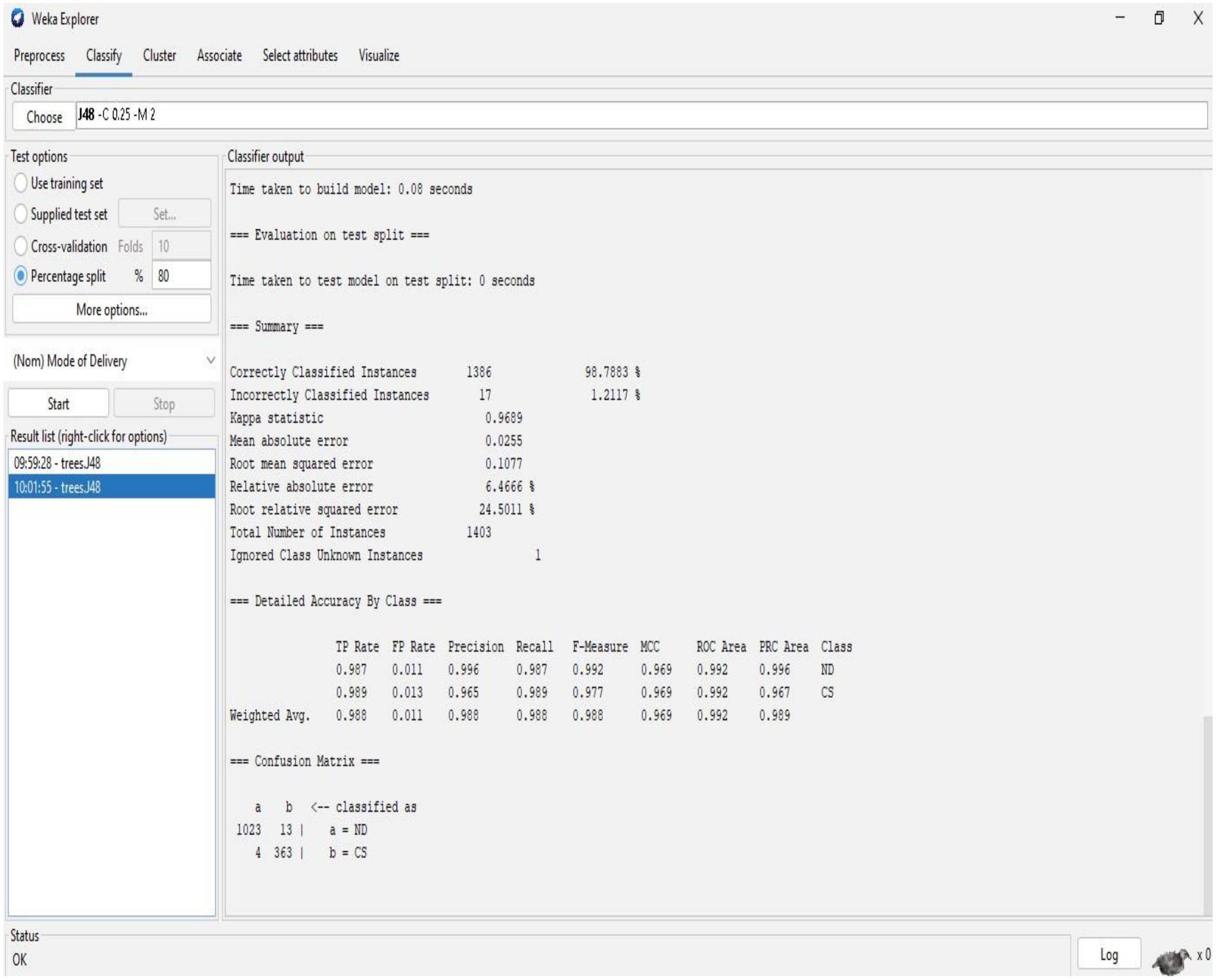

Figure 4. 3 Classifier output based on J48 Decision Tree using 80% split

=== Confusion Matrix ===

Table 4. 4 Confusion matrix of J48 Decision tree using 80% split

	Predicted class		
	a	b	<-- classified as
Actual class	1023	13	A = ND
	4	363	B = CS

Roc Analysis for J48 Decision Tree Model

The area under the ROC curve is measured by AUC (Area Under Curve). The ROC curve is a two-dimensional graph that is used to select potentially optimal models based on the TP and FP rates. It also represents a trade-off between benefits and costs (TP) (FP). The sensitivity (TP) rate is represented on the Y-axis of the ROC curve, and the 1-specificity (FP) rate is represented on the X-axis. Each prediction result or confusion matrix instance represents one point in the ROC space. A ROC graph should be noted at several points. The lower left point (0,0) indicates that the classifier labeled all instances that did not belong to their actual class. The case where all instances are classified in their actual class is represented by the upper right point (1, 1). The point (0, 1) denotes perfect classification, and the line y = x denotes the strategy of guessing the class at random. The fraction of the total area that falls under the ROC curve is used to evaluate a classifier's overall performance. AUC ranges from 0 to 1. Larger AUC values indicate better classifier performance in general. As can be seen from the detailed accuracy by mode of delivery output, the ROC (Receiver Operating Characteristics) area of this model is highest (0.992). The Area under the ROC curve in figure 5 is higher. Higher numbers here indicate the model is the more accurate.

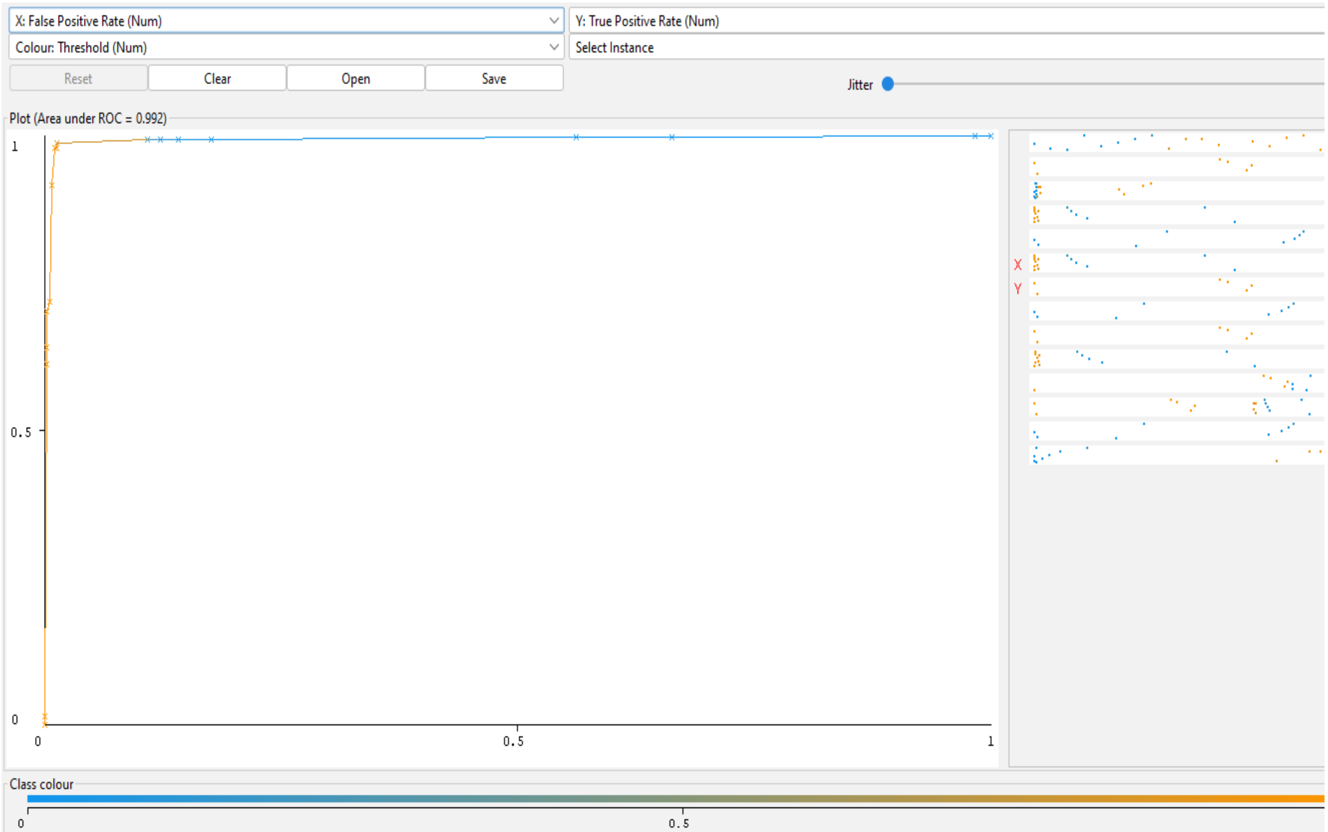

Figure 4. 4 ROC Area Curves of J48 Decision Tree

ROC curves, like lift charts, provide a means of comparing individual models and determining thresholds that yield a high proportion of positive hits. The horizontal axis of a ROC graph, as shown in the figure above, measures the false positive rate as a percentage. The true positive rate is depicted on the vertical axis. The top left-hand corner of a ROC curve is the optimal location, indicating a high TP (true-positive) rate versus a low FP (false-positive) rate.

Data Preparation

The data analysis and classification were carried out using WEKA Software application. The data set collected from Adare General Hospital consists of 7020 records of data. The researcher also considered the initial data set for this study. Performance algorithms is typically evaluated using predictive accuracy.

Model Building Using K-Nearest Neighbors

KNN is a non-parametric, lazy learning algorithm that uses a database in which the data points are separated into several classes to predict the classification of a new sample point(Islam et al., 2021). The findings observed using the KNN algorithm to build prediction models based on predefined classes of features are shown in Table 4.5.

Table 4. 5 KNN parameter option of WEKA

S.NO	**Performance Measure**	**1**	**2**	**3**
1	Testing Mode	66%	80%	10 fold
2	Confidence factor	0.25	0.25	0.25
3	Uprunning	False	False	False
4	minNumObj	2	2	2
7	Time taken to Build	0sec.	0sec.	0sec
8	Recall	0.97	0.98	0.97
9	Precision	0.97	0.98	0.98
10	F-Measure	0.97	0.98	0.97
11	ROC	0.96	0.97	0.96
12	Correctly Classified	2323	1370	6806
13	Incorrectly Classified	63	33	214
14	Mean Absolute Error	0.03	0.02	0.03
15	Accuracy	97.36%	97.65%	96.95%

As can be observed from this table 4.5 the model has accuracy of 97.36% using 66% split,97.64% using 80% and 96.5% accuracy using 10-fold cross validation test options.

Confusion Matrix for KNN

The confusion matrix for KNN presented in table 4.5 depicts that out of the total records provided to the WEKA using 66% split, 2323 (97.36%) records were correctly classified and 63 (2.64%) were incorrectly classified. Using 80% split,1370 (97.65%) records were correctly classified and 33 (3.35%) were incorrectly classified. Using 10-fold cross validation test options, 6806 (96.95%) records were correctly classified and 214 (3.05%) were incorrectly classified.

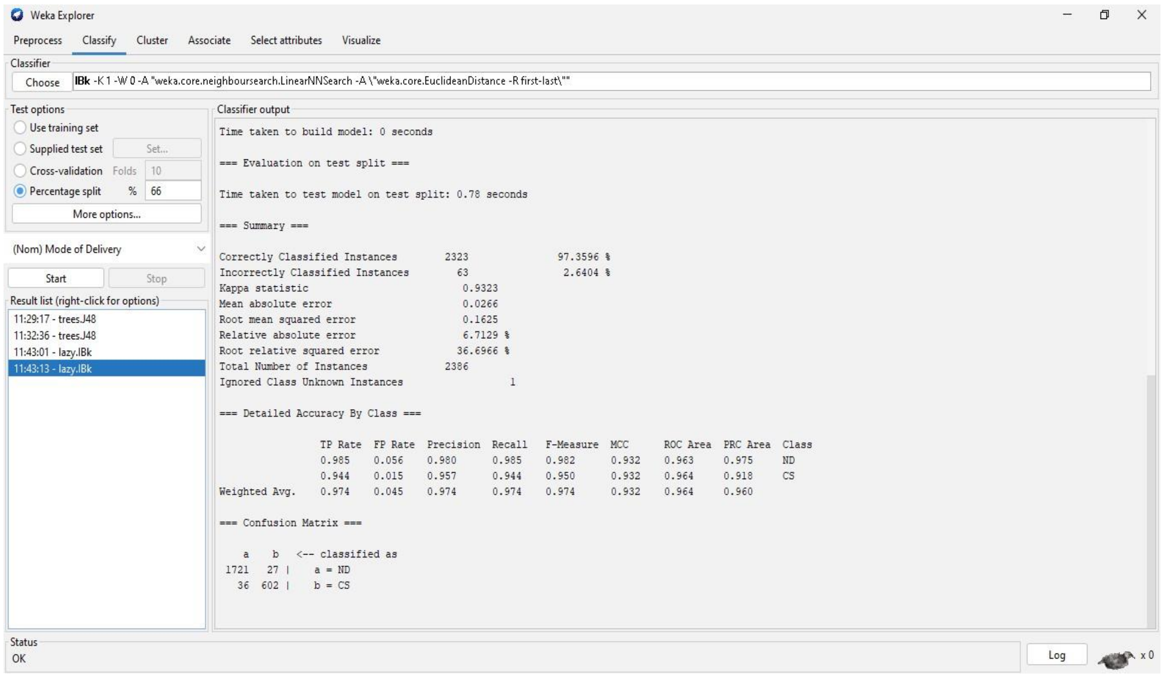

Figure 4. 5 Classifier output based on KNN using 66% split

=== Confusion Matrix ===

Table 4. 6 Confusion matrix of KNN using 66% split

	Predicted class		
	a	b	<-- classified as
Actual class	1721	27	A = ND
	36	602	B = CS

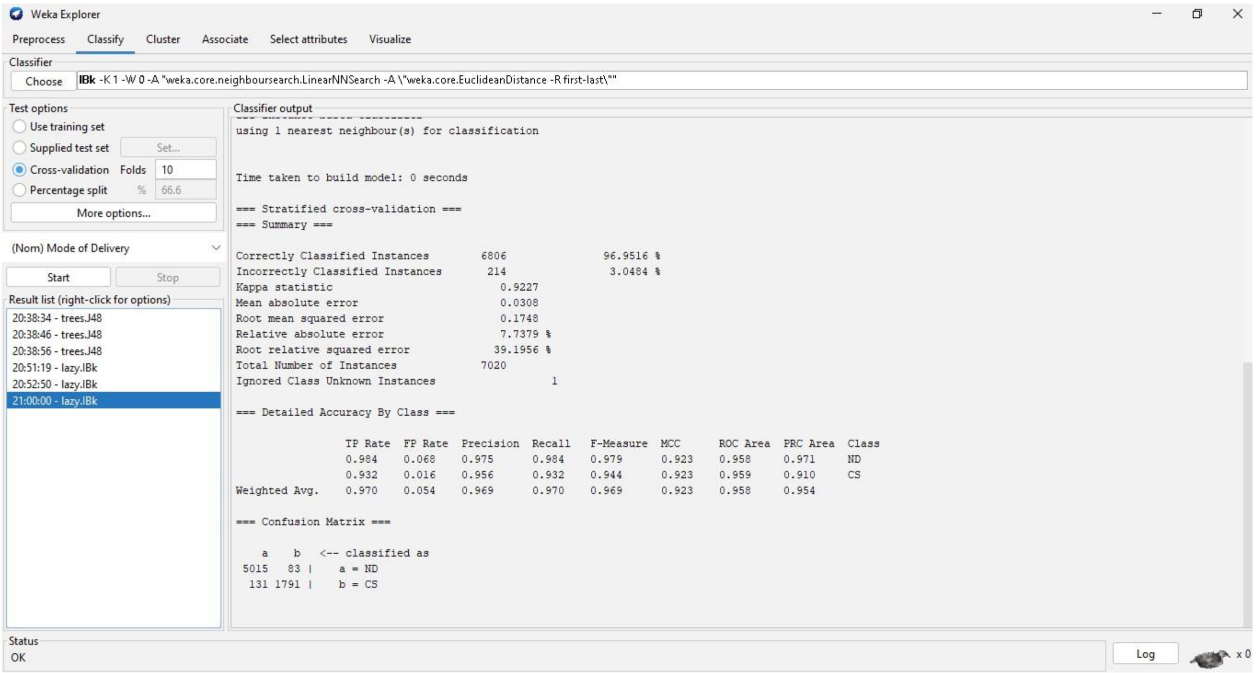

Figure 4. 6 Classifier output based on KNN using 10-fold cross validation test

=== Confusion Matrix ===

Table 4. 7 Confusion matrix of 10-fold cross validation test options

	Predicted class		
	a	b	<-- classified as
Actual class	5015	83	A = ND
	131	1791	B = CS

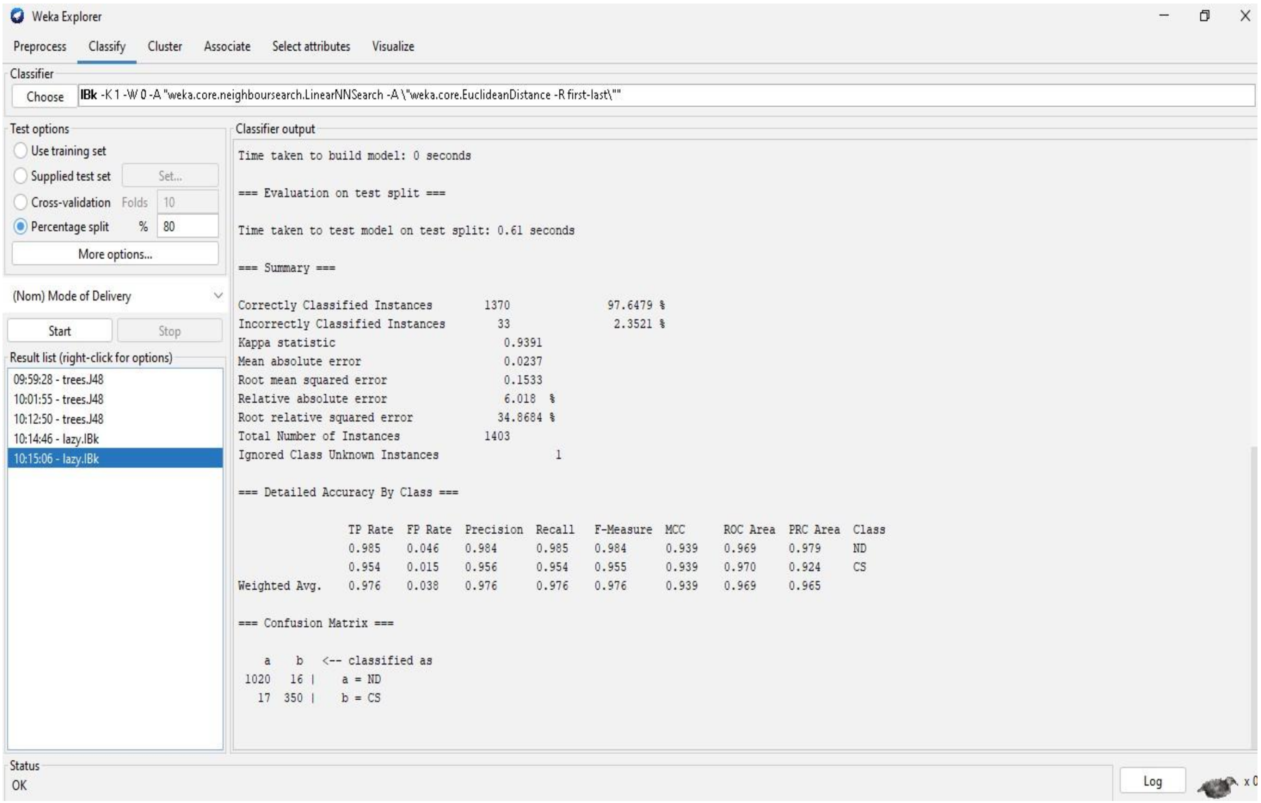

Figure 4. 7 Classifier output based on KNN using 80% split

=== Confusion Matrix ===

Table 4. 8 Confusion matrix of KNN 80% split

	Predicted class		
	a	b	<-- classified as
Actual class	1020	16	A = ND
	17	350	B = CS

Roc Analysis for KNN Model

As can be seen from the detailed accuracy by mode of delivery output, the ROC (Receiver Operating Characteristics) area of this model is 0.9686. The Area under the ROC curve in figure 9 is higher. Higher numbers here indicate the model is the more accurate.

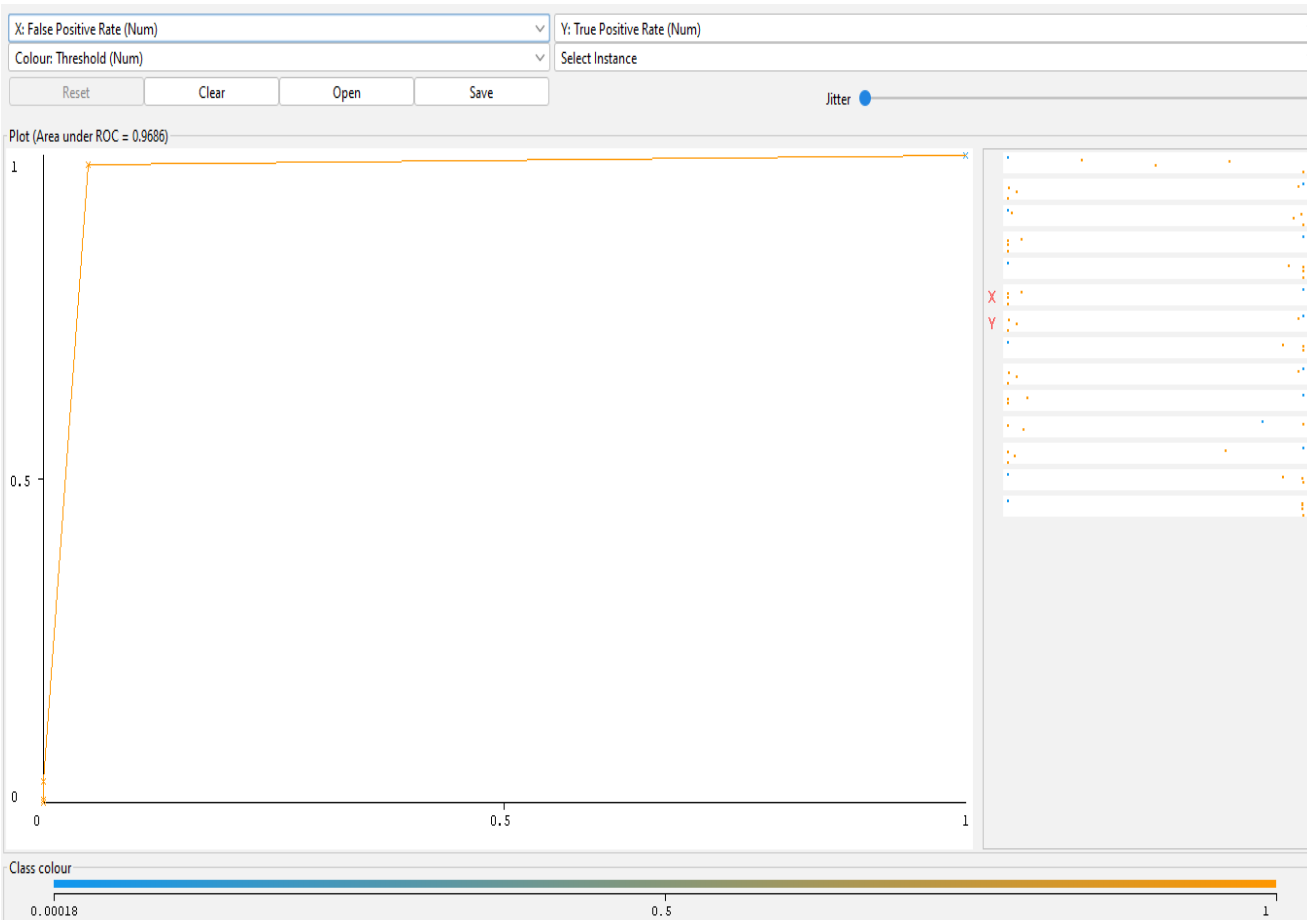

Figure 4. 8 ROC Area Curves of KNN

Model Building Using Random Forest

Random forest is an ensemble learning method for classification, regression, and other tasks that works by training a large number of decision trees and then outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees rate.(Hartshorn, 2016). The results obtained for Random Forest algorithm on predefined classes of features are shown Table 4.9

Table 4. 9 Random Forest parameter option of WEKA

S.NO	**Performance Measure**	**1**	**2**	**3**
1	Testing Mode	66%	80%	10 fold
2	Confidence factor	0.25	0.25	0.25
3	Uprunning	False	False	False
4	minNumObj	2	2	2
7	Time taken to Build	1.18sec.	1.16sec.	1.14sec
8	Recall	0.98	0.99	0.98
9	Precision	0.98	0.99	0.98
10	F-Measure	0.98	0.99	0.98
11	ROC	0.99	0.99	0.99
12	Correctly Classified	2347	1384	6884
13	Incorrectly Classified	39	19	136
14	Mean Absolute Error	0.03	0.03	0.03
15	Accuracy	98.36%	98.64%	98.06%

As can be observed from this Table 4.9, the model has accuracy of 98.34% using 66% split,98.64% using 80% and 98.06% accuracy using 10-fold cross validation test options.

Confusion Matrix for Random Forest

The confusion matrix for random forest presented in table 4.9 depicts that out of the total records provided to the WEKA using 66% split, 2347 (98.36%) records were correctly classified and 39 (1.66%) were incorrectly classified. Using 80% split,1384 (98.64%) records were correctly classified and 19 (1.36%) were incorrectly classified. Using 10-fold cross validation test options, 6884 (98.06%) records were correctly classified and 136 (1.94%) were incorrectly classified.

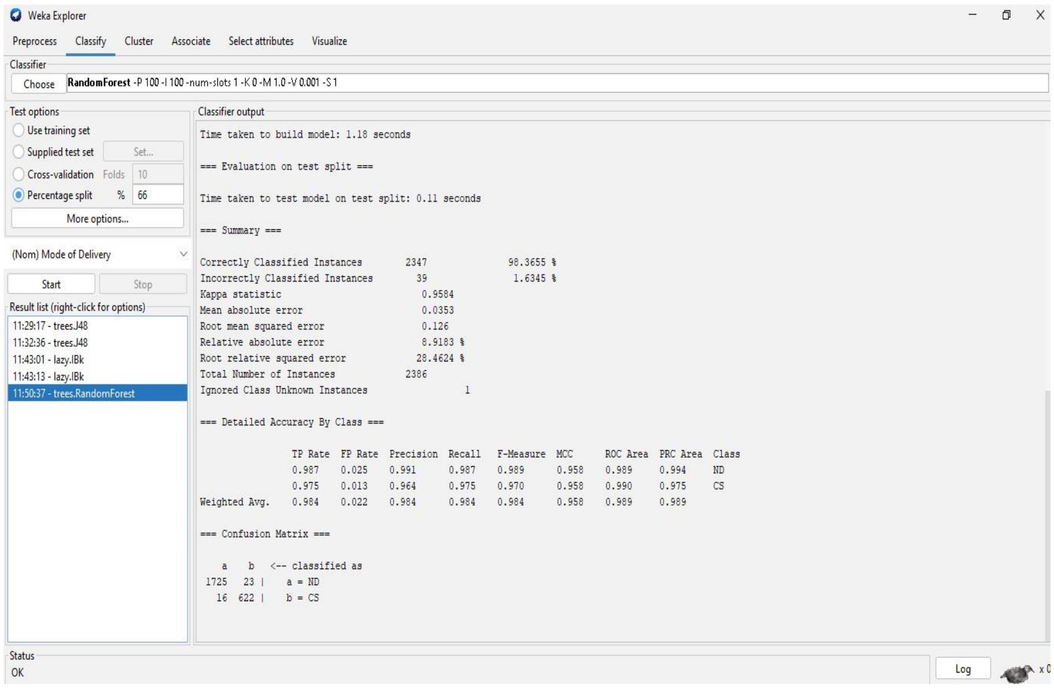

Figure 4. 9 Classifier output based on KNN using 66% split

=== Confusion Matrix ===

Table 4. 10 Confusion matrix of KNN 66% split

	Predicted class		
	a	b	<-- classified as
Actual class	1725	23	A = ND
	16	622	B = CS

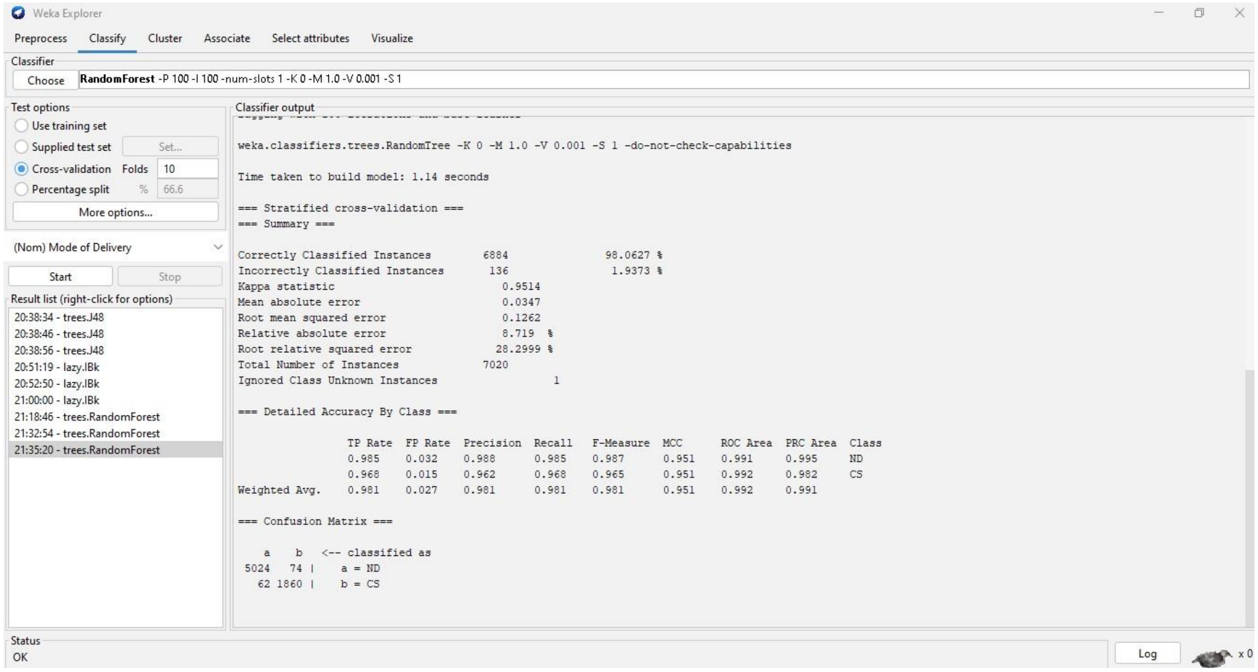

Figure 4. 10 Classifier output based on KNN using 10-fold cross validation test

=== Confusion Matrix ===

Table 4. 11 Confusion matrix of KNN using 10-fold cross validation test options

	Predicted class		
	a	b	<-- classified as
Actual class	1698	23	A = ND
	16	607	B = CS

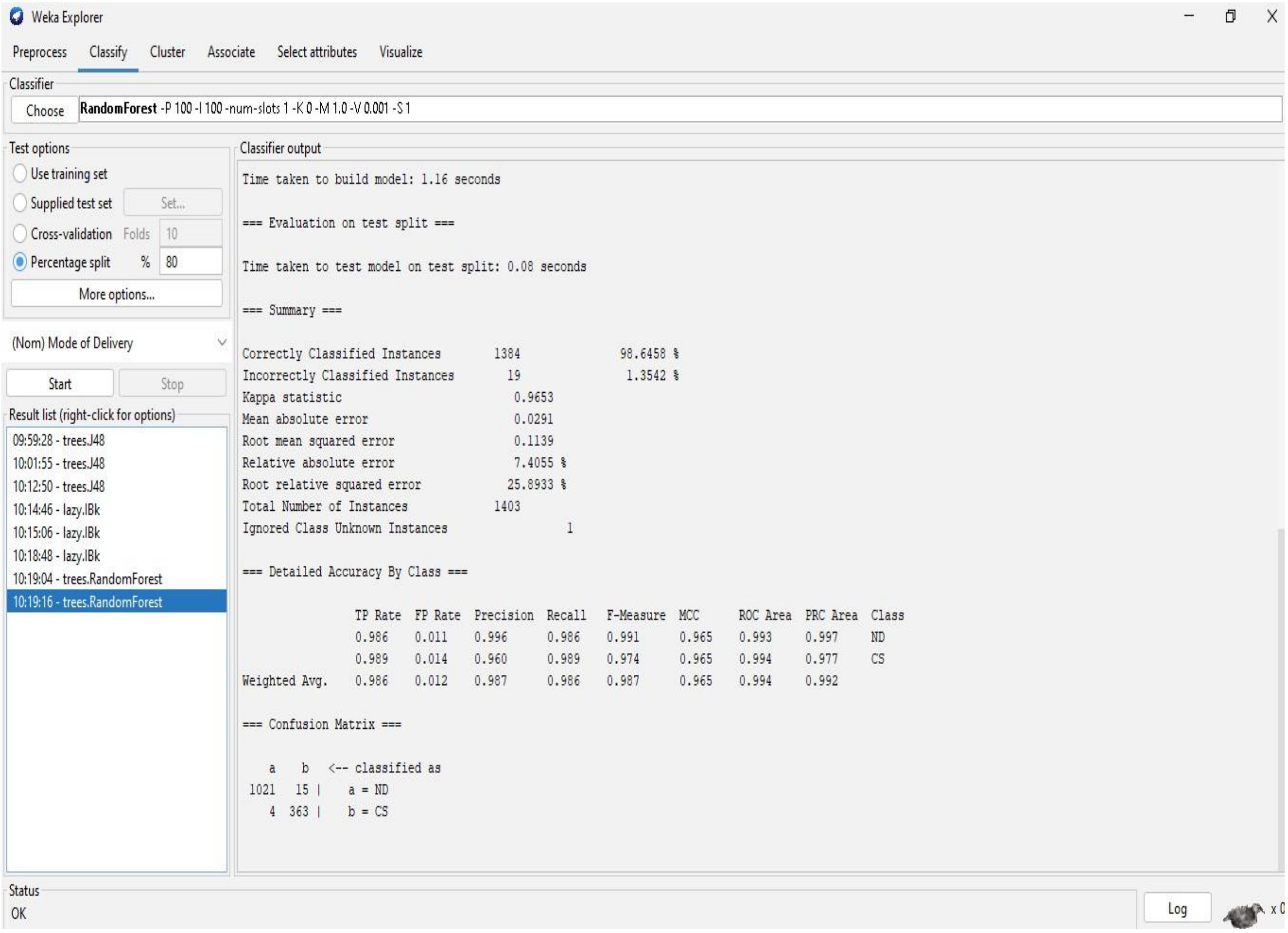

Figure 4. 11 Classifier output based on random forest using 80% split

=== Confusion Matrix ===

Table 4. 12 Confusion matrix of random forest using 80% split

	Predicted class		
	a	b	<-- classified as
Actual class	1021	15	A = ND
	4	363	B = CS

Roc Analysis for Random Forest

As can be seen from the detailed accuracy by mode of delivery output, the ROC (Receiver Operating Characteristics) area of this model is 0.9935. The Area under the ROC curve in figure 13 is higher. Higher numbers here indicate the model is the more accurate.

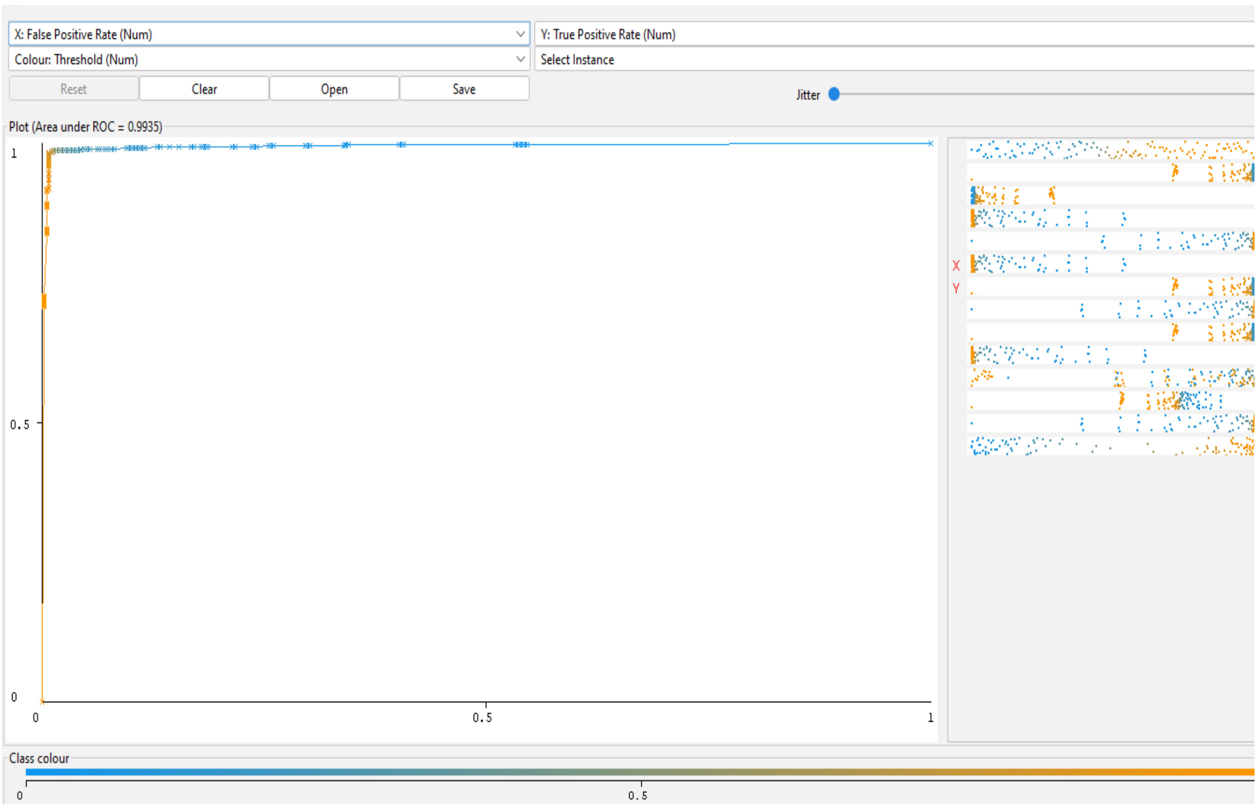

Figure 4. 12 ROC Area Curves of Random Forest

Model Building Using Support Vector Machine

In order to map data to higher dimensional feature spaces, SVM employs a technique known as kernelling. The kernel trick is used to map data in successively more dimensions until a hyperplane can be created to categorize it. SVM can create a hyperplane to categorize the data and uses the kernel approach to map the data into three dimensions.(Panesar, 2019). The results obtained for SVM algorithm on predefined classes of features are shown Table 4.13.

Table 4. 13 SVM parameter option of WEKA

S.NO	**Performance Measure**	**1**	**2**	**3**
1	Testing Mode	66%	80%	10 fold
2	Confidence factor	0.25	0.25	0.25
3	Uprunning	False	False	False
4	minNumObj	2	2	2
7	Time taken to Build	2.93sec.	2.69sec.	2.99sec
8	Recall	0.98	0.99	0.98
9	Precision	0.98	0.99	0.98
10	F-Measure	0.98	0.98	0.98
11	ROC	0.98	0.99	0.98
12	Correctly Classified	2349	1386	6895
13	Incorrectly Classified	37	17	125
14	Mean Absolute Error	0.01	0.01	0.02
15	Accuracy	98.45%	98.79%	98.23%

As can be observed from this table 4.13, the model has accuracy of 98.45% using 66% split,98.79% using 80% and 98.23% accuracy using 10-fold cross validation test options.

The confusion matrix for support vector machine

The confusion matrix for support vector machine presented in table 4.13 depicts that out of the total records provided to the WEKA using 66% split, 2349 (98.45%) records were correctly classified and 39 (1.55%) were incorrectly classified. Using 80% split,1386 (98.79%) records were correctly classified and 17 (1.21%) were incorrectly classified. Using 10-fold cross validation test options, 6895 (98.23%) records were correctly classified and 125 (1.77%) were incorrectly classified.

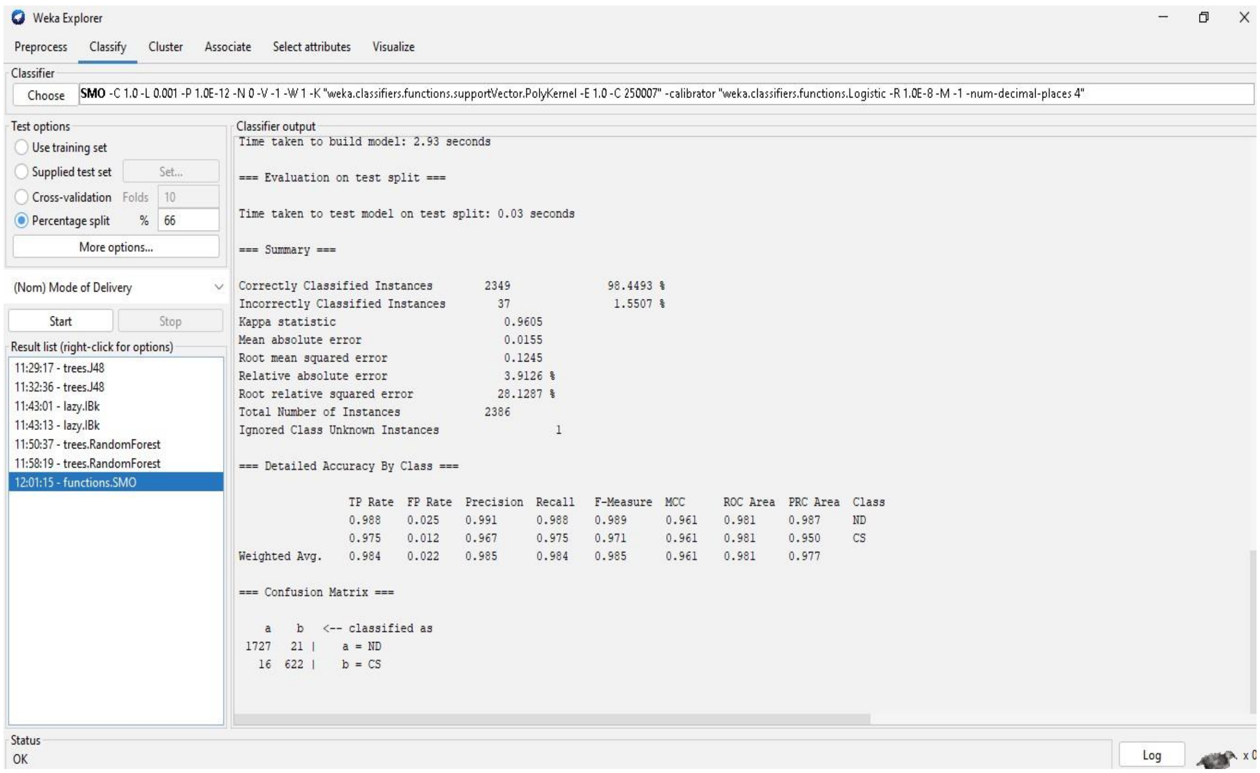

Figure 4. 13 Classifier output based on SVM using 66split

=== Confusion Matrix ===

Table 4. 14 Confusion matrix of SVM using 66% split

	Predicted class		
	a	b	<-- classified as
Actual class	1727	21	A = ND
	16	622	B = CS

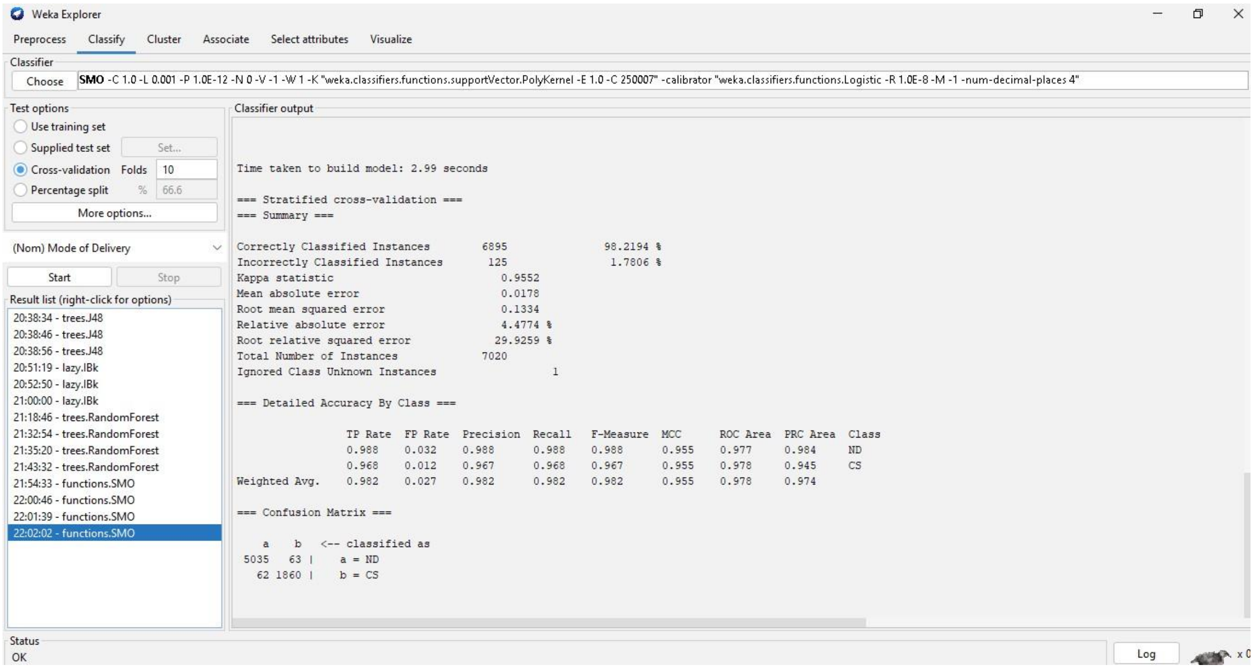

Figure 4. 14 Classifier output based on SVM using 10-fold cross validation test options

=== Confusion Matrix ===

Table 4. 15 Confusion matrix of SVM using 10-fold cross validation test options

	Predicted class		
	a	b	<-- classified as
Actual class	5035	63	A = ND
	62	1860	B = CS

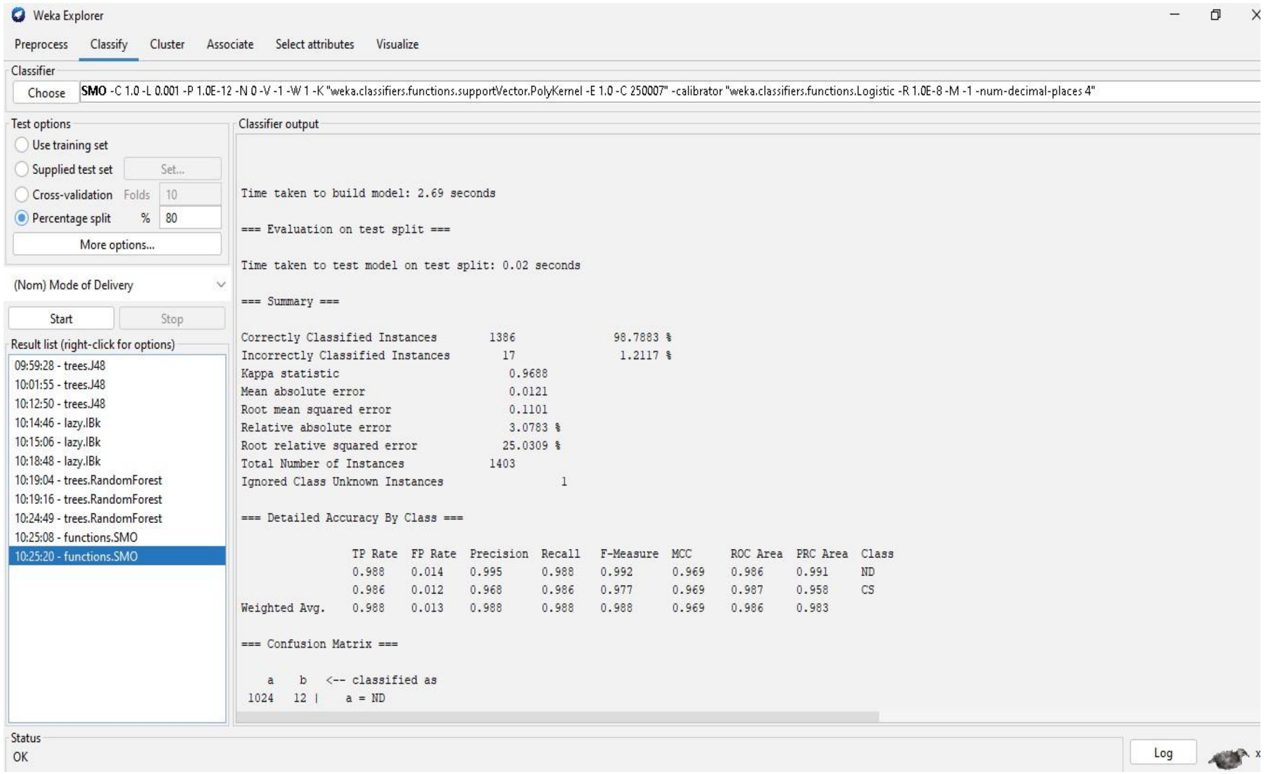

Figure 4. 15 Classifier output based on SVM using 80% split option

=== Confusion Matrix ===

Table 4. 16 Confusion matrix of SVM using 80% split option

	Predicted class		
	a	b	<-- classified as
Actual class	1024	12	A = ND
	5	362	B = CS

Roc Analysis for support vector machine

As can be seen from the detailed accuracy by mode of delivery output, the ROC (Receiver Operating Characteristics) area of this model is 0.9861. The Area under the ROC curve in figure 17 is higher. Higher numbers here indicate the model is the more accurate.

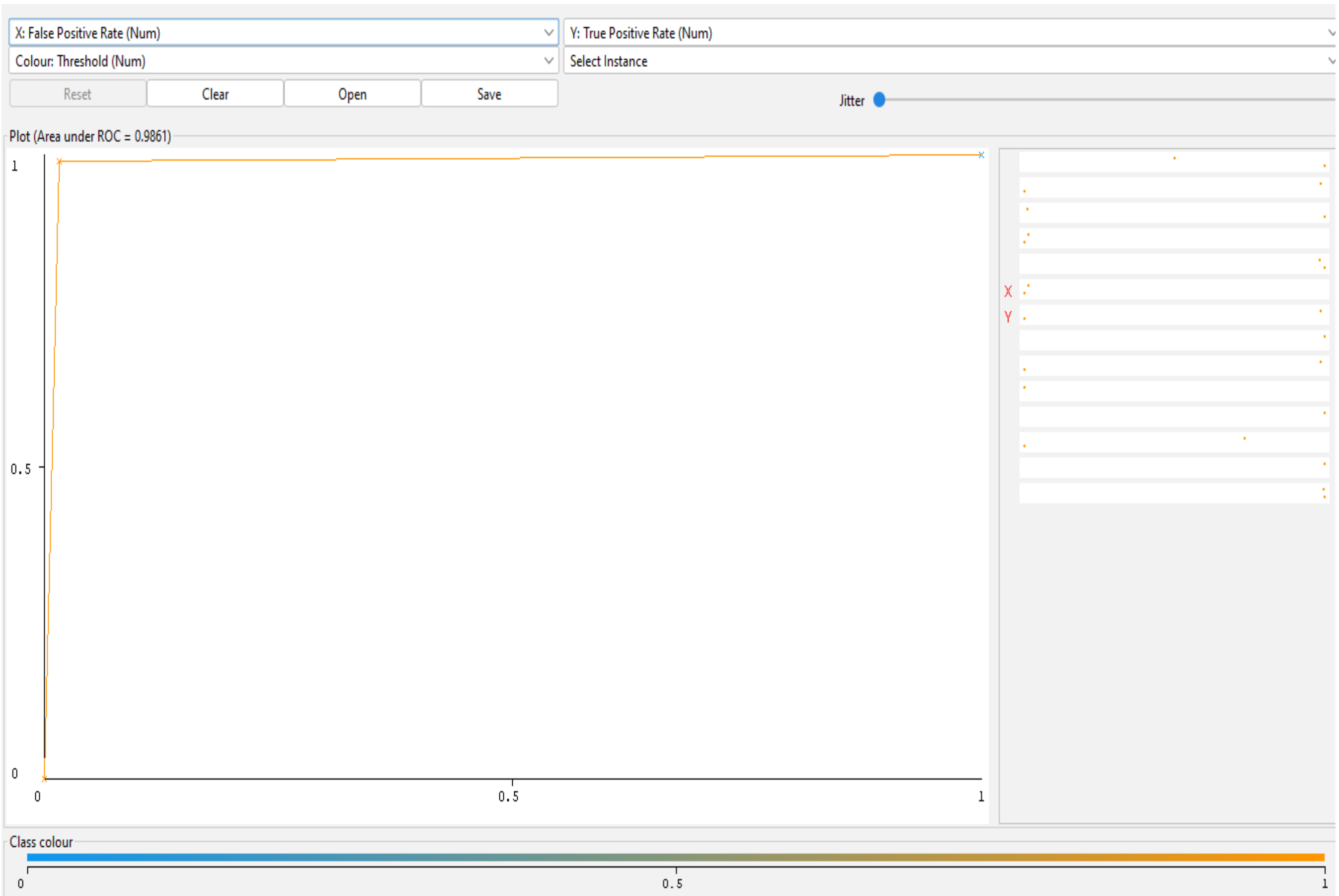

Figure 4. 16 ROC Area Curves of Random Forest

Model Building Using Naive Bayes

Naive Bayes uses Bayes' theorem to calculate the probability an event will occur given another event has already occurred. The results obtained for Random Forest algorithm on predefined classes of features are shown Table 4.17.

Table 4. 17 Naive bayes parameter option of WEKA

S.NO	**Performance Measure**	**1**	**2**	**3**
1	Testing Mode	66%	80%	10 fold
2	Confidence factor	0.25	0.25	0.25
3	Uprunning	False	False	False
4	minNumObj	2	2	2
7	Time taken to Build	0.01sec.	0.02sec.	0.02sec
8	Recall	0.98	0.98	0.98
9	Precision	0.98	0.98	0.98
10	F-Measure	0.98	0.98	0.98
11	ROC	0.99	0.99	0.99
12	Correctly Classified	2342	1381	6887
13	Incorrectly Classified	44	22	133
14	Mean Absolute Error	0.08	0.08	0.08
15	Accuracy	98.15%	98.43%	98.10%

As can be observed from this table 4.17, the model has accuracy of 98.12% using 66% split,98.43% using 80% and 98.10% accuracy using 10-fold cross validation test options.

The confusion matrix for Naive Bayes

The confusion matrix for naive bayes presented in table 4.17 depicts that out of the total records provided to the WEKA using 66% split, 2342 (98.15%) records were correctly classified and 44 (1.85%) were incorrectly classified. Using 80% split,1381 (98.43%) records were correctly classified and 22 (1.53%) were incorrectly classified. Using 10-fold cross validation test options, 6887 (98.10%) records were correctly classified and 133 (1.90%) were incorrectly classified.

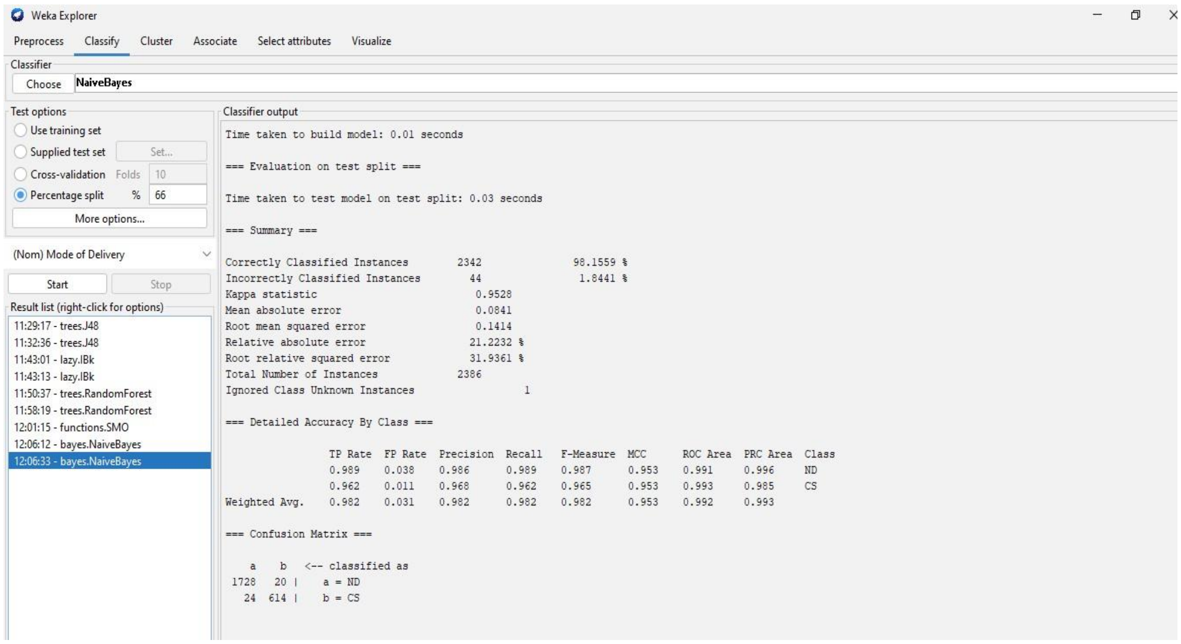

Figure 4. 17 Classifier output based on Naive Bayes using 66% split option

=== Confusion Matrix ===

Table 4. 18 Confusion matrix of Naive Bayes using 66% split option

	Predicted class		
	a	b	<-- classified as
Actual class	1728	20	A = ND
	24	614	B = CS

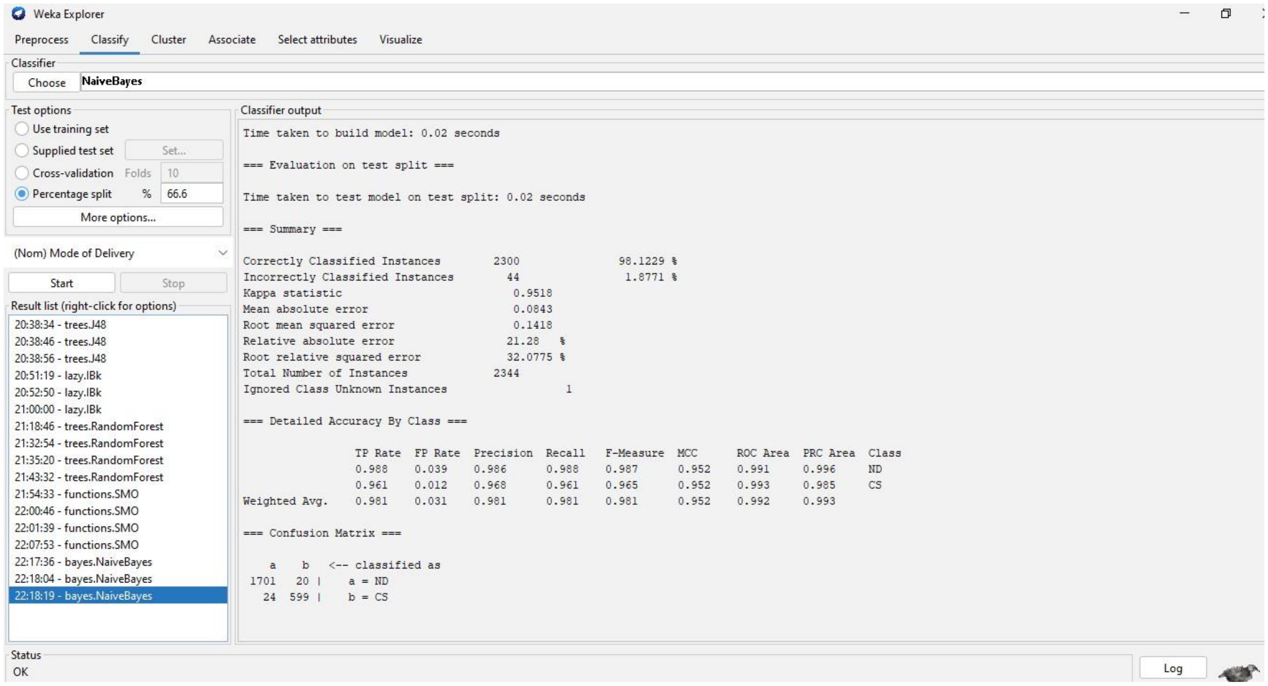

Figure 4. 18 Classifier output based on Naïve Bayes using 10-fold cross validation test

=== Confusion Matrix ===

Table 4. 19 Confusion matrix of Naive Bayes using 10-fold cross validation test

	Predicted class		
	a	b	<-- classified as
Actual class	1701	20	A = ND
	24	599	B = CS

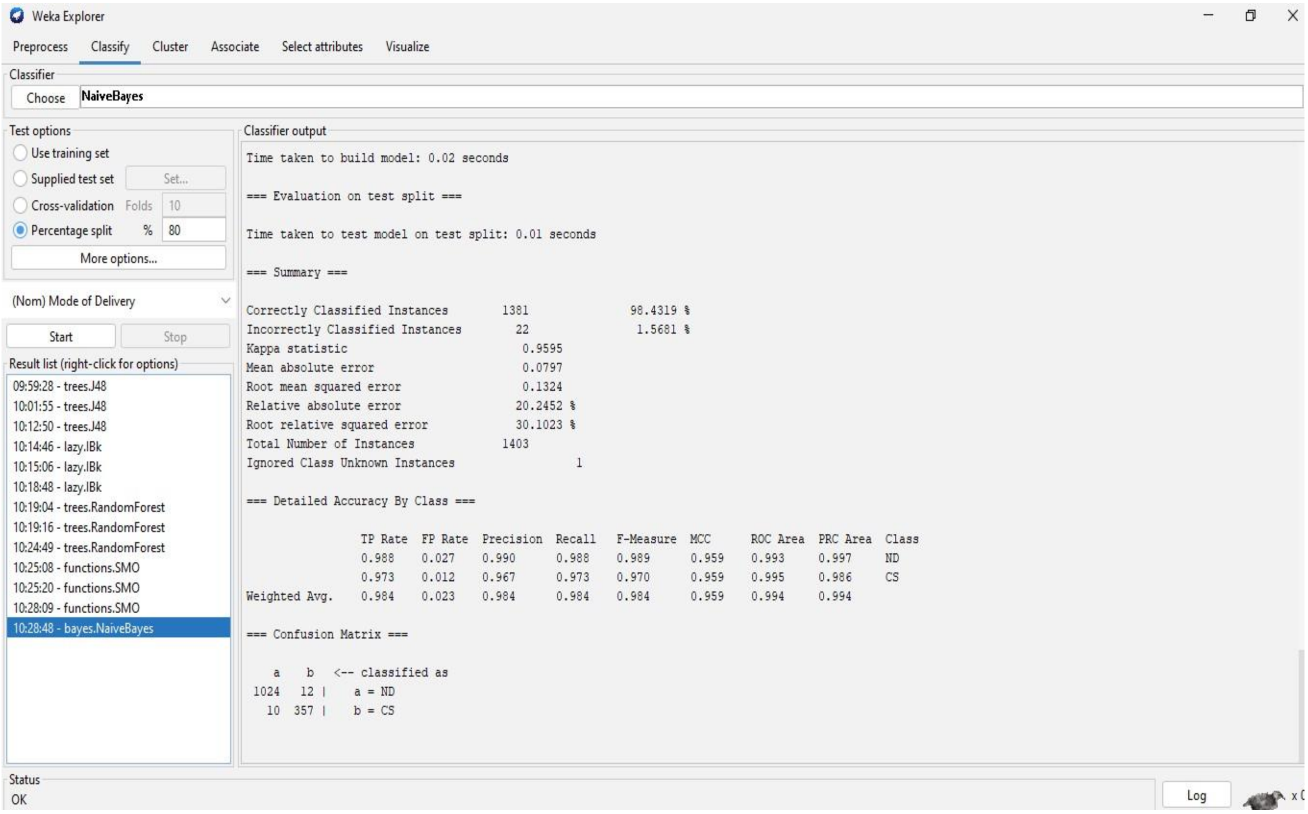

Figure 4. 19 Classifier output based on naive bayes using 80% split option

=== Confusion Matrix ===

Table 4. 20 Confusion matrix of naive bayes using 80% split option

	Predicted class		
	a	b	<-- classified as
Actual class	1024	12	A = ND
	10	357	B = CS

Roc Analysis for Naive Bayes

As can be seen from the detailed accuracy by mode of delivery output, the ROC (Receiver Operating Characteristics) area of this model is 0.9932. The Area under the ROC curve in figure 21 is higher. Higher numbers here indicate the model is the more accurate.

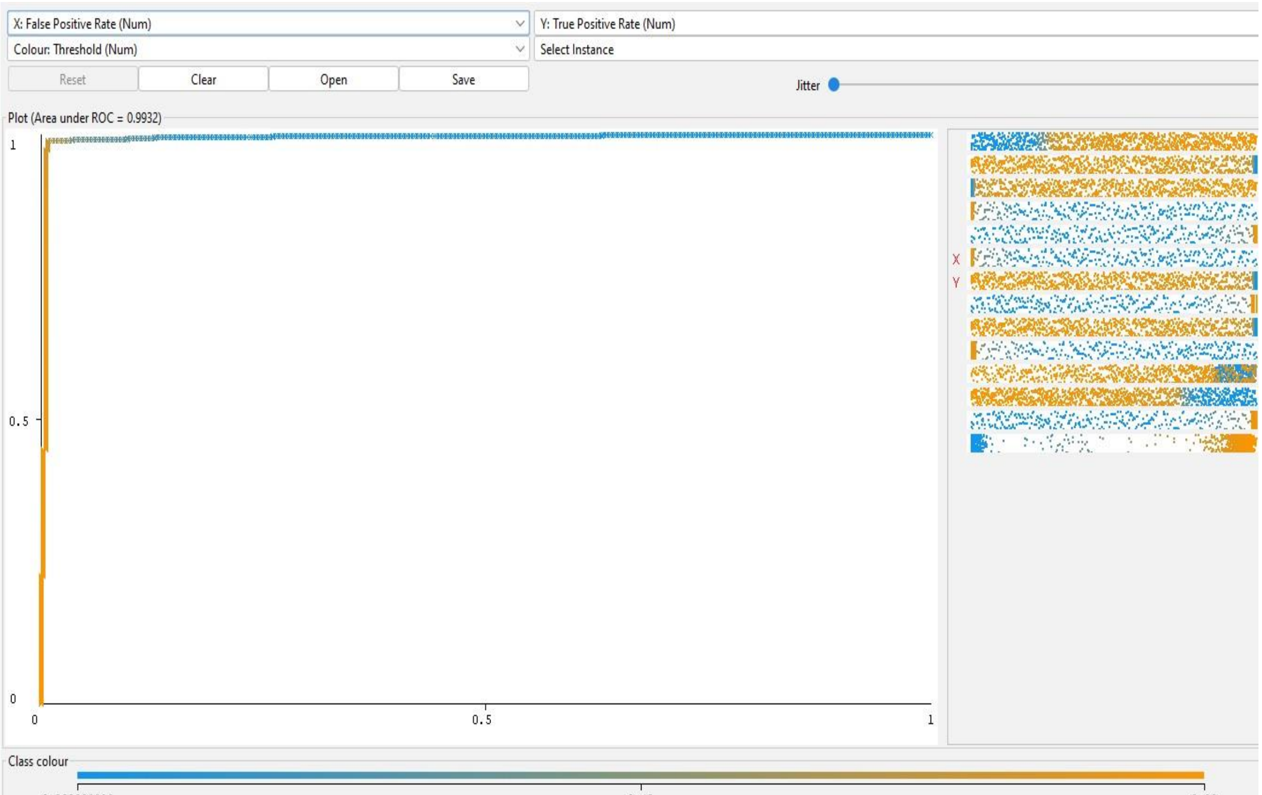

Figure 4. 20 ROC Area Curves of Naive Bayes

Model Building Using stack classifier

Stacking is an ensemble learning technique that involves combining the best predictions of multiple classifiers to create a new training set for a meta-classifier (Islam et al., 2021). The results obtained for stack classifier algorithm on predefined classes of features are shown table 4.21

Table 4. 21 Stack parameter option of WEKA

S.NO	**Performance Measure**		**1**	**2**	**3**
1	Testing Mode		66%	80%	10 fold
2	Confidence factor		0.25	0.25	0.25
3	Uprunning		False	False	False
4	minNumObj		2	2	2
7	Time taken to Build		33.26sec.	33.81sec.	33.05sec
8	Recall		0.98	0.99	0.98
9	Precision		0.98	0.99	0.98
10	F-Measure		0.98	0.99	0.98
11	ROC		0.99	0.99	0.98
12	Correctly Classified		2349	1386	6895
13	Incorrectly Classified		37	17	125
14	Mean Absolute Error		0.01	0.01	0.02
15	Accuracy		98.45%	98.79%	98.23%

As can be observed from this table 4.21, the model has accuracy of 98.45% using 66% split,98.79% using 80% and 98.23% accuracy using 10-fold cross validation test options.

The confusion matrix for stack classifier

The confusion matrix for presented in table 4.21 depicts that out of the total records provided to the WEKA using 66% split, 2349 (98.45%) records were correctly classified and 37 (1.55%) were incorrectly classified. Using 80% split,1386 (98.79%) records were correctly classified and 17 (1.21%) were incorrectly classified. Using 10-fold cross validation test options, 6895(98.23%) records were correctly classified and 125 (1.77%) were incorrectly classified.

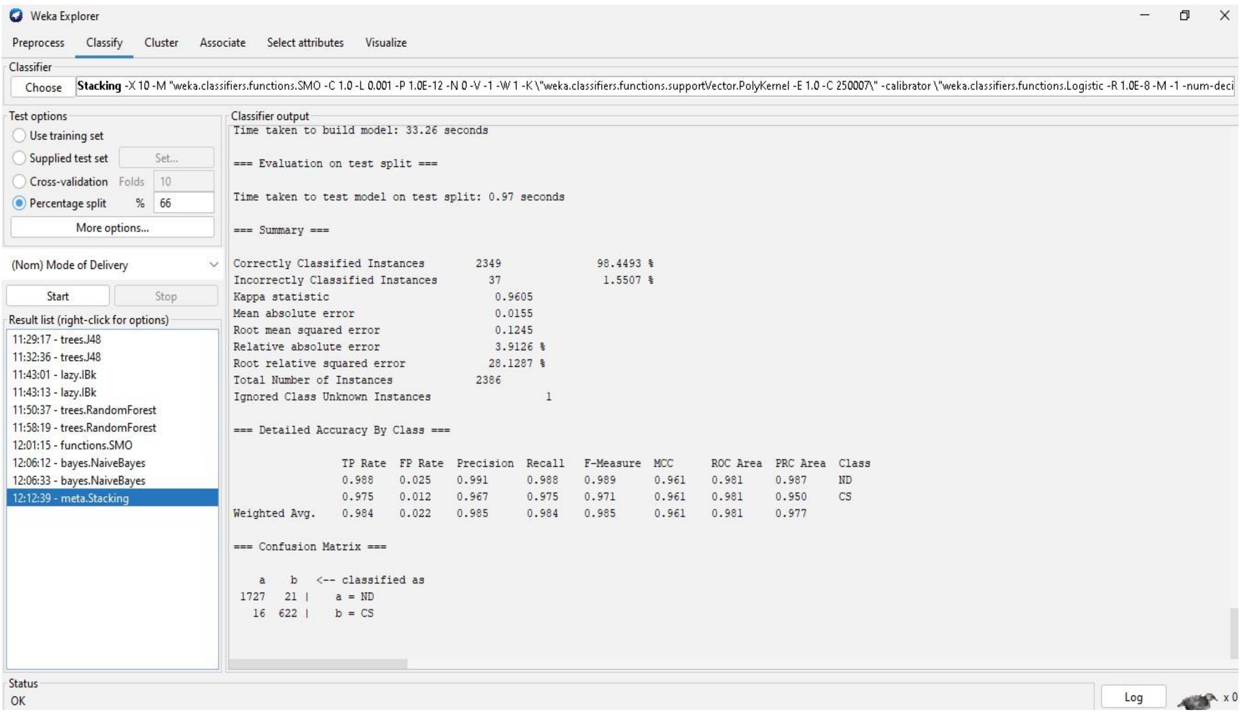

Figure 4. 21 Classifier output based on stack classifier using 66% split option

=== Confusion Matrix ===

Table 4. 22 Confusion matrix of stack classifier using 66% split option

	Predicted class		
	a	b	<-- classified as
Actual class	1727	21	A = ND
	16	622	B = CS

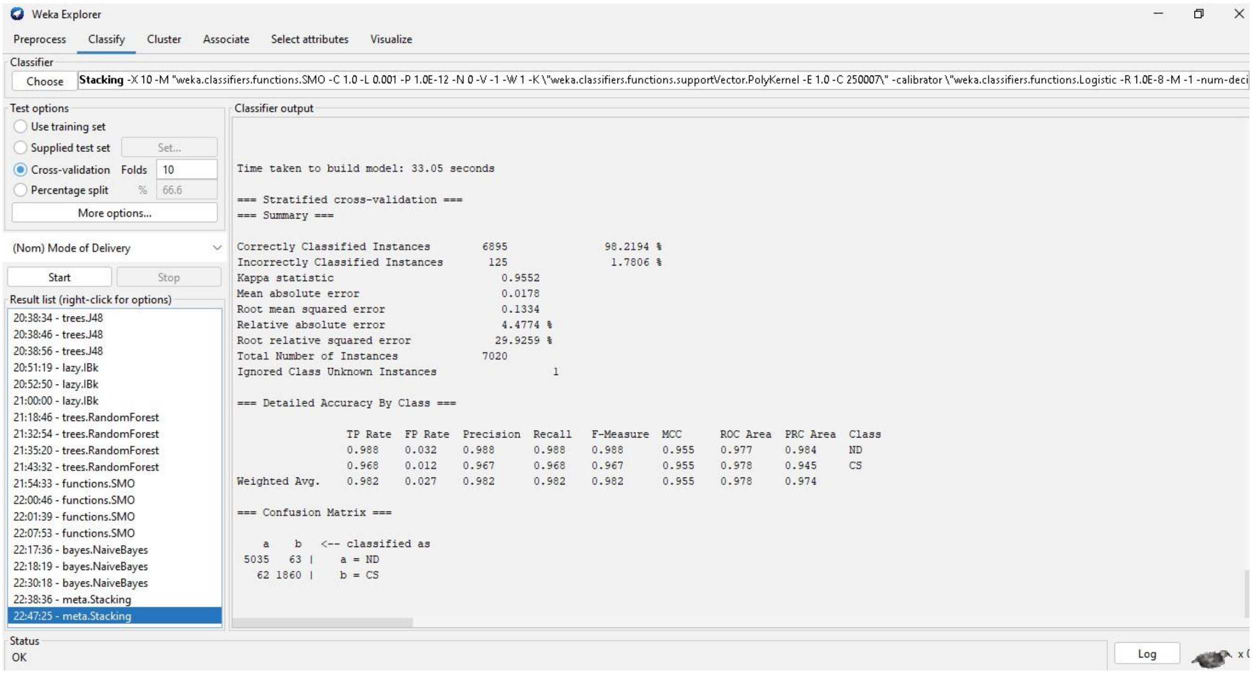

Figure 4. 22 Classifier output based on stack classifier using 10-fold cross validation test

=== Confusion Matrix ===

Table 4. 23 Confusion matrix of stack classifier using 10-fold cross validation test

	Predicted class		
	a	b	<-- classified as
Actual class	5035	63	A = ND
	62	1860	B = CS

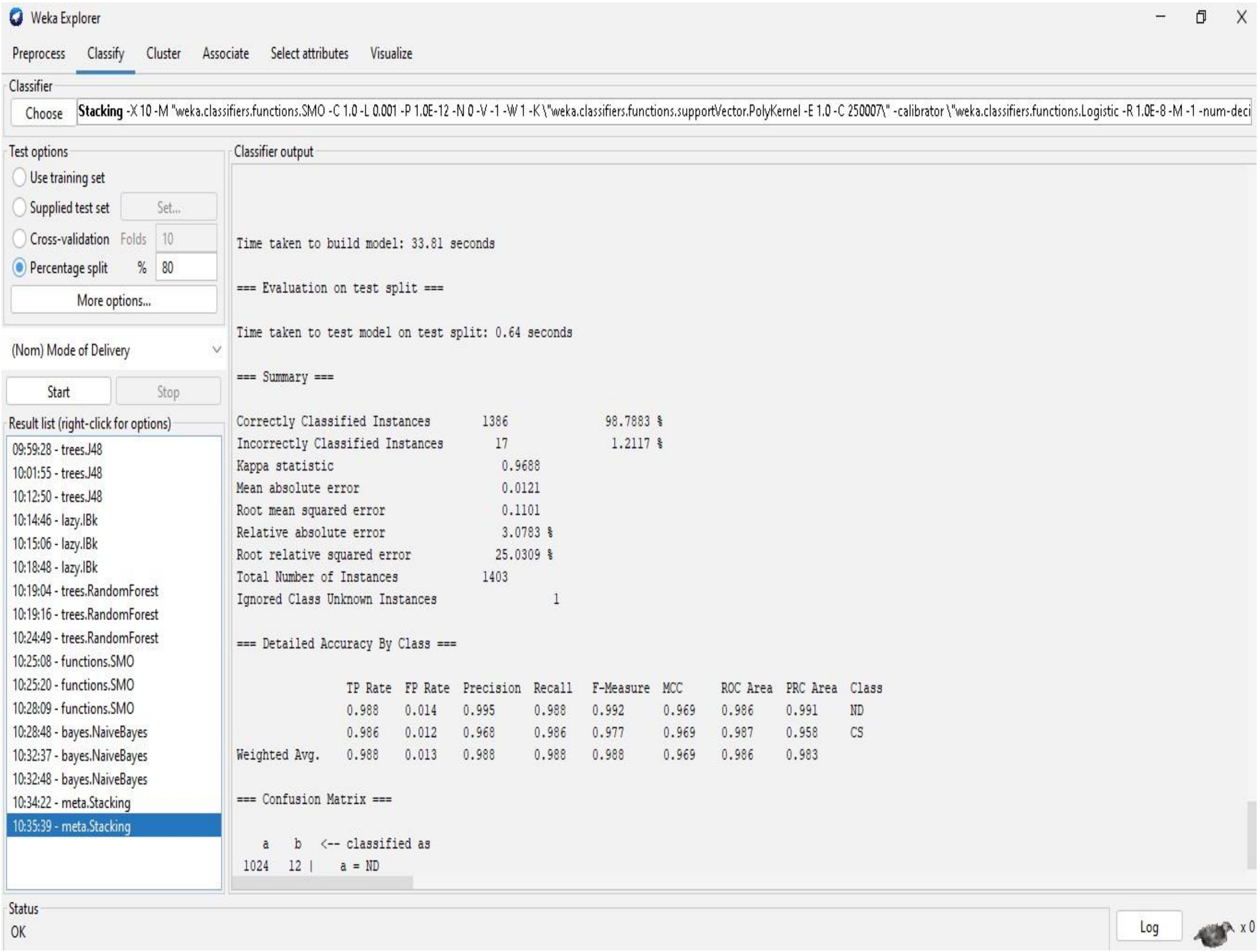

Figure 4. 23 Classifier output based on stack classifier using 80% split option

=== Confusion Matrix ===

Table 4. 24 Confusion matrix of stack classifier using 80% split option

	Predicted class		
	a	b	<-- classified as
Actual class	1024	12	A = ND
	5	362	B = CS

Roc Analysis for stack classifier

As can be seen from the detailed accuracy by mode of deliver output, the ROC (Receiver Operating Characteristics) area of this model is 0.9861. The Area under the ROC curve in figure 25 is higher. Higher numbers here indicate the model is the more accurate.

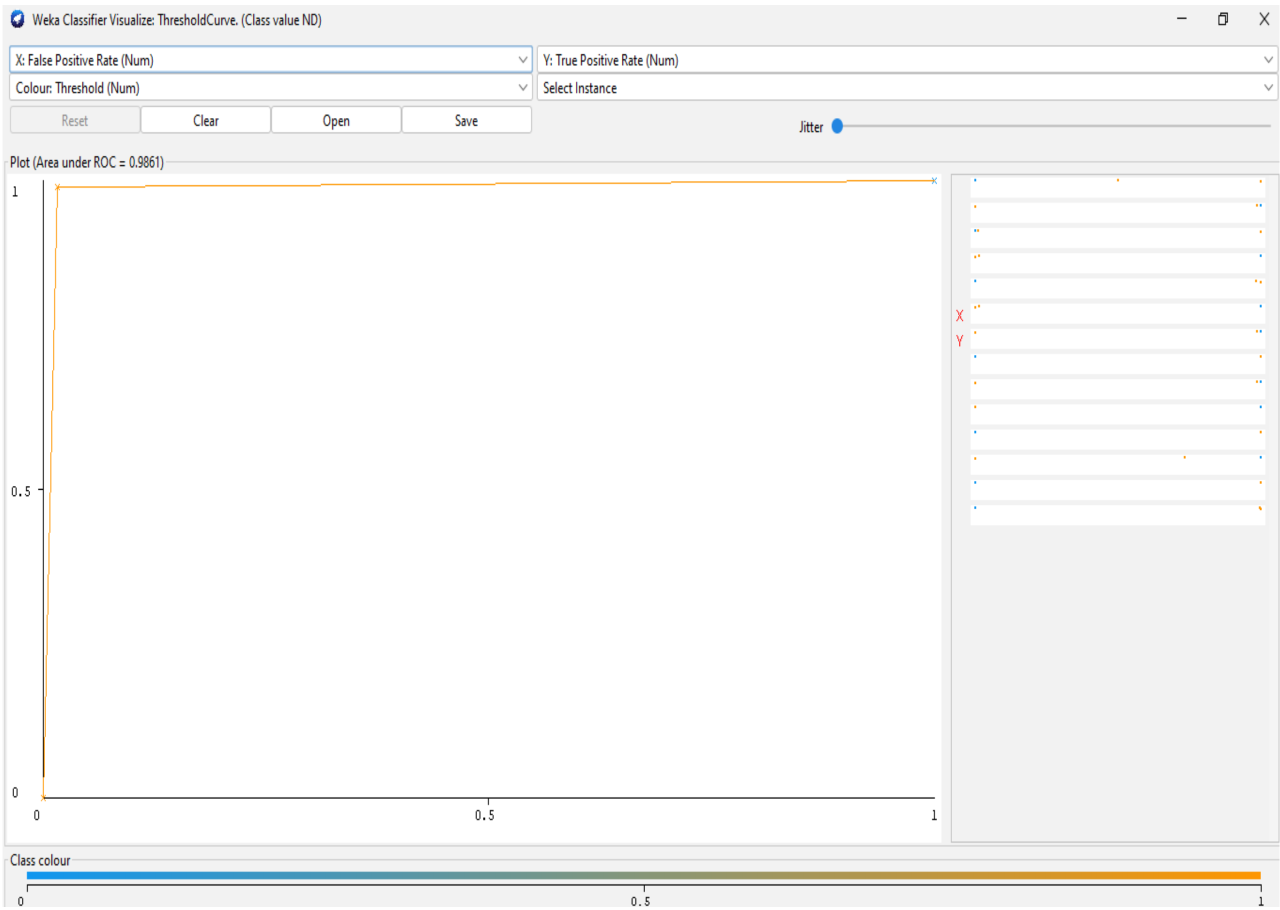

Figure 4. 24 ROC Area Curves of stack classifier

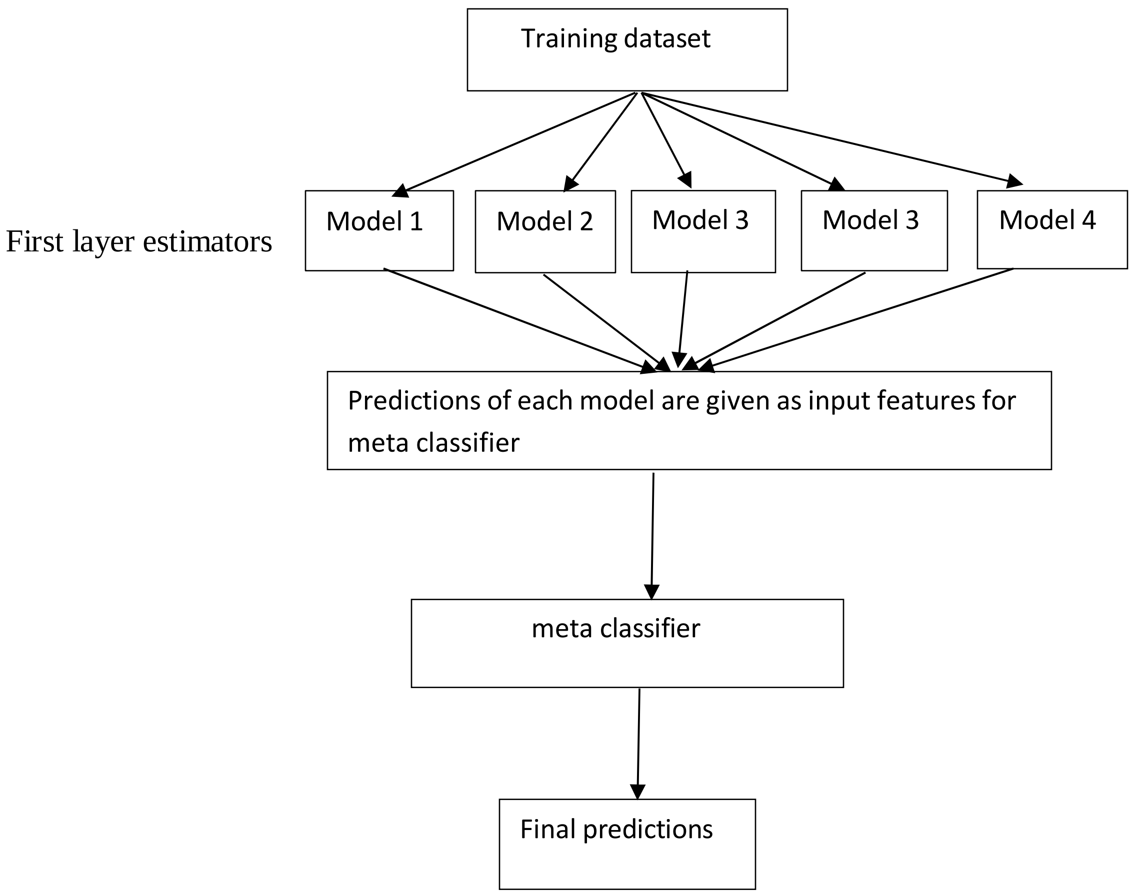

Figure 4. 25 Architecture of stacking classifier

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

Conclusion

Machine learning for prediction and classification is becoming increasingly popular in the field of health care. Machine learning methods have been used in a number of medical research studies. Such experiments' results have been used for comparison, prediction, and predictive analysis. Many studies have been conducted in order to automate decision-making processes in a variety of fields, particularly medical data analysis. The researcher's goal in this study was to create a safe mode childbirth predictive model for Adare General Hospital Hawassa using Machine learning. Choosing safe childbirth methods is critical for the safety of both mothers and infants, but the best features to consider when making such decisions have yet to be discovered. Predictive modeling is the general idea of creating a model that can make predictions. In order to make those predictions, such a model typically includes a machine learning algorithm that learns specific properties from a training dataset. The data was collected from Adare General Hospital Hawassa. from 2020 to 2021 for the research purpose First the data was preprocessed for data cleaning, attribute and feature selection, and data transformation. This experimental research was made by using six predictive modeling techniques, J48 decision tree, Random Forest, Naive Bayes, Support Vector Machine, K-nearest neighbor and stack combining the five algorithms to address the problem. The experiment result shows that stack has a higher performance rate than other five algorithms. The result showed that the J48 Decision tree model has accuracy of 97.36% using 66% split,98.79% using 80% and 98.2% accuracy using 10-fold cross validation test options. KNN model has accuracy of 97.36% using 66% split,97.64% using 80% and 96.5% accuracy using 10-fold cross validation test options. Random forest model has accuracy of 98.36% using 66% split,98.64% using 80% and 98.06% accuracy using 10-fold cross validation test options. Support vector machine model has accuracy of 98.45% using 66% split,98.79% using 80% and 98.23% accuracy using 10-fold cross validation test options. Naive bayes model has accuracy of 98.15% using 66% split,98.43% using 80% and 98.10% accuracy using 10-fold cross validation test options. Stack model has accuracy of 98.45% using 66% split,98.79% using 80% and 98.23% accuracy using 10-fold cross validation test options**.** In general, the results from this study were interesting and encouraging; it can be used as decision support for physicians to predict safe mode of child birth.

Recommendation

This research work was carried out for academic purpose and is should be considered as a preliminary effort to give insight into the application for prediction safe mode of childbirth. This research work can contribute a lot towards a comprehensive study in this area in the future. The results of this study have also shown that stack model is well applicable in the predicting safe mode of childbirth in adare general hospital Hawassa. Accordingly, based on the findings of this study, the researcher forwards the following recommendations that the following issues need to be addressed in future studies:

The main objective of this study was to develop a model that can predict safe mode of child birth for adare general hospital. All the experiments conducted using J48 decision tree, Random Forest, Naive Bayes, Support Vector Machine, K-nearest neighbor and stack algorithms produced efficient models and interpretable rules. Hence it is important for adare general hospital to utilize the model developed in order to use a decision support for choosing safe mode of child birth. Since this study has used a small percentage of the data which comprises only 2 years data of adare general hospital Hawassa to build a model J48 decision tree, Random Forest, Naive Bayes, Support Vector Machine, K-nearest neighbor and stack. It is better to build more comprehensive models by using more additional data from different hospitals. Although encouraging results were obtained from this study, particularly, using stack classifier, there might be a probability to obtain more accurate and better performing results using other classification and prediction techniques which were not used by the researcher due to time constraint. Therefore, it is recommended that these classifiers should be applied and proved to this data.

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7. APPENDIX

APPENDIX A: J48 DECISION TREE OUTPUT

=== Run information ===

Scheme: weka. classifiers. trees. J48 -C 0.25 -M 2

Relation: PSM18

Instances: 7021

Attributes: 19

Age

Surgical History

APH

GA

Wt

B/P

Lie

FHB

Presentation

Position

Contraction

Cervix Dilation

Membrane

No of Px

Amniotic Fluid

Placenta

Placental clacification

BPP

Mode of Delivery

Test mode: split 80.0% train, remainder test

=== Classifier model (full training set) ===

J48 pruned tree

```
------------------

Amniotic Fluid = Adequate
|   BPP = Reassuring
|   |   Presentation = Cephalic
|   |   |   Placenta = Fundal
|   |   |   |   Contraction <= 0
|   |   |   |   |   GA <= 39
|   |   |   |   |   |   Membrane = Intact
|   |   |   |   |   |   |   Cervix Dilation <= 3: ND (5.0)
|   |   |   |   |   |   |   Cervix Dilation > 3
|   |   |   |   |   |   |   |   Wt <= 3: ND (6.0/1.0)
|   |   |   |   |   |   |   |   Wt > 3
|   |   |   |   |   |   |   |   |   Age <= 31: CS (3.0)
|   |   |   |   |   |   |   |   |   Age > 31: ND (3.0/1.0)
```

| | | | | | Membrane = R(B): ND (5.0/2.0)

| | | | | | Membrane = R(C): CS (4.0/1.0)

| | | | | | Membrane = R(M)+II: CS (27.0/1.0)

| | | | | | Membrane = R(M)+III: CS (0.0)

| | | | | | Membrane = R(M)+I: CS (0.0)

| | | | | GA > 39: CS (17.0)

| | | | Contraction > 0

| | | | | Membrane = Intact

| | | | | | B/P <= 90: ND (3100.0/18.0)

| | | | | | B/P > 90

| | | | | | | B/P <= 92: ND (43.0)

| | | | | | | B/P > 92: CS (3.0)

| | | | | Membrane = R(B): ND (299.0/2.0)

| | | | | Membrane = R(C)

| | | | | | Lie = Longitudinal: ND (980.0/14.0)

| | | | | | Lie = Oblique: ND (0.0)

| | | | | | Lie = Transverse: CS (2.0)

| | | | | Membrane = R(M)+II: CS (256.0/44.0)

| | | | | Membrane = R(M)+III: CS (5.0)

| | | | | Membrane = R(M)+I: ND (154.0/1.0)

| | | Placenta = Low lying

| | | | Lie = Longitudinal

| | | | | Membrane = Intact

| | | | | | Position = OA: ND (346.0/6.0)

| | | | | | Position = Face: CS (1.0)

| | | | | | Position = Brow: CS (3.0)

| | | | | Membrane = R(B): ND (28.0/1.0)

| | | | | Membrane = R(C): ND (91.0/1.0)

| | | | | Membrane = R(M)+II: CS (28.0/2.0)

| | | | | Membrane = R(M)+III: ND (0.0)

| | | | | Membrane = R(M)+I: ND (21.0)

| | | | Lie = Oblique: CS (8.0/1.0)

| | | | Lie = Transverse: CS (2.0)

| | | Placenta = Placenta previa: CS (2.0)

| | | Placenta = Placenta previa: CS (565.0/4.0)

| | Presentation = Breech: CS (111.0/2.0)

| BPP = Non-reassuring: CS (183.0/1.0)

Amniotic Fluid = Severe: CS (719.0/8.0)

Classifier output

```
=== Summary ===

Correctly Classified Instances        1386               98.7883 %
Incorrectly Classified Instances        17                1.2117 %
Kappa statistic                          0.9689
Mean absolute error                      0.0255
Root mean squared error                  0.1077
Relative absolute error                  6.4666 %
Root relative squared error             24.5011 %
Total Number of Instances             1403
Ignored Class Unknown Instances                   1

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.987    0.011    0.996      0.987    0.992      0.969    0.992     0.996     ND
                 0.989    0.013    0.965      0.989    0.977      0.969    0.992     0.967     CS
Weighted Avg.    0.988    0.011    0.988      0.988    0.988      0.969    0.992     0.989

=== Confusion Matrix ===

    a    b   <-- classified as
 1023   13 |    a = ND
    4  363 |    b = CS
```

APPENDIX B: NAIVE BAYES OUTPUT

=== Run information ===

Scheme: weka.classifiers.bayes.NaiveBayes

Relation: PSM18

Instances: 7021

Attributes: 19

Age

Surgical History

APH

GA

Wt

B/P

Lie

FHB

Presentation

Position

Contraction

Cervix Dilation

Membrane

No of Px

Amniotic Fluid

Placenta

Placental clacification

BPP

Mode of Delivery

Test mode: split 80.0% train, remainder test

=== Classifier model (full training set) ===

Naive Bayes Classifier

	Class	
Attribute	*ND*	*CS*
	(0.73)	*(0.27)*

==

Age		
mean	*27.5555*	*27.821*
std. dev.	*5.6784*	*5.8555*
weight sum	*5098*	*1922*

precision	*1*	*1*
Surgical History		
No	*5099.0*	*1862.0*
Yes	*1.0*	*62.0*
[total]	*5100.0*	*1924.0*
APH		
No	*5099.0*	*1849.0*
Yes	*1.0*	*75.0*
[total]	*5100.0*	*1924.0*
GA		
mean	*37.9306*	*37.9781*
std. dev.	*0.7632*	*0.8532*
weight sum	*5098*	*1922*
precision	*1*	*1*
Wt		
mean	*3.0388*	*3.0658*
std. dev.	*0.535*	*0.53*
weight sum	*5098*	*1922*
precision	*0.5*	*0.5*

B/P		
mean	*71.7359*	*71.9743*
std. dev.	*8.9229*	*9.7589*
weight sum	*5098*	*1922*
precision	*3.7667*	*3.7667*
Lie		
Longitudinal	*5098.0*	*1865.0*
Oblique	*2.0*	*30.0*
Transverse	*1.0*	*30.0*
[total]	*5101.0*	*1925.0*
FHB		
mean	*125*	*125*
std. dev.	*0.0017*	*0.0017*
weight sum	*5098*	*1922*
precision	*0.01*	*0.01*
Presentation		
Cephalic	*5097.0*	*1793.0*
Breech	*3.0*	*131.0*
[total]	*5100.0*	*1924.0*

Position		
OA	*5099.0*	*1869.0*
Face	*1.0*	*38.0*
Brow	*1.0*	*18.0*
[total]	*5101.0*	*1925.0*
Contraction		
mean	*2.3352*	*1.9605*
std. dev.	*1.1818*	*1.2391*
weight sum	*5098*	*1922*
precision	*1*	*1*
Cervix Dilation		
mean	*3.0118*	*3.0492*
std. dev.	*1.4316*	*1.4177*
weight sum	*5098*	*1922*
precision	*1.5*	*1.5*
Membrane		
Intact	*3488.0*	*1080.0*
R(B)	*329.0*	*103.0*
R(C)	*1061.0*	*322.0*

R(M)+II	*48.0*	*367.0*
R(M)+III	*1.0*	*10.0*
R(M)+I	*177.0*	*46.0*
[total]	*5104.0*	*1928.0*
No of Px		
Singleton	*5073.0*	*1875.0*
Twin	*27.0*	*43.0*
Triplet	*1.0*	*7.0*
[total]	*5101.0*	*1925.0*
Amniotic Fluid		
Adequate	*5091.0*	*1212.0*
Severe	*9.0*	*712.0*
[total]	*5100.0*	*1924.0*
Placenta		
Fundal	*4612.0*	*925.0*
Low lying	*484.0*	*235.0*
Placenta previa	*1.0*	*3.0*
Placenta previa	*5.0*	*763.0*
[total]	*5102.0*	*1926.0*

Placental clacification

No	*4092.0*	*1654.0*
Grade II	*398.0*	*125.0*
Grade III	*66.0*	*24.0*
Grade I	*546.0*	*123.0*
[total]	*5102.0*	*1926.0*

BPP

Reassuring	*5098.0*	*1699.0*
Non-reassuring	*2.0*	*225.0*
[total]	*5100.0*	*1924.0*

Classifier output

```
=== Summary ===

Correctly Classified Instances        1381               98.4319 %
Incorrectly Classified Instances        22                1.5681 %
Kappa statistic                          0.9595
Mean absolute error                      0.0797
Root mean squared error                  0.1324
Relative absolute error                 20.2452 %
Root relative squared error             30.1023 %
Total Number of Instances             1403
Ignored Class Unknown Instances                  1

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.988    0.027    0.990      0.988    0.989      0.959    0.993     0.997     ND
                 0.973    0.012    0.967      0.973    0.970      0.959    0.995     0.986     CS
Weighted Avg.    0.984    0.023    0.984      0.984    0.984      0.959    0.994     0.994

=== Confusion Matrix ===

    a    b   <-- classified as
 1024   12 |    a = ND
   10  357 |    b = CS
```

APPENDIX C: SVM TREE OUTPUT

=== Run information ===

Scheme: weka.classifiers.functions.SMO -C 1.0 -L 0.001 -P 1.0E-12 -N 0 -V -1 -W 1 -K "weka.classifiers.functions.supportVector.PolyKernel -E 1.0 -C 250007" -calibrator "weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -num-decimal-places 4"

Relation: PSM18

Instances: 7021

Attributes: 19

Age

Surgical History

APH

GA

Wt

B/P

Lie

FHB

Presentation

Position

Contraction

Cervix Dilation

Membrane

No of Px

Amniotic Fluid

Placenta

Placental clacification

BPP

Mode of Delivery

Test mode: split 80.0% train, remainder test

=== Classifier model (full training set) ===

SMO

Kernel used:

Linear Kernel: K(x,y) = <x,y>

Classifier for classes: ND, CS

BinarySMO

Machine linear: showing attribute weights, not support vectors.

```
        -0.0001 * (normalized) Age
 +       1      * (normalized) Surgical History=Yes
 +       0.5708 * (normalized) APH=Yes
 +       0.0019 * (normalized) GA
 +       0.0001 * (normalized) Wt
 +       0.003  * (normalized) B/P
 +      -1.3336 * (normalized) Lie=Longitudinal
 +       0.6673 * (normalized) Lie=Oblique
```

+ 0.6663 * (normalized) Lie=Transverse

+ 2.0006 * (normalized) Presentation=Breech

+ -1.3337 * (normalized) Position=OA

+ 0.6666 * (normalized) Position=Face

+ 0.6671 * (normalized) Position=Brow

+ -0.0006 * (normalized) Contraction

+ 0.0007 * (normalized) Cervix Dilation

+ -0.6669 * (normalized) Membrane=Intact

+ -0.6671 * (normalized) Membrane=R(B)

+ -0.667 * (normalized) Membrane=R(C)

+ 1.3338 * (normalized) Membrane=R(M)+II

+ 1.3345 * (normalized) Membrane=R(M)+III

+ -0.6673 * (normalized) Membrane=R(M)+I

+ -0.6668 * (normalized) No of Px=Singleton

+ -0.6668 * (normalized) No of Px=Twin

+ 1.3336 * (normalized) No of Px=Triplet

+ 2.0012 * (normalized) Amniotic Fluid=Severe

+ -0.8574 * (normalized) Placenta=Fundal

+ -0.8571 * (normalized) Placenta=Low lying

+ 0.5708 * (normalized) Placenta=Placenta previa

+ 1.1437 * (normalized) Placenta= Placenta previa

+ -0.0003 * (normalized) Placental clacification=No

+ 0 * (normalized) Placental clacification=Grade II

+ 0.0004 * (normalized) Placental clacification=Grade III

+ -0.0001 * (normalized) Placental clacification=Grade I

+ 2.0007 * (normalized) BPP=Non-reassuring

+ 3.8571

Classifier output

```
Correctly Classified Instances        1386               98.7883 %
Incorrectly Classified Instances        17                1.2117 %
Kappa statistic                          0.9688
Mean absolute error                      0.0121
Root mean squared error                  0.1101
Relative absolute error                  3.0783 %
Root relative squared error             25.0309 %
Total Number of Instances             1403
Ignored Class Unknown Instances                  1

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.988    0.014    0.995      0.988    0.992      0.969    0.986     0.991     ND
                 0.986    0.012    0.968      0.986    0.977      0.969    0.987     0.958     CS
Weighted Avg.    0.988    0.013    0.988      0.988    0.988      0.969    0.986     0.983

=== Confusion Matrix ===

    a    b   <-- classified as
 1024   12 |    a = ND
    5  362 |    b = CS
```