Addis Ababa University

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Telecommunication Engineering Graduate Program

Mapping Customer Relationship Management Data to Customer Experience Using Machine Learning: In The Case of Ethio Telecom

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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This thesis has been submitted for examination with my approval as a university advisor.

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Abstract

Making a positive customer experience is a strategic priority for a business company. To enable a seamless customer experience, the company used methods like surveys to rate the experience. Survey-based measurement systems of customer experience is expensive and time consuming. Another method the company uses to get customer experience insight is by utilizing new technology such as social media platforms and mobile applications. However, technology such as social media platforms failed to obtain managerial insights. A better approach to a seamless customer experience is to take full advantage of wealth data available in the customer relationship management system.

The main objective of this paper is to make use of classification algorithms widely used in machine learning research and then map CRM data to customer experience. To do this, 1208 individual records were collected from ethio telecom. The collected data is customer sentiment about their experience (a dependent variable) and independent data from the CRM system. And prepare the data set and use a classifier to map CRM data to customer experience and see the impact on classifier performance.

The comparisons will be made between Naive-Bayes, J48, and Random-Forest. And finally, J48 has a better accuracy performance of 82.03 %.

The result implies using CRM system data and mapping to customer experience is possible. However, the data type, data size, and data feature all have a significant impact on classifier performance.

Keywords: Customer Experience, Naïve Bayes, J48, and Random Forest

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Table of Contents

List of Figures

List of tables

List of Acronyms

2G	Second-Generation Network
3G	Third Generation Network
4G	Fourth Generation Network
ARFF	Attribute Relation File Format
CES	Customer Effort Score
CRM	Customer Relationship Management
CX	Customer Experience
CS	Customer Services
CSAT	Customer Satisfaction Score
CART	Classification and Regression Trees
CSV	Comma Separated Values
ERP	Enterprise resource planning
GUI	Graphical User Interface
GDPR	General Data Protection Regulation
IBM	International Business Machines Corporation
ISD	Information System Division
JSON	JavaScript Object Notation
NPS	Net Promoter Score
VAS	Value Added Services
WEKA	Waikato Environment for Knowledge Analysis

CHAPTER ONE: INTRODUCTION

The customer experience can be defined as a customer's response to interactions with an organization before, during, or after purchase through multiple channels [1].

At present, customer experience is becoming the main differentiator among service providers. Telecom companies collect different kinds of data to ensure their services answer customers' needs. From little to huge universal businesses, their focus is on the customer experience due to the key role encounters play in making a difference in purchase choice. Boosting customer experience makes marketing more effective.

Most product and service providers have the popular phrase "customer experience" in their mission statement. For instance, Amazon, the world's biggest online retailer, says its mission statement is to provide the best customer experience in the markets by promising attractive e-commerce services to satisfy target customers' needs [2]. Computer company Dell's mission statement also states that it aims to be the most successful computer company in the world by delivering the best customer experience in all markets [3]. Ethiotelecom accepts the concept of customer experience and incorporates it into vital topics known as strategic themes. And it is intended to serve as a BRIDGE that takes the company to its next path. B stands for best customer experience, R stands for a reputable brand, I stands for innovative product/services/technology excellence, D stands for developing a people-oriented learning organization, G stands for growth in financial capacity, and E stands for excellence in operation.

According to Ambar Kakkar in the web journal of understanding customer experience in the services industry, 66 % of customers say that "they are willing to pay more for great experiences" [4]. So customer experience is everything. Profitability, loyalty, and retention are improved with customer experience [5] [6].

Customer relationship management is a platform typically used by professionals to manage a brand's relationships and interactions with customers [7]. According to Daniel Bishop in a blog on mapping data to customer experience, customer relationship management is the linchpin that connects customer data to customer experience [8]. It can be looked upon as the technical backbone to manage this entire customer journey, as explained by Tony Kavanagh [7]. Operational, analytical, and collaborative CRMs are the three types of CRMs. While all CRMs have some core functionality in common, their principal functions differ [7]. With the successful utilization of CRM technology, businesses can procure the rewards of having a loyal and engaged customer base [8].

One way to map CRM data to the customer experience is through classification modeling. It can be depicted as the mathematical problem of approximating a mapping function (f) from input variables (X) to output variables (Y) [9]. The work of the modeling algorithm is to find the best mapping function in a way that can give optimum model building time with resources available and optimum accuracy with regard to error [9]. Generally, all function approximation tasks can be classified into classification tasks and regression tasks [9]. The output variables are regularly called “labels or categories”. The mapping function predicts the class or category for a given perception [9].

The researcher investigated a novel approach to customer experience insight, which is to map customer experience from CRM data. Due to the survey method of customer experience is more time- and cost-consuming, difficult to design and develop, and has limited access to specific locations. And managerial problems in the social media plate form. Customer sentiment opinion is obtained from customer services, and significant attributes that might represent customer experience are selected from CRM system, and then mapped to customer experience opinion using a classification model.

1.1 Statement of the Problem

Assessing customer experience is a critical part of any telecom operator's business. This is also true for the case of ethiotelecom, which is a test case for this research. To achieve this, one approach is to use social media data. It is one of the methods for gaining insight about customer experience, but it does not make use of the CRM data stored on the CRM server.

The most popular method is to conduct a survey. This method also did not exploit customer data available in the CRM system. The major problems here are:

- More costly and
- Time-consuming in its data collection and processing

So it is critical to use CRM data to assess customer experience because it is easy to design and develop, it has faster data collection and processing methods, and it is a cost-effective method. In addition to these advantages, it can also include access to individuals in distant locations, the ability and convenience to reach difficult-to-contact participants, and it reduces both researcher and participant effort and time.

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1.2 Objectives

1.2.1 General objective

The main objective of the study is to map CRM data to customer experience using machine learning techniques on ethio telecom data.

1.2.2 Specific objectives

The specific objectives of this study are listed as follows:

- To collect data from CRM.
- To prepare data to make suitable for the algorithm.
- To identify relevant parameters.
- To identify appropriate data mining technique and algorithm.
- To compare model classifier.
- To recommend future works based on the findings the research.

1.3 Scope and Limitation of the Study

The focus of this study will be to map mobile user CRM data to customer experience. By integrating other telecom data, the accuracy of customer experience prediction will be high, but due to the constraints of the data, time and financial, the study will only focus on prepaid mobile users and map their CRM data to customer experience

1.4 Literature Review

Customer happiness is a critical component of any business's success. Various studies are conducted to learn about a customer's experience. One way to collect customer feedback is to conduct a survey [10].

A customer survey is the most straightforward and traditional method of getting feedback from a customer. However, the majority of customers are uninterested in completing feedback forms. Another flaw in this strategy is that it may or may not include an adequate questionnaire and may be biased on certain criteria, such as the feedback form having only specific questions. Other methods for collecting customer feedback include websites or online mobile applications. After the travel, the passenger can be sent an email with a link asking for feedback. However, there is no guarantee that it will work successfully. Another option is to send a message to passengers' cellphones asking them to rate the service on a scale of 1 to 5, with 1 being the worst and 5 being the best. All of the industry's traditional procedures are constrained to a set of parameters [11].

As Antonia Cramer explains how to collect data via a survey method, it might be digital or paper-based. Both ways have their drawbacks. That is statistics, and respondents can only react to the questions that are asked [12].

Alex Bischoff states that the Customer Satisfaction Score (CSAT), Net Promoter Score (NPS), and customer effort score (CES) are well-known metrics for measuring customer experience and satisfaction [13]. All methods collect input on how customers feel about the business, products, and services [13]. No single metrix will provide you with a complete view of the customer experience [14]. However, this metric survey methodology is employed in a variety of businesses. As well as being seen as a customer's voice [14].

As Grzegorz explains, the survey method is vulnerable to estimation mistakes since measuring human emotional responses is extremely difficult [10].

Social media is another method for a customer to express their opinion about their experience. It gives a place for users to freely voice their opinions on any concerns they may have encountered during their journey [11].

A lot of research has been done in the area of CX, which is very good, but all of the methods for measuring customer experience in the above research did not incorporate the data in the CRM system. Big resources are available in the CRM system. CRM systems collect customer information from multiple channels, or points of contact, between the customer and the business [15]. This study incorporates data from a CRM system as well as customer service voice as an opinion of a customer.

1.5 Research Methodology

The main steps followed in this research are as shown below:

Review literature: - Literature, research papers, and website were reviewed for getting information about the problems, solutions, and knowing which type of work was done by others on this topic and their methods.

Data collection and preprocessing: - In order to get the data from ethiotelecom, a formal non-disclosure agreement is done between the researcher and ethiotelecom and then the researcher takes this letter and gives it to the responsible division, which is ISD and customer services. Collected CRM data from ISD and individual opinions about their CX from customer service. And individual opinion about CX is considered as the target level. The data set were prepared and converted to the appropriate format.

Model experiment: - The preprocessed data is classified into a training set and a testing set. Use a training set to train a model and a test set to test the trained model. The results compared before selecting an accurate model.

Independent variable as input and using classifiers as a mapping function to CX (dependent variable).

The model was experimented using the open source “Weka” machine Learning (ML) tool Version 3.9.5 and operate it on computer processor Intel(R) Core(TM) i7-8665U CPU @ 1.90GHz 2.11 GHz.

Evaluate model: - The researcher uses classifiers and then key metrics such as accuracy, precision, recall and F-Measure as criteria to assess how well a model works.

1.6 Significance of the Study

The study will have a new scientific contribution. In addition to that, telecom operators will find the following benefits:

- This study contributed to an understanding of customer loyalty, satisfaction, and profitability.
- The investigation is supported by CRM systems and data mining techniques, which give the opportunity to contribute to the field of CRM analysis by applying general knowledge in a specific environment.
- The telecom organization (ethio telecom) can make use of the results to develop effective strategies.

1.7 Organization of the Thesis

Chapter two gives background knowledge about CRM, data mapping and, the importance of Data Mapping for customer experience and the number of data Classes.

Chapter three provides theoretical knowledge of machine learning, classifiers, and gives emphasis to the algorithms used in the research.

Chapter four describes the methods conducted to do the research. The data collection, preparation, and analysis methods are then described in this chapter.

In chapter five the results are presented and discussed. Finally, conclusions and recommendations are provided in Chapter six

CHAPTER TWO: Concept of CRM, Data Mapping and Data Class

This chapter provides a discussion on the fundamental concept of CRM, data mapping and types of class in classification. And how CRM data can be mapped to customer experience using classifiers in machine learning. In the telecom industry's history, customer churn can indeed be the smallest disappointment. According to Chowdary in [16] the common cause of dissatisfaction of a customer in the telecom provider can be, complicated billing, spam marketing emails, difficult customer service, internet speed, connectivity, or high plans. According to this study 90\% of all mobile subscribers are on prepaid service. Prepaid services are services offered without a subscription or contract and tend to include the least amount of customer information. In other studies in India, the churn rate is high in prepaid services as compared to postpaid services [17].
The best option to reduce churn is to make better decisions using machine learning on the rich data in the industry's servers. And as a sector is saturated, customer experience becomes a main differentiator among businesses. This research tries to gain insight about customer experience from CRM system data.

2.1 CRM

CRM is a platform used by professionals to manage a brand's relationships and interactions with customers [7]. CRM has progressed to the point that it can better manage a brand's relationship with its customers throughout their lifetime [7]. There are three functions that are shared by all CRM platforms; those are contact management, interaction monitoring, and lead management [7].

Contact management is one function in CRM and it is used to store contact information, including names, phone numbers, addresses including email addresses, and social media accounts [7]. Interaction monitoring is used In order to capture interactions with specific customers, to enter notes, and track customer contact history [7].

Lead management enables the CRM to manage the process by identifying sales scores [7]. Additionally CRM functionality can includes live chat, email marketing integration and templates, Social media management and etc [7].

2.2 Data Mapping

Before we get started on the mapping, let's speak about function. In mathematics and programming, it is a familiar word. A function in mathematics describes how elements from one set are connected to elements from another set. A function in programming transforms an input into an output. The two definitions are mutually intelligible [18]. The Figure 2.1 shows the combines aspects of both definition.

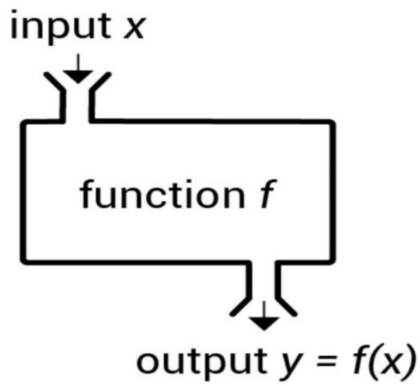

Figure 2.1 Function Represent [18]

Mapping can have the input to a function f is usually denoted with the letter x and have the letter y designates the output of a function [18]. To states it in the equation that y is the output of the application of function f to the input x : $f(x) = y$ [18].

Data mapping is about identifying the category an object belongs to [19]. Data mapping in its simplest term is to map source data fields to their related target data fields. An object in this research context is a data item and is fully represented by features. Each value refers to a measurable property that makes sense to consider in the scenario under analysis.

The data mapping technique is used to bring together and make sense of all of the diverse data sources [19]. Although data mapping with classifiers has progressed, there is still no clear agreement on which classifier should be employed. With the fast digitalization of the cutting edge world and with competition accessible in business organizations, success depends on the customer experience given to the customer.

2.3 Mapping CRM Data to Customer Experience

Every single day's petabytes of data are bucketing into telecom organizations, data flows into these servers at a rate that is beyond our imagination [20]. According to the oracle, the data growth is increased year by year. Businesses that can get a better handle on it can outperform their competitors [21].

Studying customer satisfaction levels will give us a clear picture of the factors that have led to satisfaction in the past few weeks or months [22]. A time taken by a study has a huge impact on the final output of the study usage. If the study takes too long, then it is useless because the world, people, and preferences change fast, so we should have results instantly [22]. If we know the factors that could affect this experience, then we can improve the experience through the huge amount of data we store in the telecom servers [22].

This day we must give special attention to satisfaction of a customer because of internet economy. Jeff Bezos, president of Amazon.com, expressed in wonderful expression. He said: “If you have an unhappy customer on the Internet, he doesn’t go and tell six friends, he tells 6,000 friends”.

The most reason for CRM is to assist companies to oversee their relationship with customers, and increment profits with a streamlined process [15]. According to Samantha Bonanno CRM software offers three major benefits for the business: first, easy access to customer data. And secondly streamlined processes through automation. And at last actionable insights into business performance and customer behavior [23]. A few CRM computer program vendors offer analytics usefulness, where clients can make customizable dashboards and reports based on customer information [23]. As explained by Samantha these reports offer assistance in segmenting customers, follow income, and overseeing personalized campaigns. Samantha argues, the feature can get some from CRM system likes Contact management which Stores contact information such as names, addresses, and social media accounts in a searchable database, interaction tracking, lead management, email integration, document management, quotes/proposal management, pipeline management, and workflow automation and also additionally reporting and forecasting features.

2.4 Relevance of Data Mapping for Business

Every company deals with massive amounts of data coming from countless sources. Especially telecom sectors data comes from different wide every day, every minute and possibly every second. Because of this hugeness, and reside in different formats, difficult to integrate it into a unified database for the data analysts to gather insights [22].

Telecom data is big data, big data reproduces with volume, velocity, variety, veracity [24]. Data mapping encompasses a huge part to play here. With effective data mapping, managers and other stakeholders access significant information that's easy to understand and less confusing than drawing experiences from disconnected databases. Data mapping using artificial intelligence and machine learning are ideally suited to the task of analytic of big data. According to a McKinsey Global Institute analysis, in more than two-thirds of use cases, machine learning can improve performance beyond that provided by other analytics techniques [25].

Training the machine is helps to recognize personal data, as defined by privacy procedures, allows it to test, compete, and link millions of records in large measure, quickly and comprehensively. This can be the as it were a way to coordinate data at adequate speed and unwavering quality to quicken observable into the mapped information for speedier, more definitive analytics and trade insights, and business intelligence, and for use in new applications [25].

Data mining techniques provide a tool to generate various classifications. In other words, Classification is a data mining function that assigns items in a collection to target categories or classes. And final the goal of classification is to accurately predict the target class for each case in the data. A classification task begins with a data set in which the class assignments are already known or with label data set. Classification is called supervised learning because you have prior knowledge of available classes or categories.

One advantages of data mining can be, leads the company to get all information in an organized manner and with easy access to information, and results the business manager in faster decision-making. To list out some of the advantages of data mining:

- It Increased efficiency in all business operations and then through improved customer relations, it increases sales and overall profit.
- It gives the managers and workers the capacity to identify any emerging trends and act on them.
- It gives the capacity to distinguish any rising patterns and act on them starting from level manager to laborer staff.

The benefits of telecommunications customer experience management are huge to list: deliver the right offer to the right customer at the right time through analyzing historical and real-time data on customer preferences and behaviors to determine needs and select appropriate offers, make a narrow customer segmentation delivering a unique experience to every customer to increase the likelihood of conversion and improve customer loyalty and defend competitors by implementing modern programs to target at-risk customers [26].

2.4 Number of Data Classes

There is no clear rule for the number of data classes, but according to [27] the recommended class to map is with 3-7 data classes. Naturally, data class number decisions depend on the goals of the work and the data available on hand: For instance, on the United States political map, there are only 2 classes, which are the red state and blue state maps. When more classes are accessible, at that point less information generalization which is exceptionally great, but this comes at the cost of neatness and the related chance of outline perusing mistakes. A map with 3 classes, like low, medium, and high, will be easy to see and remember. For this thesis, average, satisfied and unsatisfied class are considered, which is three data classes. Actuality there is no ideal number of classes for a map, so an experiment is needed in the area.

As described in the above paragraph the data available on hand determine the number of the class. In this research, each individual customer's opinion is asked by the customer services department. This customer opinion is categorized into three classes. When more than two classes are available in the data set then it is called multi-class classification. According to [28] Classification is the process of predicting the group to which a given data item belongs.

2.5.1 Binary Classification

It is a type of supervised classification, and the algorithm has to assign the processed object to one of only two possible categories. A good example of this is email spam detection (spam or not), churn prediction (churn or not) and Conversion prediction (buy or not), medical discipline cancer detection (cancer or not cancer), and fraud detection (fraud or not fraud).

Popular algorithms that can be used for binary classification include Logistic Regression, k-Nearest Neighbors, Decision Trees, Support Vector Machine, and Naive Bayes [29]. Evaluation metrics in binary classification depend on the problem statement which the researcher wants to solve and also on the distribution of the target class label [29]. The popular binary classification metrics are accuracy, log-loss, F1-score and AUC-ROC sore [29]. Generality binary classification is the simplest type of classification problem with two possible values

2.5.2 Multiclass Classification

The algorithm must assign objects to one of many possible categories. Each object can be consigned to one and as it were one category. At the same time. Jason defines multiclass classification as classification tasks that have more than two class labels. And good examples for this face classification, plant species classification, and optical character recognition. Popular algorithms that can be used for multi-class classification include k-Nearest Neighbors, Decision Trees, Naive Bayes, and Random Forest. Algorithms that are planned for binary classification can be adjusted for utilizing for multi-class problems. The evaluation metrics can be F-Measure, precision and recall.

2.5.3 Multi-label Classification

The algorithm is anticipated to supply an array of categories that the object belongs to. A good example of this is how to classify a blog post. It can be sports, technology, and perhaps political issue at the same time. According to Japhson Classification algorithms used for binary or multi-class classification cannot be utilized specifically for multi-label classification. Specialized forms of standard classification algorithms include multi-label versions of the algorithms, Multi-label Decision Trees, Multi-label Random Forests, and Multi-label Gradient Boosting.A popular matrix to for this classification can be F-measure, Precision, Recall, Hamming Loss and log-loss [29]. .

CHAPTER THREE: MACHINE LEARNING

In this chapter, detailed explanations of basic machine learning algorithms and classification model analysis are described. Different researchers define machine learning differently according to IBM Machine learning is a branch of artificial intelligence and computer science that focuses on the utilizing of data and algorithms to mimic the way that people learn, continuously moving forward its exactness [30]. According to Jason Brome, The field focuses on learning, or gaining skills or knowledge through experience. This normally involves extracting relevant concepts from past data [31].

3.1 Categories of Learning in Machine Learning

Supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning are the four primary categories of machine learning algorithms [32]. Let's see each of them in detail.

Supervised machine learning algorithm: All materials are "labeled" to inform the machine of the appropriate value, allowing it to correctly forecast the value [32]. Supervised machine learning analyzes a known preparing dataset, and after that makes predictions about the yield values. It can to make comparisons between the proper and planning yield, and the yield, and after that make modification [33].

Unsupervised machine learning algorithm: There are no labels on the items [32]. It explores the data and after, describes hidden structures from unlabeled data [33]. This sort of calculation comes inconveniently and does not decide what the right output is [33].

Semi-supervised learning algorithm: Only a small portion of the data is labeled [32]. Computers simply need to look for characteristics in labeled data and then classify the rest of the data [32].

Reinforcement learning algorithm: It uses observations gathered from the interaction with the environment to take actions that would maximize its value or minimize the risk [32]. Just like unsupervised machine learning, there is no label material but, need to tell the algorism which step is wrong and right [32].

For this thesis work supervised machine learning algorithm is selected because the data available in hand is labeled one.

3.2 Machine Learning in Customer Experience

As machine learning and artificial intelligence customer experience are a keyword in all businesses especially in services-based business, with passionately varying results [34]. Its factor is getting to be progressively vital to hold the present-day customer. This research believes that machine learning can have significance in customer experience prediction.

As an example, sentiment analysis, which uses machine learning to determine how people feel about a company's brand, products, and services. Machine learning helps marketers manage the scale and complexity of journey coordination. By working speed 24 hours a day, seven days a week without fatigue or complaint [32].

3.3 Classification Models

Classification models are currently used in a wide range of areas like marketing, scientific discovery, fraud detection, and so on. The concept in classification requires the construction of a classifier, that is, a function that assigns a class label to instances described by a set of attributes [35]. Classification is a will know technique of data mining, which is used to predefined classification data. The techniques in classification need, classifying data into a fixed number of groups and using it for categorical variables [36].

This research uses classification techniques for predicting customer experiences. It uses three types of classification techniques to construct prediction models those are Naive Bayes, J48 and Random Forest. Moreover, the three algorithms that were used to construct the models and the output metrics of the algorithms that were used to measure the performance of the algorithms and comparison are explained thoroughly.

The reason the researcher chose these three algorithms is that most of the literature in classification areas uses these algorithms, and another reason is that the data is more suitable for these algorithms.

3.3.1 Naive Bayes

It is based on Bayes' theorem and assumes that the existence of one feature in a class has no effect on the presence of other features [37]. To state Bayes' theorem, give a hypothesis "H" and evidence "E". The equation in Figure 3.1 below shows the probability of the hypothesis before getting evidence "P(H)" and the probability of the hypothesis after getting evidence "P(H/E)". Each term of Bayes' theorem explain in the Figure 3.1.

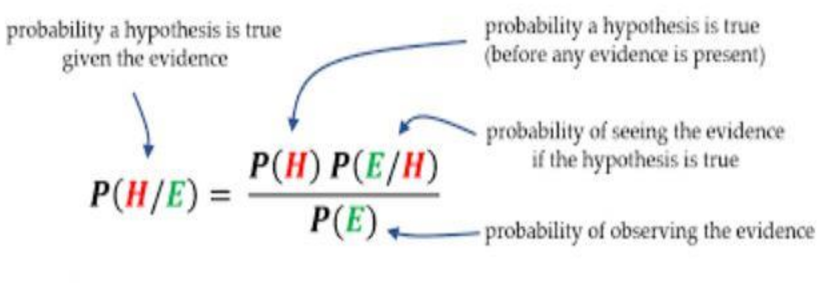

Figure 3.1 Bayes 'Theorem Explanation [38]

Advantages and disadvantages of Naive Bayes.

Advantages

- Predicting the test data set's class is simple and quick. It's also good at multi-class prediction [37].
- When the assumption of independence is true, a Naive Bayes classifier outperforms other models such as logistic regression, and it requires less training data [37].
- When compared to numerical input variables, it performs well with categorical input variables (s) [37].

Disadvantages

- “Zero Frequency” [37].
- Bad estimator [37].
- Unrealistic assumption of independent predictors [37].

Naive Bayes algorithms can be applied in real-time prediction, multi-class prediction, text classification, sentiment analysis, spam filtering, and recommendation system [37].

3.3.2 J48

It is a group of decision tree classifiers. It is widely used for classification and decision-making processes. J48 consists of three components: root node, branch node, and leaf node. Root (top of the tree) represents the test condition for different attributes, the branch represents all possible outcomes that can be there in the test, and leaf nodes contain the label of the class to which it belongs [39]. In simple terms, it is built on a recursive divide and conquer method, which is a top-down strategy. Starting at the root node, by choosing which attribute to split, then create a branch for each possible attribute value, which divides the instances into subsets, one for each branch that extends from the root node [40].

Advantages and disadvantages of J48.

Advantages

- Easy to understand and interpret, perfect for visual representation [41].
- Can work with numerical and categorical features [41].
- Requires little data preprocessing [41].
- Non-parametric model: no assumptions about the shape of data [41].

Disadvantage

- It has a tendency to over fit [41].

J48 is preferable to apply for non-linear data sets to be effective. In real life a variety of fields, including engineering, civil engineering, law, and business use this algorithm [42]

3.3.3 Random Forest

According to Mishra .et.al [43] Random Forest is an expansion of bagging for decision trees that can be utilized for classification or regression.

Random Forest is a classifier that combines several decision trees on different subsets of a dataset and takes the average results to increase the dataset's predicted accuracy. In other words, rather than relying on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority votes of predictions [44]. The greater the number of trees in the forest, the higher the accuracy and the less chance of overfitting [44]. The concept behind random forest is depicted in Figure 3.2 below.

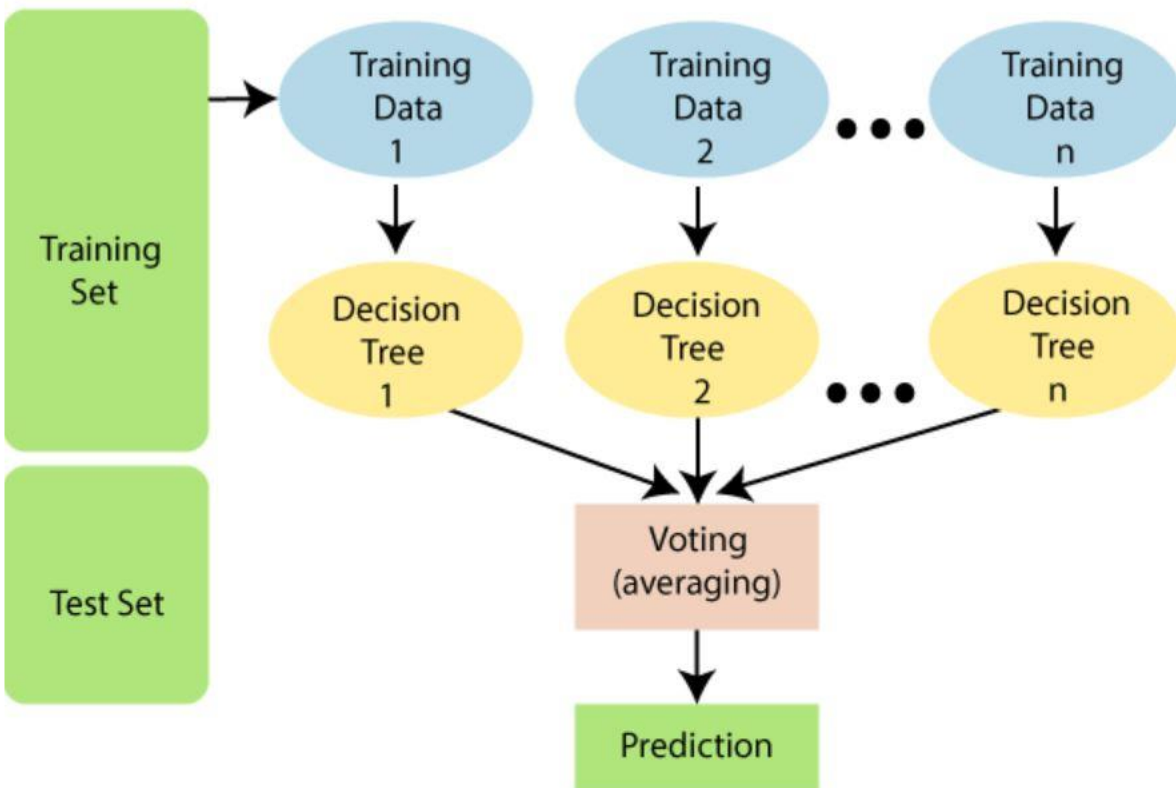

Figure 3.2 Random-Forest Algorithm [44].

Advantages and disadvantages of Random Forest.

Advantages:

- For large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

Disadvantage:

- It is not more suitable for regression tasks.

CHAPTER FOUR: Methodology

The approaches for mapping CRM data to customer experience are discussed in this chapter. First, data collection, preprocessing, and then future selection are presented. And then the system model and algorithm are discussed, and finally, experimentation and evaluation techniques are presented.

4.1 Data Collection

The steps taken in this study to get the required data will be discussed here. A formal non-disclosure agreement is made between the researcher and ethiotelecom. The researcher then takes this letter and gives it to the responsible division, which is the customer service and information system division.

The dataset contained 1217 contacts and 6 attributes. Each 1217 record of customer experience opinion is collected from the customer services department on two different days. On October 7, 2021, 400 records were obtained, and the remaining 800 records were on August 11, 2021. The attributes relevant to predicting customer experience were obtained from CRM systems in telecom systems (ethio telecom).

To list out relevant attributes, include the following: two month sequence of recharge expense of services number, offer to choose, post-response satisfaction during customer service calling, option used to recharge (recharge Choose), call frequency to customer services, and technology type (2G, 3G, and 4G). Table 4.1 shows sample of collected data.

Table 4.1 Sample Data

Services number	Recharge amount in 2 month	Offer choose	Post respond satisfaction	Recharge choose	Call Frequency to94	Technology Type	Customer Experience Opinion
973133090	200	Basic Service with VAS	0	USSD with others	7	3G	Average
954537512	600	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
916415900	10	Basic Service	1	USSD	7	2G	Unsatisfied
963206758	810	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
985192321	735	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
909250670	80	Basic Service with VAS	0	USSD with others multi option	3	3G	Average
972773047	700	Basic Service with VAS	2	USSD with others multi option	1	3G	Satisfied
983653044	200	Basic Service with VAS	0	USSD with others multi option	4	3G	Average
925337368	430	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
964808024	320	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
972913635	150	Basic Service	2	USSD	2	3G	Average
962118333	300	Basic Service with VAS	2	USSD with others multi option	7	3G	Satisfied
946118751	320	Basic Service with VAS	2	USSD with others multi option	2	3G	Satisfied
909663543	300	Basic Service with VAS	2	USSD with others multi option	3	3G	Satisfied
964651261	400	Basic Service with VAS	2	USSD with others multi option	4	3G	Satisfied
926917818	400	Basic Service with VAS	2	USSD with others multi option	4	3G	Satisfied
921539973	120	Basic Service with VAS	0	USSD with others	3	3G	Average
996778856	70	Basic Service with VAS	0	USSD with others	2	3G	Average
931126183	100	Basic Service with VAS	0	USSD with others	1	3G	Average
996984241	75	Basic Service	1	USSD	3	3G	Satisfied
918162998	125	Basic Service with VAS	0	USSD with others multi option	3	3G	Average
983665007	100	Basic Service with VAS	0	USSD with others	2	3G	Average
953792727	5	Basic Service	1	USSD	4	3G	Unsatisfied

The dependent variable (customer experience opinion of each customer) tells us whether subscribed telecom company customers have a satisfied customer experience, an average customer experience, or an unsatisfied customer experience.

4.2 Preprocessing Data

Before data is introduced to the data mining tool, data needs to be cleaned and prepared in the required format. Those tasks could be resolving inconsistent data formats and resolving inconsistent data encoding, and stripping out unwanted data fields.

4.2.1 Data Cleaning

From 1217 recorded data, nine of the subscribers were postpaid. These nine records were discarded. Finally, only 1208 of the instances and six attributes that were available in the dataset were used for the experimental studies. Add the missing value to the minimal value. There are three services whose recharge amount is 0 birr, but the research work considers them to have a minimal value of 5 birr

4.2.2 File Format

WEKA supports a couple of popular text file formats, such as CSV, JSON, and ARFF. The data collected was an excel file, so change it to the main file format used in WEKA. For this thesis, the CSV (comma-separated values) file format is selected.

CSV: contains a record of the text file and is spared in a table structure.

4.3 Feature Selection

According to Jason Brownlee, key benefits of feature selection on the data sets are: It reduces overfitting, improves accuracy and reduces training time [43]. The number of features in prediction model development should be optimal. It is not to say that more features mean more information. Figure 4.1 shows the classifier's behavior as the number of features (variables) increases. It increases until reaches its optimal level, then decreases as the number of features increases.

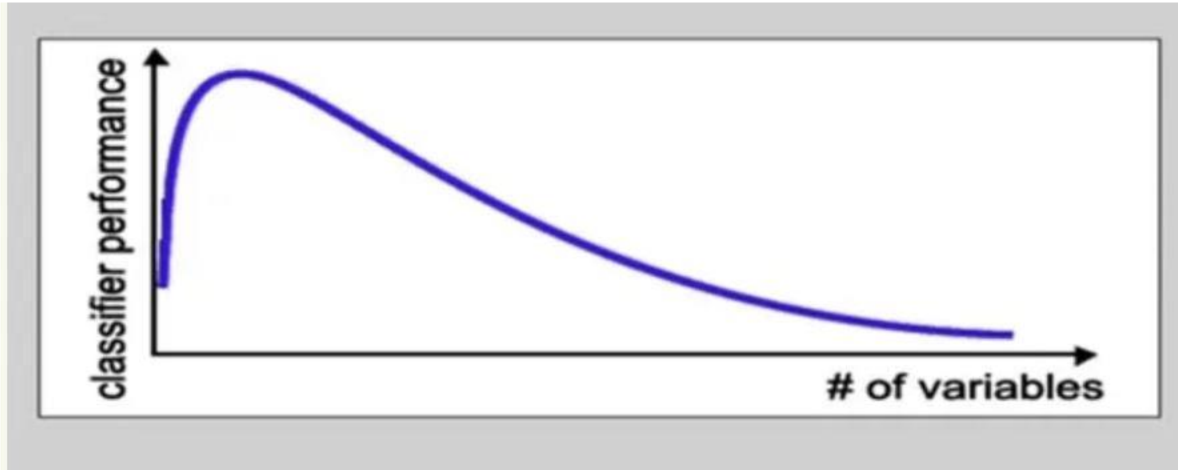

Figure 4.1 Classifier Behavior [45]

The term “customer experience” refers to all of a customer's interactions with a company. However, user experience and customer service are two basic building blocks of customer experience [46]. User experience is about interacting with and users of your product/services, while customer service is the support that organizations provide their customers when they face problems with any of the services/product [46]. To achieve the goal of the research, which is mapping CRM data to customer experience, this thesis includes attributes available in these two components. Six features are described below.

A Monthly volume expenses

The amount of money (Birr) a subscriber spends during the two consecutive months. With Christian Homburg's study in [47], customer satisfaction does have a positive impact on willingness to pay. As reported by Christian Homburg, Nicole Koschate and Wayne D. Hoyer Satisfied Customers (customers that have good experience) spend more (pay more). According to Super Office, as much as 86 % of customers are willing to pay more for goods and services if they are couched within a good customer experience. So this thesis work select volume of expense as one option to consider as if the customer pays more the research considered as satisfied one.

According to Super Office, 86 % of customers are willing to pay more for goods and services if they are couched within a customer experience [8]. Ambar Kakkar and Mayzin Han agree on the issue. They said, “Satisfied customers are likely to spend more" [5]. 42 % of customers would pay more for a great experience, and 72\% would choose one brand over another if they received special treatments [5].

B Offer to choose

The subscriber option to use offer specifically VAS services package. According to Anna Johansson, customers want options and choices [48]. Have options that make customers more satisfied (make their experience good) [48]. VAS assures good CX [49]. According to Sania Amir, telecom companies are taking measures to ensure fast and efficient services for their subscribers to gain a competitive advantage in the market by providing value-added services [49].

C Frequency of VAS

Frequently doing something indicates that the services are easy and one of the common good characteristics of a satisfied customer. Making the services easy to find and engage will motivate the subscriber to use services frequently. From the perspective of the customer, a good CX includes usability (easy to find and engage) [50]

D Call frequency to customer services

Customer Call frequency is one of the call center metrics that tracks the number of times the same customer calls [51]. Repeat calls are frequently made by dissatisfied customers [52].

E Technology type a customer uses

The kind of technology the subscriber is registered for (4G, 3G, and 2G). Cutting-edge utilization of technology in business, create a better chance to deliver a truly exceptional CX to the customers [53].

F Recharge choose offer

The subscriber used option to recharge services number. Have different option make a customer satisfied as described in [48].

G Customer services post complaint Satisfaction

The subscriber respond to CS during the specific day of the call. Customer services post complaint satisfaction gives a direct indication about their experience. Customer services post compliant satisfactions option in ethiotelecom is look like this:

- Customer press 2 if satisfied
- Customer press 1 if unsatisfied
- Customer press 0 if average

For lots of reasons, variables within a dataset can be related. To list a few examples, it can be one variable that could cause or depend on the values of another variable. Another reason could be that one variable could be lightly associated with another variable. And two variables could depend on a third unknown variable.

The methods used for data reduction can be classified into two types: wrapper and filter methods. The filter methods are discussed below. The filter approach is independent of the learning algorithm and is computationally simple, fast, and scalable. The two main feature ranking and feature selection techniques in the filter are correlation and information gain.

Correlation is a popular technique for selecting the most relevant attributes in the dataset. Weka supports correlation-based feature selection with the CorrelationAttributeEval technique that requires the use of a Ranker search method. It evaluates the value of attributes by measuring the correlation (Pearson's) between them and the class they belong to. Table 4.2 shows the correlation rank of each attribute in the customer experience data set.

Table 4.2 Correlation rank

Attribute List	Correlation AttributeEval	Search Method	Evaluation Mode
Recharge of 2 month	0.2525	Attribute Ranking	Evaluate all training data
Recharge choose	0.4358		
Post respond satisfactions	0.3329		
Offer choose	0.4032		
Call frequency to 994	0.0528		
Technology Type	0.0186		

Information gain another popular future selection techniques. Weka supports it with a name called InfoGainAttributeEval Evaluator. Like correlationAttributeEval, the Ranker Search Method must be used. It evaluates the worth of an attribute by measuring the information gained with respect to the class. Like in correlationAttributeEval, the minimal number of instances in this technique is also one. The Table 4.3 describes the evaluator technique of InfoGainAttributeEval in the customer experience dataset. In both methods, the attribute technology type gets the minimum rank.

Table 4.3 Information Gain

Attribute List	InfoGain AttributeEval	Search Method	Evaluation Mode
Recharge of 2 month	0.62823	Attribute Ranking	Evaluate all training data
Recharge choose	0.5604		
Post respond satisfactions	0.54801		
Offer choose	0.2761		
Call frequency to 994	0.01261		
Technology Type	0.00161		

The researcher uses two different feature selection techniques to produce the most accurate models. But with these two techniques, the accuracy of the model is the same.

4.4 Classifier and Algorithms

Suitable classifier selections for the particular data sets were, for the most part, found harder [54]. Depending on the type and nature of the attributes in the data set, the classifier performance can vary [54]. The wrong selection leads to poor performance [54].

The objective of classification is to accurately predict the value. This paper gives a comparison of various classification techniques. The performance of these classifiers was analyzed with the help of correctly classified instances, incorrectly classified instances, and the time taken to build the model. The well-known classifiers discussed here are Bayes and Tree.

Bayes Classifier

Bayes techniques are used as one of the classification solutions in machine learning tasks. In this thesis work, of six Bayes methods, only Naive Bayes is used. Naive Bayes is an extension of the Bayes theorem in that it expects the independence of attributes [55]. This is not absolutely true when the case is the classification of text from a document extraction, as there are relationships between the words that accumulate into concepts [55]. Naive Bayes is also additionally called “idiot's Bayes”, “simple Bayes”, and “independence Bayes” [55]. One of the advantages of this classifier is that it is easy to build the model without any need for complicated iterative parameter estimation schemes [55]. It is best when huge datasets are used [55]. It is robust, easy to interpret, and frequently does shockingly well in spite of the fact that it may not be the leading classifier in any specific application [55].

Tree classifier

The concept behind this classifier consists of the root node, leaf node, parent node, and child nodes. The root node is the top-most node in the decision tree, and that leaf node is the bottom-most node. A node divided into sub-nodes is called a parent node, and the sub-nodes are called child nodes. Tree classifiers in Weka tools contain eight different algorithms. To list them DecisionStump, HoeffdinggTree, J48, LMT, M5P, RandomForest, RandomTree and REPTree. The selected Weka classifier is Bayes and tree. The algorithms the researcher chose to analyze are Naive Bayes from Bayes, and J48 and Random forest from the tree. The research work compares the accuracy and the performance between these three algorithms.

With the J48 algorithm, we can clearly visualize the tree. The highest contributor for model building on the J48 algorithm is found in the first top three in rank information gain. Figure 4.2 shows the visualization tree of J48 algorithms.

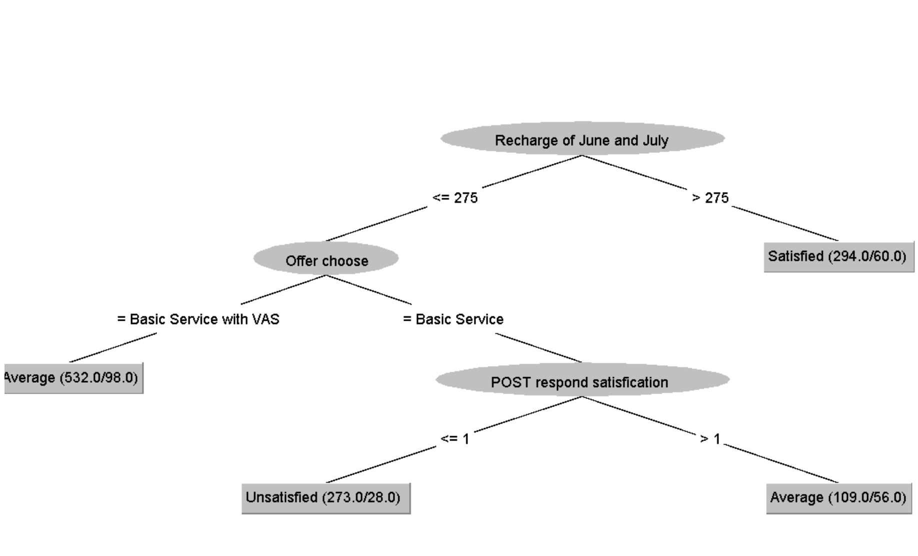

Figure 4.2 Visualize Tree

4.5 System Model

The system model begins with the literature review and is followed by data collection from CRM and CS. Customer's opinion (sentiment) about their experience is taken as a labeled dataset. Which is either “satisfied,” “average” or “unsatisfied” and treated as the dependent variable. CRM system provides an independent variable. The preprocessed data is classified into a training set and a testing set. Use a training set to train a model and a test set to test the trained model. The results compared before selecting an accurate model. The procedure used in the research activity is depicted in Figure 4.3.

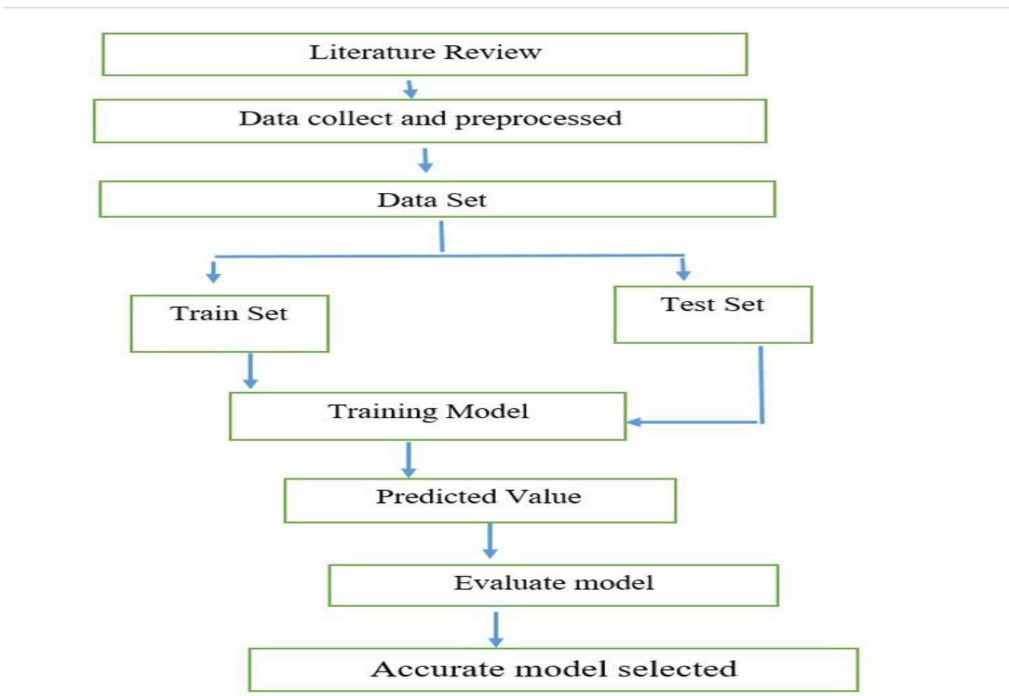

Figure 4.3: System model

4.6 Test Techniques

There are different evaluating mechanisms in machine learning algorithms. Four test options are discussed here. To list them, use the training set, supplied test set, cross-validation, and percentage split.

Using the option “use training set”, apply the training set concept, starting with training on all of the data and then testing on all of the same data. Utilizing the same correct data for both preparing and testing, which would clarify 100 % accuracy. But it isn't fundamentally valuable. The second option is the supplied test set. The word by itself is explanatory; the researcher supplies it with a test set. The third option is a percentage split. It is a way of partitioning the data set into two sets of a certain percentage, one set for training and one for testing. And it is recommended when your algorithm is slow. Finally, the cross-validation is like percentage splits. It is the most commonly used testing method in papers and the recommended option for getting more realistic results. This research paper uses cross-validation as a validation method. Figure 4.4 shows the cross validation method with fold 10.

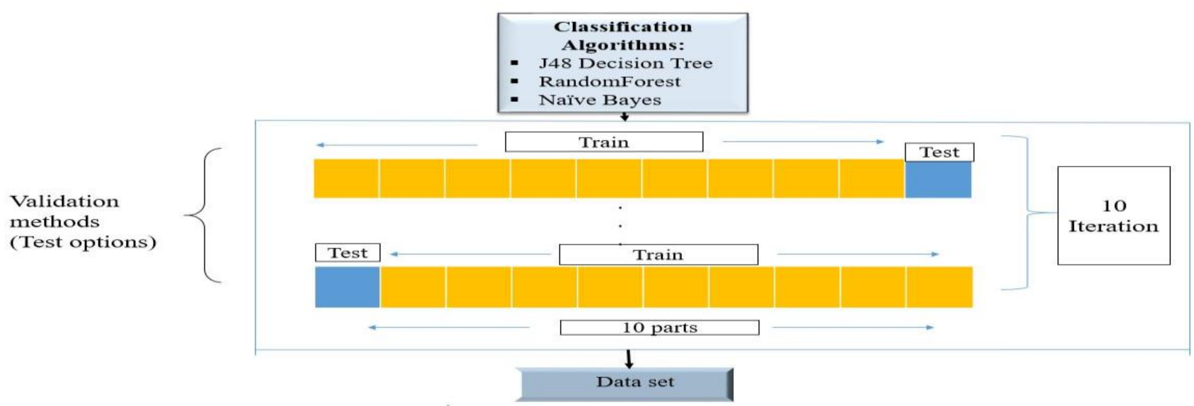

Figure 4.4: Cross-Validation

4.7 Evaluation Metrics

To evaluate a model, the researcher uses a metric called accuracy. Detailed accuracy descriptions include precision, recall, F-Measure, TP Rate, FP Rate, MCC, ROC Area, and PRC Area also used in this research.

Accuracy: - The ratio of the number of correct predictions to the total number of input samples.

$$Accuracy = \frac{Number of correct predictions}{Total number of predictions made} \tag{4.1}$$

Precision: - A measure that evaluates a classifier's ability to identify only the correct instances for each class.

$$Precision = \frac{TP}{TP+FP} \tag{4.2}$$

Recall: - The ability of a classifier to find all correct instances per class

$$Recall = \frac{TP}{TP+FN} \tag{4.3}$$

F-measure: It is a method for combining precision and recall into a single measure that captures both attributes and weights them equally. It is, a weighted harmonic mean of recall and precision. It is sometimes known as the F-Score.

The confusion matrix for a multi-class classification is shown in Table 4.4 below. The confusion matrix would be a 3 x 3 matrix like below which have average class, satisfied and unsatisfied class.

Table 4.4 Confusion Matrix

ML		Actual		
		Average	Satisfied	unsatisfied
Predicted	Average	503	41	22
	Satisfied	63	223	9
	Unsatisfied	75	7	265

For each class, the true positive and true negative, as well as the false positive and false negative, would be computed by adding the cell values as follows:

Average	Satisfied	Unsatisfied
TP = cell1	TP = cell5	TP = cell9
FP = cell2+cell3	FP = cell4+cell6	FP = cell7+cell8
TN = cell5+cell6+cell8+cell9	TN = cell1+cell3+cell7+cell9	TN = cell1+cell2+cell4+cell5
FN = cell4+cell7	FN = cell2+cell8	FN = cell3+cell6

Based on the above formula, the TP, FP, TN, and FN values for a dataset are shown below

Average	Satisfied	Unsatisfied
TP = 503	TP = 223	TP = 265
FP = 41+22	FP = 63+9	FP = 75+7
TN = 223+9+7+265	TN = 503+22+75+265	TN = 503+41+63+223
FN = 63+75	FN = 41+7	FN = 22+9

CHAPTER FIVE: RESULTS AND DISCUSSION

This chapter contains two primary sections: the result section and the discussion of that result section. The first section is divided into four sections. The procedure started with a description of the dataset type, followed by the correlation attribute, model performance analysis, and finally model validation performance. In the second part, the outcome is discussed

5.1 Experiment Results

The customer experience data set with the selected features, the experiments, and the evaluation schemes was discussed here.

5.2 Balanced Dataset

During The customer experience dataset has 1208 instances. The dependent attribute which is customer experience opinions have three labels. To list it average, satisfied and unsatisfied each label has 566, 295 and 347 number of customer opinion respectively. Table 5.1 describes customer experience opinion in the customer experience dataset (input sample) and output result. Understanding from confusion matrix of the research the data set have a balanced. A balanced dataset is one in which each output class (or target class) is approximately represented by the same number of samples [56].

The input sample and output sample didn't have a significant difference.

Table 5.1 Input and Output Sample

<table>
<tr><td colspan="2" rowspan="4">Input Sample</td><td colspan="3">Output</td></tr>
<tr><td rowspan="3">J48</td><td>Average</td><td>503</td></tr>
<tr><td>Satisfied</td><td>223</td></tr>
<tr><td>Unsatisfied</td><td>265</td></tr>
<tr><td>Average</td><td>566</td><td rowspan="3">Random Forest</td><td>Average</td><td>466</td></tr>
<tr><td>Satisfied</td><td>295</td><td>Satisfied</td><td>223</td></tr>
<tr><td>Unsatisfied</td><td>347</td><td>Unsatisfied</td><td>277</td></tr>
<tr><td colspan="2" rowspan="3"></td><td rowspan="3">Naive Bayes</td><td>Average</td><td>416</td></tr>
<tr><td>Satisfied</td><td>235</td></tr>
<tr><td>Unsatisfied</td><td>291</td></tr>
</table>

The average, satisfied, and unsatisfied records in the input sample are 566, 295, and 345, respectively. The output sample has a result of 503, 223 and 265 average satisfied and unsatisfied results, respectively, in J48 algorithm.

5.3 Attributes for Mapping CRM Data to CX

CorrelationAttributeEval and information gain is used to illustrate the rank. In both techniques of ranking the accuracy of algorithm have similar score. Table 5.2 describes the attribute Evaluator rank. Technology type had a negligible impact on both correlationAttributeEval and information gain ranking techniques.

Table 5.2 Attribute Evaluator

Attribute List	Correlation AttributeEval	InfoGain AttributeEval	Search Method	Evaluation mode
Recharge of 2 month	0.2525	0.62823	Attribute Ranking	Evaluate all trading data
Recharge choose	0.4358	0.5604		
Post respond satisfactions	0.3329	0.54801		
Offer choose	0.4032	0.2761		
Call frequency to 994	0.0528	0.01261		
Technology Type	0.0186	0.00161		

5.1.3 Models Performance Analysis

The performance comparisons of the three algorithm are summarized here. The accuracy of the ML algorithms was listed in Table 5.3 below. The accuracy results for this data set indicate J48 performs better with an accuracy of 82.03 %.

Table 5.3 Accuracy Result

Algorithm	Result (%)
Naïve-Bayes	77.98
Random-Forest	79.96
J48	82.03

Figure 5.1 describes the accuracy of each algorithm in the column chart. J48 score accuracy of 82.03 %, Random-Forest score 79.96 % and Naive-Bayes score 77.98 %

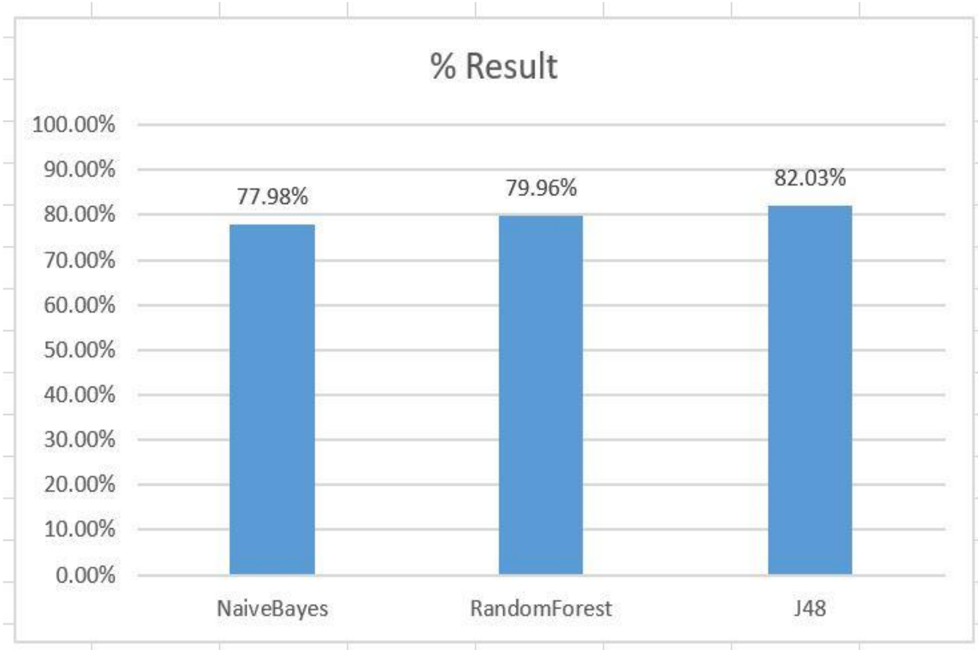

Figure 5.1 Accuracy of Algorithm

A detailed performance summary of the dataset, is listed in Table 5.4 below. Precision, recall, and F-Measure all have values of 0.826, 0.820, and 0.820, respectively in J48.

Table 5.4 Performance Summary

Algorithms	Performance result				Time
	class	Precision	Recall	F-Measure	
Naïve-Bayes	Average	0.839	0.735	0.783	0.01 sec
	satisfied	0.778	0.797	0.787	
	Unsatisfied	0.710	0.839	0.769	
	Weighted	0.787	0.780	0.780	
J48	Average	0.785	0.889	0.833	0.02 sec
	Satisfied	0.823	0.756	0.788	
	Unsatisfied	0.895	0.764	0.824	
	Weighted	0.826	0.820	0.820	
Random-Forest	Average	0.799	0.823	0.811	0.32 sec
	Satisfied	0.780	0.756	0.768	
	Unsatisfied	0.817	0.798	0.808	
	Weighted	0.800	0.800	0.799	

Table 5.5 describe error statics of each algorithms. Root relative square error, relative absolute error, root mean square, mean absolute error, and kappa statics indicate the error in machine learning. In comparison to the baseline, kappa statics for Naive-Bayes, J48, and Random-Forest are 0.6607, 0.7131, and 0.6847, respectively.

Table 5.5 Error Log Statics

Error log Statics	Naive Bayes	J48	Random Forest
Root relative squared error	70.642 %	68.0924 %	67.5116 %
Relative absolute error	35.5241 %	39.351 %	36.6196 %
Root mean squared error	0.3259	0.3141	0.3114
Mean absolute error	0.1512	0.1675	0.1559
Kappa	0.6607	0.7131	0.6847

Figure 5.2 and Figure 5.3 describes error result in pie chart.

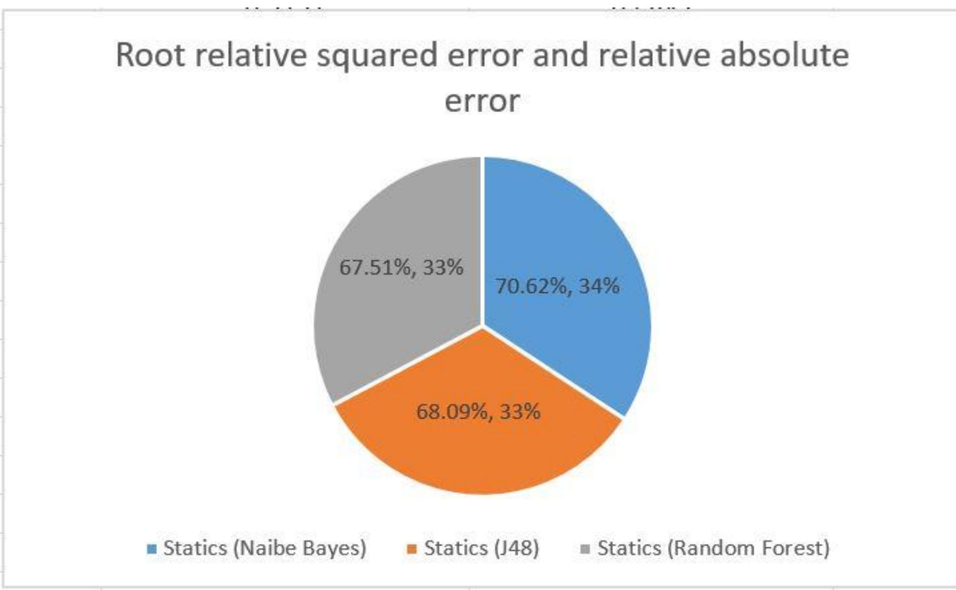

Figure 5.2 Accuracy of Algorithm in Pie Chart

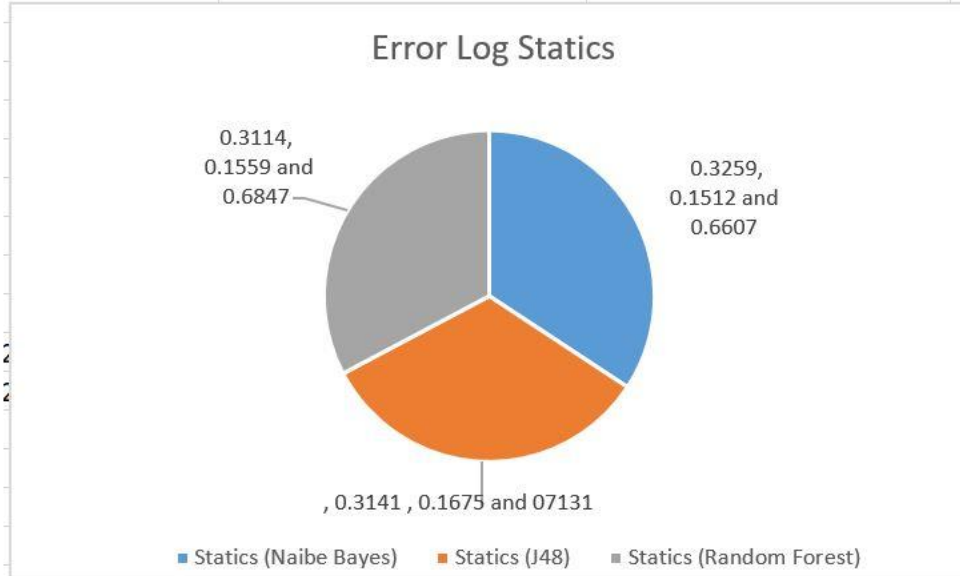

Figure 5.3 Error Log Statics

Understanding from the result of J48 kappa statics is higher as compared to the other two algorithms, which are Naive Bayes and Random Forest.

5.1.4 Models Validation Performances

The correctly classified instances and incorrectly classified instances are described in Table 5.6 below. From 1208 total data-set 991 are correctly classified and 217 are incorrectly classified in J48 algorithm.

Table 5.6 Correctly Classified vs incorrectly classifieds instance for each algorithms.

Algorithms	correctly classified	incorrectly classifieds
Naïve Bayes	942	266
J48	991	217
Random Forest	966	242

According to the researcher, it is crucial to establish a baseline of performance. A baseline serves as a benchmark against which other machine learning algorithms can be measured [57]. The Zero Rule algorithm is the starting point for both classification and regression issues [57].

To demonstrate their expertise on this problem, those machine learning algorithms must outperform the baseline result in accuracy. The base line result of this research using Zero algorithms is 46.85 %. In this study, all three analogies scored higher than the baseline. Figure 5.4 describes correctly and incorrectly classified instances of each algorithm in column chart.

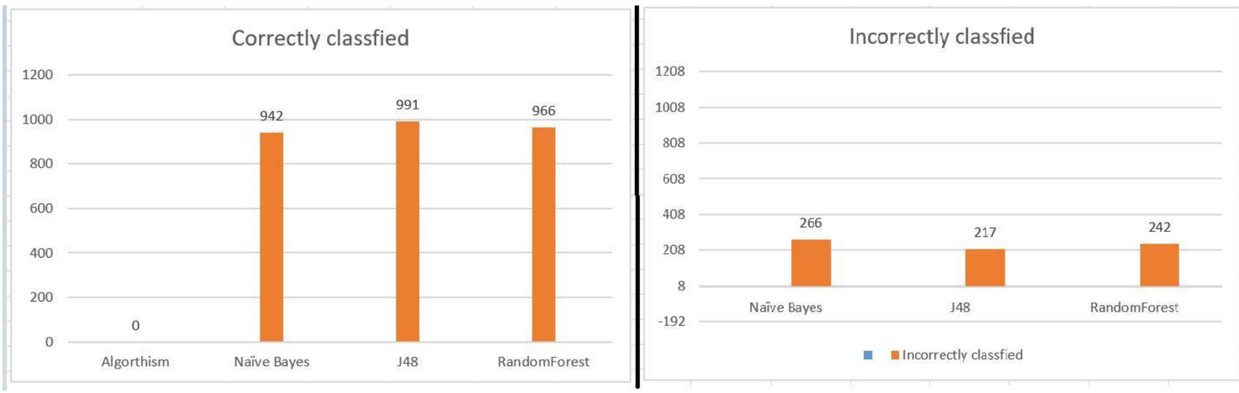

Figure 5.4 Correctly Vs Incorrectly classified Instances

5.2 Discussion on the Results

The experimentation is done and the results are captured in the table and figure above. 566 of the 1208 customer experience instants have an average customer experience opinion, 295 have a satisfied customer experience opinion, and 347 have an unsatisfied customer experience opinion.

Table 5.3 lists the results. Naive-Bayes has an accuracy of 77.98 %, J48 has an accuracy of 82.03 %, and Random Forest has an accuracy of 79.96 %. By comparing the correctly classified instance values for these classification algorithms, the J48 algorithm illustrates the optimal result. Table 5.4 shows the time for building the model. For building the model for Naive Bayes takes 0.01 sec, for J48 0.02 sec, and for Random-Forest 0.32 sec. By comparing the values for the time taken to build the model for these classification algorithms, the Random-Forest algorithm illustrates the worst result when compared to other two classification algorithm.

5.3 Interpretation of Results

This thesis was conducted on the CRM dataset to understand how classification algorithms can be used to map CRM data to customer experience in less time-consuming and less expensive ways. Naive-Bayes, J48, and Random-Forest were used to classify the customer experience. J48 was better at classifying the data set. The customer falls into one of three categories: average, satisfied, or dissatisfied. Customer experience concept by itself is sensitive, so we must give special attention to all customers in the class. However, for satisfied, dissatisfied, and average-class customers, suggestions are given in table 5.7 below.

Table 5.7 Class of a Customer

Class	**Approached conducted**
Satisfied	1, Customer loyalty management program 2, Prepare brand gift
Average	1, Unique marketing approach 2, Unique campaign management
Unsatisfied	1, Unique marketing approach 2, Unique campaign management 3, Discount offer 4, Going extra mile for the customer comfort

For the customer who is categorized in the satisfied group, it is better to prepare a loyalty program. And as they are one of the brand ambassadors, it is better to give them a gift. For customers who are categorized in the average and unsatisfied groups, it is better to prepare a unique marketing approach and unique campaign management. Furthermore, for dissatisfied customers, an extra mile for their comfort including discount offer.

Chapter six: Conclusions and Recommendations

The conclusion and the recommendation are the two fundamental parts available here.

6.1 Conclusions

To stay ahead of the competition, the telecom industry is focusing on customer experience. A customer experience survey allows the company to record a customer's feelings based on their experiences at different touch points. However, with this technique, is more costly and time consuming. And using the survey method, CX insight is inconvenient to include individual in distant location. As a result, combining CRM System data is a better way to improve customer experience management. Here, we propose a machine learning-based mapping of CRM data to CX as a solution.

The correlation result shows that features such as recharge choices, offer choices, post-respond satisfaction, recharge amount in two months, and call frequency have a significant impact on customer experience. A feature such as technology type has no bearing on the customer experience. Three chosen classification methods were analyzed and investigated in this study. J48 algorithm performs with an accuracy of 82.03 %. And then the Random-Forest algorithm has an accuracy 79.96 %. And finally Naive-Bayes has accuracy 77.98 %. Random-Forest is worst at building time.

From this research work, we conclude that the performance of a model depends on the nature of the data and the type of the data attribute. The goodness of the data representation has a big impact on the performance of machine learning algorithms: a poor data representation is likely to reduce the performance of machine learners, while a good data representation can lead to high performance. With this data representation, the score of 82.03 % with J48 is enough.

This thesis work could be a more cost-effective and time-saving approach for gathering customer experience. If it were applied in the telecom environment, it would be a good option.

6.2 Recommendation for Future Work

This research could be quite useful to ethio telecom in measuring customer experience. Future research could include other systems, such as ERP. Social media data, and other unobserved attributes to improve the accuracy of the customer experience of the predicting model.

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Appendix

Mapping Customer Relationship Management Data to Customer Experience Using Machine Learning: In The Case of Ethio Telecom

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Abstract — **Making a positive customer experience is a strategic priority for a business company. To enable a seamless customer experience, the company used methods like surveys to rate the experience. Survey-based measurement systems of customer experience is expensive and time consuming. Another method the company uses to get customer experience insight is by utilizing new technology such as social media plate forms and mobile applications. However, technology such as social media plate forms failed to obtain managerial insights. A better approach to a seamless customer experience is to take full advantage of wealth data available in the customer relationship management system. The main objective of this paper is to make use of classification algorithms widely used in machine learning research and then map CRM data to customer experience. To do this, 1208 individual records were collected from ethio telecom. The collected data is customer sentiment about their experience (a dependent variable) and independent data from the CRM system. And prepare the data set and use a classifier to map CRM data to customer experience and see the impact on classifier performance.**

The comparisons will be made between Naive-Bayes, J48, and Random-Forest. And finally, J48 has a better accuracy performance of 82.03%.

The result implies using CRM system data and mapping to customer experience is possible. However, the data type, data size, and data feature all have a significant impact on classifier performance.

Keywords— Customer Experience, Naïve-Bayes, J48, and Random-Forest

I. INTRODUCTION

The customer experience can be defined as a customer's response to interactions with an organization before, during, or after purchase through multiple channels [1]. At present, customer experience is becoming the main differentiator among service providers. Telecom companies collect different kinds of data to ensure their services answer customers' needs. From little to huge universal businesses, their focus is on the customer experience due to the key role encounters play in making a difference in purchase choice. Boosting customer experience makes marketing more effective.

Customer experience is everything. Profitability, loyalty, and retention are improved with customer experience [2][3].

To access cx different approach are conducted surveys and social media data the most common one. Both methods did not exploit customer data available in the CRM system. The major problems surveys approach are: it is more costly and time-consuming in its data collection and processing. So it is critical to use CRM data to assess customer experience because it is easy to design and develop, it has faster data collection and processing methods, and it is a cost-effective method.

In addition to these advantages, it can also include access to individuals in distant locations, the ability and convenience to reach difficult-to-

contact participants, and it reduces both researcher and participant effort and time.
Customer relationship management is a platform typically used by professionals to manage a brand's relationships and interactions with customers [4]. According to Daniel Bishop in a blog on mapping data to customer experience, customer relationship management (CRM) is the linchpin that connects customer data to customer experience [5]. It can be looked upon as the technical backbone to manage this entire customer journey, as explained by Tony Kavanagh [4]. Operational, analytical, and collaborative CRMs are the three types of CRMs. While all CRMs have some core functionality in common, their principal functions differ [4]. With the successful utilization of CRM technology, businesses can procure the rewards of having a loyal and engaged customer base [5].
One way to map CRM data to the customer experience is through classification modeling. The work of the modeling algorithm is to find the best mapping function in a way that can give optimum model building time with resources available and optimum accuracy with regard to error [6].

II. METHODOLOGY

1217 record of customer experience opinion is collected from the customer services department on two different days. On October 7, 2021, 400 records were obtained, and the remaining 800 records were on August 11, 2021. The attributes relevant to predicting customer experience were obtained from CRM systems in telecom systems (ethio telecom). The dependent variable (customer experience opinion of each customer) tells us whether subscribed telecom company customers have a satisfied customer experience, an average customer experience, or an unsatisfied customer experience. Before data is introduced to the data mining tool, data needs to be cleaned and prepared in the required format. Those tasks could be resolving inconsistent data formats and resolving inconsistent data encoding, and stripping out unwanted data fields. From 1217 recorded data, 9 of the subscribers were postpaid. These 9 records were discarded. Finally, only 1208 of the instances and 6 attributes that were available in the dataset were used for the experimental studies. And change the dataset to appropriate file formats. The researcher uses two different feature selection techniques to produce the most accurate models. CorrelationAttributeEval technique and InfoGainAttributeEval with this from 6 attribute 5 attribute is selected. Table 1 shows correlation and information gain rank.

Table I
Attribute evaluator correlation and information gain

Attribute List	Correlation AttributeEval	InfoGain AttributeEval
Recharge of 2 month	0.2525	0.62823
Recharge choose	0.4358	0.5604
Post respond satisfactions	0.3329	0.54801
Offer choose	0.4032	0.2761
Call frequency to 994	0.0528	0.01261
Technology Type	0.0186	0.00161

In both methods, the attribute technology type gets the minimum rank so five feature is selected by discarded technology type. Figure 1 describes the system model for the study. The model begins with the literature review and is followed by data collection from CRM and CS. Customer's opinion (sentiment) about their experience is taken as a labeled Dataset. Which is either "satisfied," "average" or "unsatisfied" and treated as the dependent Variable. CRM system provides an independent variable.

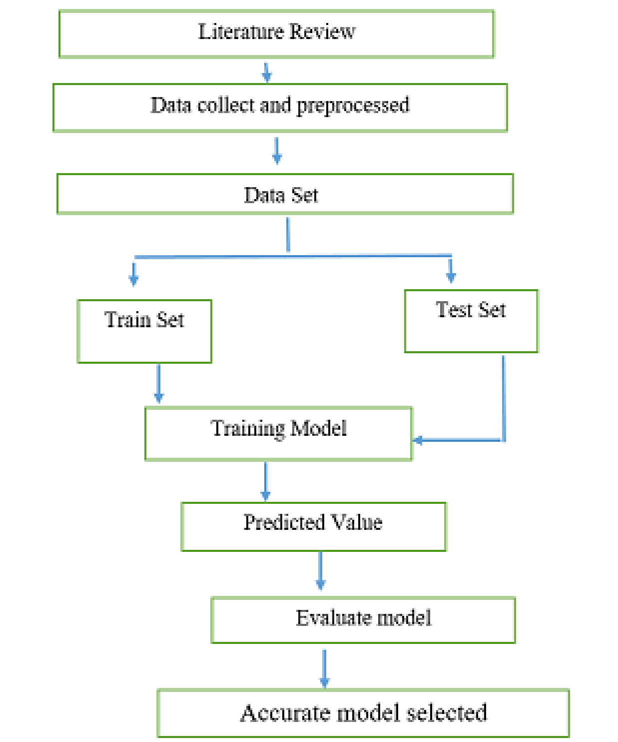

Figure 1: system model

The test methods for this research is cross validation with 10 fold. Figure 2 shows cross validation methods.

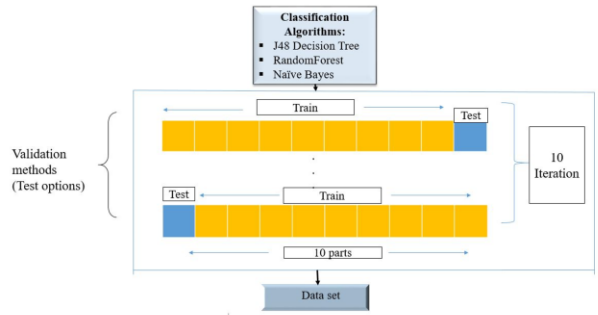

Figure 2: Cross-Validation

The algorithms selected to do the research is Naive Bayes, J48 and Random Forest.

Naive Bayes: It is based on Bayes' theorem and assumes that the existence of one feature in a class has no effect on the presence of other features [7].

Random Forest: Random Forest is a classifier that combines several decision trees on different subsets of a dataset and takes the average results to increase the dataset's predicted accuracy.

J48: It is a group of decision tree classifiers. It is widely used for classification and decision-making processes. J48 consists of three components: root node, branch node, and leaf node. Root (top of the tree) represents the test condition for different attributes, the branch represents all possible outcomes that can be there in the test, and leaf nodes contain the label of the class to which it belongs [8]. In simple terms, it is built on a recursive divide and conquer method, which is a top-down strategy. Starting at the root node, by choosing which attribute to split, then create a branch for each possible attribute value, which divides the instances into subsets, one for each branch that extends from the root node[9].

Evaluation Metrics: The researcher uses classifiers and then key metrics such as accuracy, precision, recall and F-Measure as criteria to assess how well a model works.

III. RESULTS AND DISCUSSION

The experiments are carried out with selected algorithms results are shown in Table 2

Table II
Accuracy Result

Algorithm	Result (%)
Naïve-Bayes	77.98
Random-Forest	79.96
J48	82.03

J48 algorithms outperform better with score point of 82.03%. Figure 3 describes the result in column chart.

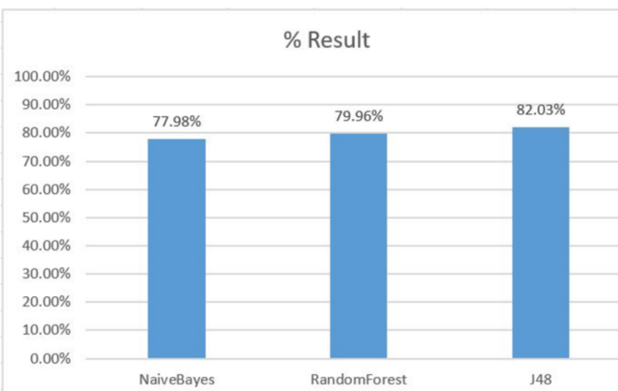

Figure 3: Accuracy Result

The correctly classified instances and incorrectly classified instances are described in Table 3 below. From 1208 total data-set 991 are correctly Classified and 217 are incorrectly classified in J48 algorithm.

Table III
Correctly classified instance and incorrectly classifieds instance for each algorithms.

Algorithms	correctly classified	incorrectly classifieds
Naïve Bayes	942	266
J48	991	217
Random Forest	966	242

Detail performance summary which show precision, recall and F-Measure is describes in table 4.

Table IV
Performance Summary

Algorithms	Performance result				Time
	class	Precision	Recall	F-Measure	
Naïve-Bayes	Average	0.839	0.735	0.783	0.01 sec
	satisfied	0.778	0.797	0.787	
	Unsatisfied	0.710	0.839	0.769	
	Weighted	0.787	0.780	0.780	

J48	Average	0.785	0.889	0.833	0.02 sec
	Satisfied	0.823	0.756	0.788	
	Unsatisfied	0.895	0.764	0.824	
	Weighted	0.826	0.820	0.820	
Random-Forest	Average	0.799	0.823	0.811	0.32 sec
	Satisfied	0.780	0.756	0.768	
	Unsatisfied	0.817	0.798	0.808	
	Weighted	0.800	0.800	0.799	

The confusion matrix for a multi-class classification, for each class, the true positive and true negative, as well as the false positive and false negative, would be computed by adding the cell values. Table 4 show the confusion matrix.

Table V
Confusion Matrix

ML		Actual		
		Average	Satisfied	unsatisfied
Predicted	Average	503	41	22
	Satisfied	63	223	9
	Unsatisfied	75	7	265

Each algorithms error results are describe in Table 6 below. J48 has a kappa statics of 0.7131.

Table VI
Error Log Statics

Error log Statics	Naive Bayes	J48	Random Forest
Root relative squared error	70.642%	68.0924 %	67.5116%
Relative absolute error	35.5241 %	39.351 %	36.6196%
Root mean squared error	0.3259	0.3141	0.3114
Mean absolute error	0.1512	0.1675	0.1559
Kappa	0.6607	0.7131	0.6847

This thesis was conducted on the CRM dataset to understand classification algorithms can be used to map CRM data to customer experience in less time-consuming and less expensive ways. Naive-Bayes, J48, and Random-Forest were used to classify the customer experience. J48 was better at classifying the data set. Random Forest is worst in model building time.

The customer experience concept by itself is sensitive, so we must give special attention to all customers in the class. However, for satisfied, dissatisfied, and average-class customers, suggestions are given in table 7 below for the concerned telecom operator.

Table VII
Class of a customer and approached conducted

Class	**Approached conducted**
Satisfied	Customer loyalty man agent Program and Prepare Brand gift
Average	Unique marketing approaches and camping magnet
Unsatisfied	Unique marketing approaches, unique camping magnet, discount offers and going extra mile for the customer comfort

IV. CONCLUSION

From this research work, we conclude that the performance of a model depends on the nature of the data and the type of the data attribute. The goodness of the data representation has a big impact on the performance of machine learning algorithms: a poor data representation is likely to reduce the performance of machine learners, while a good data representation can lead to high performance. With this data representation, the score of 82.03 % with J48 is enough.

This thesis work could be a more cost-effective and time-saving approach for gathering customer experience. If it were applied in the telecom environment, it would be a good option.

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