Addis Ababa University
College of Natural Sciences
School of Information Sciences

Designing a model for identifying the reason for ATM out of service: The case of Dashen bank

By

Fasika Wondimu

A Thesis Submitted to the School of Graduate Studies of Addis

Ababa University in Partial Fulfillment of the Requirements for the

Degree of Master of Science in Information Science

12 February 2019

Addis Ababa, Ethiopia

Addis Ababa University
College of Natural Sciences
School of Information Sciences

Designing a model for identifying the reason for ATM out of service: **The case of Dashen bank**

By

Fasika Wondimu

Advisor

Dr. Million Meshesha

12 February 2019

Addis Ababa, Ethiopia

Addis Ababa University
College of Natural Sciences
School of Information Sciences

Designing a model for identifying the reason for ATM out of service: **The case of Dashen bank**

By

Fasika Wondimu

Name and Signature of Members of the Examining Board

Name	Title	Signature
______________________	Advisor	______________________
______________________	Examiner	______________________
______________________	Examiner	______________________

ACKNOWLEDGEMENT

Firstly, I give glory to God who is above all and gave me faith and trusted me in this thesis work.

Secondly, thanks for the beloved and courageous advisor Dr. Million Meshesha who worked hard with me in this thesis.

My special thanks go to my classmate Berihun Hadis who was with me in implementation of this thesis.

Thank you Dashen bank staffs Asnake Kebede and Metasebiya Ayisow who are helping me when I made data collection.

Lastly my thanks also go to Dr. Tibebe Besha for his kindly encouragement.

DEDICATED

I dedicate this thesis for my spouse Bethlehem Abera and son Joshua Fasika.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ANN	Artificial Neural Network
ATM	Automatic Teller Machine
B24	Base 24
BI	Business Intelligence
CPO	Cashier Payment Order
CSV	Comma separated value
Dashen bank S.C.	Dashen bank Share Company
DM	Data Mining
E-banking	Electronic Banking
EPP	Encrypting PIN Pad
IDS	Intrusion detection system
KDD	Knowledge Discovery in Databases
KDP	Knowledge Discovery Processes
ML	Machine Learning
MS	Micro Soft
MLP	Multilayer perception
MSE	mean square error
NB	Naive Bayes
NGO	Non-Government organization
PIN	Personal identification number
PIN	Personal Identification Number
POS	Point of Sales
ProM	Process Miner
QoS	Quality of Service
RDBMS	Relational database management system
ROC	Receiver Operating Characteristic
AUROC	Area Under the Receiver Operating Characteristics
SOP	Supervisor of Proview

UT	Usability Testing
VB	Visual Basic
WEKA	Waikato Environment for Knowledge Analysis

ABSTRACT

Yet it is true ideally that ATM service thought to be in service 24 hours a day, 7 days a week, and 365 days a year; But, frequently it has been seen on these self-service machine out of service. This study therefore aims to find the reasons for ATMs out of service, taking Dashen bank ATMs as a case.

The research follows a hybrid knowledge discovery process (KDP) model which has six steps. The first step is understanding the problem, which helps to describe the problem and identify attributes for data collection from purposely selected 14 ATMs within periods, December 31, 2017 – May 04, 2018. This is followed by understanding the data and prepare dataset for data mining tasks. Preparation of data set includes constructions of new attributes from the existing dataset, removing unnecessary attributes and inconsistence values. From the collected dataset of ProView ATMs real time monitoring console as per the objective of this research 44 events describing out of service happening were identified. The crucial step in KDP is data mining which enables to design a predictive model. In this study WEKA knowledge discovery tool is used to identify the reasons for ATM out of service.

Experimental analysis shows that J48 decision tree registers the best result with accuracy of **52.7059 %**. Finally, using the best predictive model of J48 decision tree we designed a prototype on NetBeans IDE 8.2 platform. This prototype was evaluated based on ISO 9241-11 UT test features by domain experts. According to the UT test the prototype was effective, efficient and hold on user satisfaction. However, an automatic integration of the model with ProView will help to detect and solve the problem immediately for enhancing ATM in service.

CHAPTER ONE

INTRODUCTION

1.1 Background

The Financial industry, such as banks generate continually a variety of enormous data. The accumulated data doesn't make any sense unless it becomes valuable. Enterprises analyze their historical data by appropriate technologies for business intelligence. The technology applicable for business intelligence is data mining, the goal of which is to make companies gain competitive advantage and hence profitable [1].

One of the important bank services nowadays is ATM. On ATM particularly withdrawal became the most common feature of electronic banking. Government, public sectors business and others primarily choose payment to be electronically made using ATM. Banks manage, control and provide secure electronic payment for their customers satisfaction and in turn work hard to gain profit. Customers who have a plastic card and a personal identification number (PIN) can withdraw, make deposits or transfer funds between accounts anywhere ATM located depending on bank products [12].

ATMs are data source as core bank system and produce financial transaction. ATMs are self-service machine and core bank system with bankers in bricks and mortar both generate massive data. Because of these, data is alarmingly growing in size, in speed of generation and in variety of data types. This makes data analysis one of the challenging task for human experts and necessitates the introduction of automatic data analysis techniques, called data mining. The aim of data mining is to make sense of large amounts of structured, unstructured, and semi structured data, available in a given domain [1].

According to Witten, et.al [2], data mining is the extraction of implicit, previously unknown, and potentially useful information from large amount of data that can be critical for problem solving and decision making.

Data mining is a technology that uses various classification, clustering and association rule discovery techniques to extract hidden knowledge from heterogeneous and distributed historical data stored in large databases, data warehouses and other massive information repositories so as to find patterns in data that are[3]:

- ✓ valid: not only represent current state, but also hold on new data with some certainty
- ✓ novel: non-obvious to the system that are generated as new facts
- ✓ useful: should be possible to act on the item or problem
- ✓ understandable: humans should be able to interpret the pattern

According to Dunham [4], data mining tasks are classified as predictive and descriptive. Predictive models are supervised learning because the class label identified before data analysis. It contains two processes. The first process finds the best fit model based on the classification algorithm. Then use the model for determining the class for new records and instances.

There are many different kinds of classification algorithms available for predictive modeling. Some of the well-known are Naïve Bayesian algorithm, neural network, and decision tree [1][3]. Each algorithm has its own importance and there is a specific condition where they are best suited to apply for the purpose of data mining depending on the best fit and application.

Descriptive mining tasks characterize the general properties of records in the data repository [3].Clustering of data, summarization, association rules, and sequence discovery are considered as descriptive. Descriptive mining considered as unsupervised learning. It is unlike predictive because there is no class labeled considered on descriptive mining task.

Data mining is a multidisciplinary science and reach vast array of areas such as; biomedical science, in business of commerce and financial institution, telecommunication and retail industry. Even though data mining is applicable in so many fields, Han and Kamber [3] pointed out that, it is not free from challenges regarding to mining methodology, user interaction, performance, and diverse data types with poor quality.

Data being incomplete and noisy, therefore to produce cleaned data; remove noise and incompleteness to achieve the objective of data mining proper data preprocessing methods are required.

Challenge to data mining regarding performance is the efficiency and scalability of data mining algorithms. The running time of a data mining algorithm must be predictable and acceptable in large databases [3].

Presentation and visualization of data mining results is the other requirements. The extracted knowledge presentation required to be easily understood and directly usable by humans. Therefore the presentation need to be on trees, tables, rules, graphs, charts, crosstabs, matrices, or curves.

The other challenge is requirements of the development of numerous data mining techniques. These techniques include data characterization, discrimination, association and correlation analysis, classification, prediction, clustering, outlier analysis, and evolution analysis.

Need of background knowledge on that specific area also is an issue. Therefore understanding of the domain area is the key because the domain expert can easily interpret the required knowledge.

1.2 Dashen bank and its services

Dashen bank is one of the forefront banks in Ethiopia financial industry. It is established by eleven visionary shareholders and veteran bankers with initial capital of Birr 14.9 million in September 1995[5].As of the year 2017it operates through a network of more than 370 branches, ten dedicated Forex Bureaus, 305ATMs and 812 plus Point-of-Sale (POS) terminals spread across the length and breadth of the nation[5]. It has established correspondent banking relationship with 462 banks covering 70 countries and 170 cities across the world[6].The bank also forehead on introducing up-to-date technologies because of its mission, “Provide efficient and customer focused domestic and international banking services by overcoming the continuous challenges for excellence through the application of appropriate technology”[6]. According to Gardachew [7], Dashen bank is a leader in introducing E-banking service in Ethiopia.

ATM service increases for cash withdrawal from time to time. Dashen bank 2017 annual report figured out the ATMs card banking expansion, which is grown by 28%or new 123,198 customers joined the card banking service, and there are now a total of 556,688 card holders, 305 ATMs and 837 POS (uses for cash transfer) terminals[6].These ATMs and POS terminal accept also international cards including visa, MasteCard, UnionPay, and American Express[6].These services found in different locations such as hotels and resorts, universities, hospitals, tour and travel agencies, gallery and jewelry shops, cafés and restaurants, fuel stations, supermarkets, mall, among others.

Different Dashen Bank S.C departments work cooperatively to see high in service time on ATMs. Ideally customers who have a plastic card and a PIN can withdraw cash or transfer funds between accounts at any time wherever ATMs/POSs are located.

The concern of this study is to apply data mining on the accumulated ATM data so as to improve ATM card bank services of Dashen bank. The self-service machine ATM components, both hardware and software are expected to perform the intended task effectively and efficiently and communicate with remote management in real time continuously for whatever event happening.

Application areas of data mining are enormous. According to Han and Kamber [3] DM applied for financial analysis, telecommunications, biomedicine and science, counterterrorism (including and beyond intrusion detection) and mobile (wireless) data. Financial data collected in bank and financial industries are often relatively completed, reliable, and of high quality, which facilitates systematic data analysis and data mining [3]. DM in bank industry is applied for loan payment prediction and customer credit policy analysis, detection of money laundering and other financial crimes, classification and clustering of customers for targeted marketing, and also to design and construct data warehouses for multidimensional data to find general properties of data [3].

1.3 Statement of the problem

One of the technological advancement in banking service is the introduction of ATM which makes work easy and more effective. Yet it is true ideally that ATM service should be in service 24 hours a day, 7 days a week, and 365 days a year. However, Dashen bank S.C. ATMs Proview system management and administration tool [8] availability report present the in-service, out of service, and variables that makes ATM out of service. As presented in table below, 12 selected ATMs out of service range from 0.37% - 20.12%. The report also pointed out that, the causes of out of services are Hardware faults, Cash Dispensing, Daily operation, Network issue B24, and Net connectivity. Out of these causes Daily operation, Network issue B24, and Network connectivity of ProView are the dominant factors for ATM out of service.

Table 1.1 ATM availability partial report, from Jan. 1 – Dec. 31, 2017

ATMs Names	In Service	Out-of-Service	Reasons for Out-of-Service				
			Hardware Faults	Cash Dispensing	Daily Operations	Network Issue B24	Net Connectivity of proview
PATML003_Hilton	89.63%	10.37%	0.75%	3.79%	3.23%	5.77%	2.02%
PATML004_ADAMS	80.25%	19.75%	0.20%	0.00%	5.31%	2.48%	13.89%
PATML005_SHEBELLE	79.88%	20.12%	0.00%	0.00%	2.74%	11.80%	5.64%
PATML006_ETHIOP	87.77%	12.23%	2.23%	1.82%	4.16%	3.28%	3.74%
PATML007_DHGEDA	84.97%	15.03%	1.53%	3.43%	6.36%	9.00%	1.26%
PATML009_LUCY	86.99%	13.01%	2.71%	2.72%	5.30%	5.97%	1.49%
PATML012_RASHOT	89.11%	10.89%	1.59%	1.74%	3.14%	4.19%	2.22%
PATML013_MAIN	95.92%	4.08%	0.02%	0.00%	0.00%	0.00%	3.59%
PATML019_TK	82.02%	17.98%	1.58%	2.11%	7.94%	7.52%	2.55%
PATML022_HARMONY	82.80%	17.20%	0.10%	1.66%	14.10%	9.46%	0.07%
PATML029_USEMBA	99.63%	0.37%	0.20%	0.00%	0.04%	0.00%	0.00%
PATML029_USEMBA	90.10%	9.90%	4.51%	1.16%	1.99%	2.91%	1.58%
SUM	1049.07	150.93	15.42	18.43	54.31	62.38	38.05
AVERAGE	87.43%	12.58%	1.29%	1.54%	4.53%	5.20%	3.17%

As shown in table 1.1, the ATM is out of service on average 12.58% of the time. In principle ATM out of service greater than 10% is greatly affects the business [9][10]. Dashen bank ATM also shows a 2.58% increase on out of service which needs a close attention. From the reasons for out-of-service Network issue B24 is the dominant factors with 5.20% contribution. This followed by daily operation and net connectivity 4.53% and 3.17% respectively. Hardware faults and cash dispensing cases have also a contribution for ATM out of service.

It is clear that if the ATM out of service is too much it will be a risk for the business. The bank targeted to minimize out of service to less than 10%. To this end, all ups and downs of ATM are monitored 24 hours a day from headquarter for remedial action. If it is up; there is a need to check proper working of machines components such as cash dispenser, different sensors, cash cassettes, application software and operating system so that E-payment is possible or not.

Solutions for ATM's always have delay. The simplest scenario of replenishing money in shopping centers and hotels ATMs for empty cassette have a delay of 30 - 45minutes because of traffic jam in Addis Ababa. The fastest measure taken to minimize out of service is manual observation by calling headquarters call center and on real time monitor using base 24[1] and ProView monitoring console as well. Call centers forward the incident for the responsible section. Communication to report failures and to make it online and operational might not be smooth. It takes not few minutes but even a day. Because most ATM's located in hotels, shopping centers, and universities are running by headquarters. Observation and diagnostics solution for all areas of ATMs have delays and also it is not automatic. On the other hand, preventive maintenance solution is ineffective. Because the schedule prepared for maintenance may not address some of the variables of out of service such as power, network and application.

ProView monitoring system by itself couldn't be a complete product. The first is the incompleteness of the data generated from ProView, second the availability of this application, and third system product auditing, predictive maintenance, and the configurations are untouched and produce stale reports.

There is no proactive predictive detection and preventive maintenance of ATMs out of service. This means, that a corrective action is taken after the problem happens, which takes more time, effort and cost. This results in customer's dissatisfaction of the ATM service and bank also loses revenue. For the banks analyzing such a problem and find a solution beside the routine works became a critical task. The application of DM technology enables design a model that identify the causes for ATM out of service and schedule accordingly for corrective action. On the other

[1]Base 24 is an application software used to manage ATMs

side, the size of ATMs event data including transaction is so big so that it couldn't be analyze in ordinary descriptive statistics. Also the accuracy and visualization of data mining is powerful than descriptive statistics.

There are limited studies that apply data mining on ATM service [13]. The concerns of these studies are firstly on ATM operation menu so as to minimize customers waiting time in queue[11].The study conducted by Gümüş et al.[12] consider customer satisfaction in the common use of ATMs; with the purpose of identifying the satisfaction levels of common ATM users. Madhavi et al. [13] attempt to explore ATM transaction dataset so as to pinpoint several downsides in its service to predict the ATM usage level and identify peak time of an ATM in a day/month, and spot any ATM transaction.

There is no local or international study that attempt to investigate the reasons for ATM out of service using data mining techniques.

It is therefore the aim of this study to explore the reasons for ATM out of service using data mining classification algorithms. To this end, this study attempts to explore and answer the following research questions:-

- What are the suitable attributes of ATMs that describes ATM in service and out of service?
- Which DM technique is more suitable for designing a model for identifying the reason ATM out of service?
- What are the most interesting patterns that determine the reasons for Dashen bank S.C. ATMs out of service?
- To what extent the model identifies the reasons for ATM out of service?

1.4 Objective of the study

1.4.1 General objective

The main objective of this study is to design a model using data mining technology so as to identify the reason for ATM out of service and take corrective action proactively.

1.4.2 Specific objectives

To achieve the general objective, this research accomplishes the following specific objectives:

- To review literature so as to understand and select DM techniques, algorithms and approaches well-suitable for the DM classification task at hand
- To understand the problem and collect historical data of ATM from the right source
- To generate quality data by applying data preparation tasks such as data preprocessing, data cleaning, data reduction and data transformation
- Design a model that can identify the reason for ATMs out of service.
- Evaluate the performance of models using effectiveness measures such as accuracy, recall, precision and ROC.
- Prepare usability testing test for evaluation of the model that is input for prototype

1.5 Scope and limitation of the study

Though ATM services are widely used nowadays, the problem of frequent ATM out of service affects consistent and timely service provision of Dashen bank for customers. Hence, this study aims to apply data mining to determine the reason for Dashen bank's ATMs out of service. The five reasons of out of service are hardware faults, cash dispensing, daily operation, and network issue B24, and network connectivity of Proview. Out of these reasons only daily operation, network issue B24, hardware faults, and cash dispensing which are the dominant factors considered. Generally data mining will be applicable for different kind of business. But the study looked at only Dashen bank ATM's database to extract data covering from December 31, 2017 to May 04, 2018, of 16MB size, 365,522 records, and 6 attributes from devices event table as data source.

There are two major data mining tasks: Predictive and descriptive modeling [4]. The preferred DM task is design model using classification algorithm on Weka knowledge discovery tool [2]. According to Han and Kamber [3], predictive model applied when forecasting is essential. This study selects only predictive modeling to identify the reason for ATM out of service using classification algorithm.

1.6 Significance of the study

The output of this research will benefit all bank customers, banks, and researchers. If cash withdrawal services be available at any time; it saves time, labor, cost, and can facilitate the conduct of transactions at a given time cleanly, safely and securely. This will enhance customers' satisfaction and will increase revenue of banks.

This research has an alignment with Dashen bank S.C. work plan, control, management, policy and strategy and will have an input particularly on electronic payment using ATM service. The desired output report of this work support decision maker future direction regarding ATM service. In other words, the prediction of out of service ATM will produce quality service and cost reduction. In similar fashion other banks may apply such mining and may have sound decision.

This study will be an initial attempt locally and may motivate other researchers who have an interest in the same area to conduct further research that enhance the expansion of ATM service in the country by the different commercial banks offering the service.

1.7 Methodology of the study

This study aims to give solution regarding the problem of ATM being out of service. Such issues include, why the ATM is out of service? What are the determinant components of ATM that makes cash withdrawal impossible?

Producing a solution for a given problem presupposes following a scientific principles and guidelines from the startup to the end. The principles answer systematically the question that lead to achieve the objective of the study. To these end there are varieties of methodology followed depending on research characteristics or discipline. The methodology defines the step-by-step procedure the research has to follow defining concepts or phenomenon that need research in such a way that the complexity of the problem at hand has clear picture and understandable [14].

1.7.1 Research design

This study follows experimental research. As the world book encyclopedia [15] stated, experimentation is a method used to discover facts and to test ideas. The science that proceeds with experimentation will produce proves of hypothesis by experiment.

For conducting systematically the experiment, the study uses the hybrid DM process model[1].This model is selected because of the following reasons; emphasize on understanding of the problem domain and data mining, it is research-oriented structure and the model has several feedback, and the extracted knowledge extended for another application domain. The hybrid process model has six-steps[1]; understanding of the problem, understanding of the data, preparation of the data, data mining, evaluation, and use of the Knowledge.

1.7.2 Understanding of the Problem

Kick off step is understanding of the data mining application domain, looking close at that specific domain, collaborate working with the domain expert to define clearly the problem and determine the project goals, identifying key people, and learning about current solutions to the problem. It is a key learning domain-specific terminology [1].

To understand the domain the researcher used primary sources such as discussion with the domain expert and secondary sources which includes document analysis of ProView Operation Manual V4240 and Console User Manual V4240 ,Dashen bank yearly annual reports, intranet and extranet portal, magazines, and internet have been used to have deep insight.

1.7.3 Understanding of the Data

The data for this research is available from Dashen bank S.C. ATMs database. The database on real time base for years collected, saved, and that can be retrieved. From that database the research considers the events database. The event table is data source of this research. Because the ProView monitoring console [16] contains the necessary attributes and their values for this research. Event table contains activity, time, and case or sequences of events.

Upon the foundation of kick off step this phase builds the following tasks [1]:-

- ✓ Data collection and sampling and deciding which data to use for data mining task.
- ✓ Data are checked for completeness, redundancy, missing values, believability of attribute values.
- ✓ The final task on this phase is verification of the usefulness of the data with respect to the DM goals.

In this stage, data collection activity done from ProView. ProView Data Model 4.2/40(C) Wincor Nixdorf International 2015[17], the log event database for Dashen bank ATMs monitoring have organized its data in many tables. The researchers in collaboration with domain experts have selected the event table and its attributes which is interesting for this particular research. The data found from ProView monitoring console exported in MS excel format for visualization and check the quality of data.

1.7.4 Preparation of the data

The task in this phase, upon the foundation and building of the previous two successive phases decides which data is used as an input for DM methods in the consequent step. Data mining results are highly dependent upon data preparation. Poor data preparation results incorrect results. This step takes too much time to complete the followings tasks:-

- ✓ Checking the completeness of data records which includes correcting for noise or outliers and filling missing values by correct attribute values.
- ✓ Constructions of new attributes from the given ones.
- ✓ Data transformation by normalization (make attribute values with in specified boundaries) and aggregation (using concept hierarchy).
- ✓ Data reduction is removing irrelevant and duplicate attributes and reduces number of instances by sampling.
- ✓ Data preparation also includes suiting quality data for DM tool selected.

The data preparation task is performed using MS excel and Weka. Therefore checked the completeness of records, construction of new attribute, data transformation, data reduction, and selection of attributes and filling missing values.

1.7.5 Data mining for predictive modeling

This step uses the quality data prepared in the previous step so as to find the desired knowledge. There are different techniques and algorithms that will be applicable for extraction of knowledge. There are also many different open source and commercial data mining tools. The following criterions are applied to select an appropriate DM tool [3].

- ✓ Can the tool run on different operating system or platform?
- ✓ Can it perform well with high speed?
- ✓ Can it support varieties of algorithms and data mining tasks?
- ✓ How many features and instances can be supported?
- ✓ Can users make preprocessing and visualization?

Being famous, known well by researchers, and an open source that fulfill the criterion bulleted above as data mining tool; for the task at hand Weka version 3.8.2 preferred.

Weka contains a collection of many algorithms for data mining tasks, including data preprocessing, association mining, classification, clustering, attribute selection and visualization [2]. For preprocessing task it has filtering for both supervised and unsupervised machine learning of attributes and instances.

This research to design a required model applied classification algorithms such as J48 decision tree, PART rules induction, multilayer perception neural networks, and Naive Bayes. These algorithms are utilized more on predictive modeling to forecast based on past trend and have competent results [1].

1.7.6 Evaluation of the Discovered Knowledge

The algorithms execution produces models. Finding the best fit model require classifier evaluation. Evaluation includes understanding the results, checking whether the discovered knowledge is novel and interesting, interpretation of the results by domain experts, and checking the impact of the discovered knowledge [1].

The effectiveness measure metrics such as the accuracy, precision, recall, and ROC used to evaluate the discovered knowledge. All these metrics are computed based on confusion matrix. The confusion matrix is a useful tool for analyzing how well the classifier can recognize records of different classes [1]. Given m classes, a confusion matrix is a table of at least size m by m. The table below shows that a binary classes confusion matrix.

Table 1.2 binary classes of confusion matrix

Actual Class	Predicted class	
	Negative	Positive
Negative	TN	FP
Positive	FN	TP

For binary classification: the possible outcomes of classification are TN (True negative), TP (True positive), FN (False negative), and FP (False positive).

If the actual instance class is positive and it is classified as positive, it is counted as a true positive. If the instance is positive and it is classified as negative, it is counted as a false negative. If the instance is negative and it is classified as negative, it is counted as a true negative. If the instance is negative and it is classified as positive, it is counted as a false positive.

AUROC is another metric used when the tradeoffs of ROC curve or the comparison of two operating characteristics (recall and precision) would not be enough evidence. AUROC is more powerful metric and easy to understand it is choosing a model/classifier that has maximum area greater than 0.5 and less than 1 under its corresponding ROC curve [1].

1.7.7 Use of the Discovered Knowledge

The final step is designing a prototype that shows the use of the discovered knowledge using classification algorithm. The design performed using higher level programming language called java. Java used to develop many kinds of application such as Android apps, desktop apps, and video games [26].

The prototype usability with respect to efficiency, effectiveness and satisfaction were checked, evaluated and rated by users.

1.8 Operational definition

The following terms definition are purposefully contextualized for this research.

- Out of service: an ATM service could be out of service because of the non-functionality of different inside and outside components of the machine itself; hardware parts, communication, application (software), operating system, and unresponsive remote server. Terms such as unavailability, downtime, and down are also used interchangeably with out of service when the independent self-service machine ATM can't make electronic payment successfully.

- In-service: an ATM service could be in service when the ATM machine is at the normal operation or function. Terms such as available, availability, up, uptime, and online are used interchangeably with in service when the independent self-service machine ATM can make electronic payment successfully.

1.9 Organization of the research

This research report contains six chapters. The first chapter describes background of the study, statement of the problem, objective, scope, significance, methodology and operational definition. The second chapter describes literature review about data mining tasks, techniques and algorithms, DM processes models, data mining application areas and related works. The third chapter is data preparation. Chapter four is modeling and evaluation. Chapter five is research model, use of the discovered knowledge and its implementation and evaluation and the last chapter is conclusions and recommendation.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview of data mining

Data mining is a multidisciplinary science. Its application on different kinds of fields such as medicine and commerce has surprising impact. Specialized domain experts might not dig deep to find hidden knowledge and interesting patterns on their own big data as the data mining performances. Because of this interesting fact, being computers more powerful and the size of data grows continually data mining becomes very vital [1]. Data mining uses different mathematical formulae and algorithms to find precious knowledge from historical data.

According to Bastos et.al[18], the emergence of KDD and DM methodologies are the development of automated data collection tools, the tremendous data explosion, the urgent need for interpretation and exploitation of massive data volumes, and the existence of supporting tools.

According to Cios et al.[1], data mining came to existence because of an alarming growth of data and technological advancement. An advancement of computer capacity speed; architecture and algorithms was a great motivation for the data mining. Also the World Wide Web breaks limitations of location and time and enable ease of collection of different data types- text, images, audio, and video transfer with high speed and save tera and zeta bytes of data.

All the data in the world are of no value without mechanisms to efficiently and effectively extract relevant information and knowledge from them. Early pioneers such as Fayyad, Manila, Piatetsky-Shapiro, Djorgovski, Frawley, and Smith recognized this urgent need, and the data mining field was born [1].

The subject data mining is related with statistics to model objects. In statistics, researchers frequently deal with the problem of finding the smallest data size that gives sufficiently confident estimates. DM deals with the opposite problem, namely, data size is large and are interested in building a data model that is small (not too complex) but still describes the data well[1].

As a major sub field of math's statistics play a very important role in the research of information theory, data mining, web mining and so on. For example, when we study a certain population taking the whole population for analysis it will be cumbersome therefore only limited sample size taken that help for decision. For this purpose different kinds of statistics measurement utilized such as mean, variance, MSE (mean square error), standard deviation, and confidence interval [1].

For any kind of research the methodology or approach considers reality that will be conceptualized to understand the process from the start to end. The conceptualization includes modeling. Most descriptions of modeling including data modeling have the form of mathematical equation in the area of statistics. For example, Bayes, latent semantic and neural network produce models.

Being youth science its attractiveness and shininess intensity increase. Because viewing others unknown dimensions of data and discovering surprising knowledge make it advantageous in business analysis. Others when doing their work such as government and private sectors acquire knowledge scientifically from their saved data. What is common for all is data that grow exponentially. If one have stored data without interpretation means being only resourcefulness. Any available resource needs optimum utilization. Refined data of different application domains for example health care and financial industry has great benefit accordingly to their specific domain. Business to stay alive in the competitive market gives high attention for their accumulated data.

The data that pass through knowledge discovery processes will produce knowledge that was hidden in the data. The hidden knowledge will be applicable for accurate and precise decision on business operation of the future.

2.2 Data mining tasks

According to Dunham [4], data mining tasks are classified as predictive and descriptive.

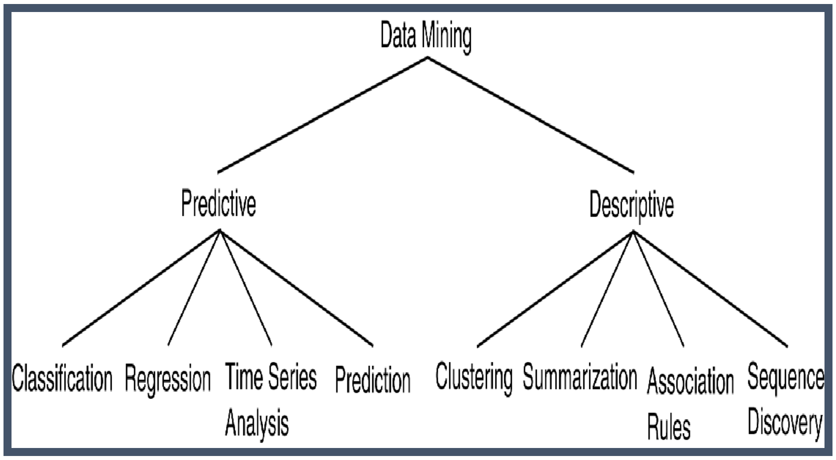

Figure 2.1: Data mining models and tasks [4]

Predictive data mining task uncover unknown pattern based on predictor dataset [4]. The revealed pattern will be a model and determine the desired application domain future trend decision. Predictive models are supervised learning because the class label identified before data analysis. The Data Classification processes are two steps [1], building the classifier or model and using classifier for classification. The first step is the learning phase. In this step the classification algorithms build the classifier. The classifier is built from the training set made up of database instances and their associated class labels. Each instance that constitutes the training set is referred to as a category or class. Then, the classifier is used for classification. Here the test data is used to estimate the accuracy of classification rules. The classification rules can be applied to the new data instances if the accuracy is considered acceptable.

There are many different kinds of classification algorithms available for predictive modeling. Some of the well-known are Naïve Bayesian algorithm, neural network, and decision tree [1]. Each algorithm has its own importance and a specific condition where they are best suited to apply for the purpose of data mining depending on the best fit and application.

Descriptive mining tasks characterize the general properties of the data in the database [3]. Clustering of data, Summarization, Association rules, and sequence discovery are considered as descriptive. A well-known example is identifying products that are purchased together called market basket analysis categorized as association rules. Descriptive mining considered as unsupervised learning. It is unlike predictive because there is no class labeled considered on descriptive mining task.

Clustering is segmenting and forming subgroups based on their similarity of dataset [1]. The degree of similarity differentiates groups from the others. The higher the degree of similarity between records, it is most likely to categorize them in the same cluster. The higher the degree of similarity yields the more homogenous cluster within that dataset that consists of heterogeneous data. Clusters or groups are identified with their similarities or nearness.

Association rules is meant for determining which instances go together. An association rule has two processes as classification. The first one is finding frequently happened pattern and the second is generating association rules between frequent records in the dataset [3].

The data mining task considered in this study is predictive model based on the classification algorithms. There are different classification algorithms, such as decision tree, Naïve Bayes, and neural network multilayer perception.

2.2.1 Decision tree

Decision trees are a way of representing a series of rules that lead to a class or value [19].The tree structure root, branches, and leaves help to realize classification. A decision tree is a flow-chart-like tree structure, where each node denotes a test on an attribute value, each branch represents an outcome of the test, and tree leaves represent classes or class distributions [3].

Hence decision trees models are commonly used in data mining to examine the data and induce the tree and its rules that will be used to make predictions [19].

The two types of decision trees are called classification and regression trees. The classification trees used to predict categorical variables whereas regression to predict continuous variables [19].

Most of decision trees models constructed in a top-down recursive divide-and-conquer manner [3]. Decision trees can be easily translated into a collection of rules and for each rule, traverse the tree starting from its root and moving down to one of the terminal nodes [1].

The main points of learning algorithm for inducing a decision tree from training tuples summarized as follows [3].

- ✓ The algorithm is called with three parameters: D (as a data partition), attribute list (describing the tuples), and Attribute selection method like information gain. Information gain is feature selection method also used in building decision trees for classification. Mathematically defined as the difference between the original information requirement and the new requirement.

$$Gain(A) = Info(D) - InfoA(D) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

  Where Info(D) is the entropy of D and InfoA (D) is the expected information required to classify a tuple from D based on the partitioning by A.

- ✓ The tree starts as a single node, N, representing the training tuples in D.
- ✓ If the tuples in D are all of the same class, then node N becomes a leaf and is labeled with that class.
- ✓ Otherwise, the algorithm calls Attribute selection method to determine the splitting criterion. The splitting criterion indicates the splitting attribute and may also indicate either a split-point or a splitting subset.
- ✓ The node N is labeled with the splitting criterion, which serves as a test at the node. A branch is grown from node N for each of the outcomes of the splitting criterion.

The recursive partitioning stops only when any one of the following terminating conditions is true:

- ✓ All of the tuples in partition D (represented at node N) belong to the same class.
- ✓ There are no remaining attributes on which the tuples may be further partitioned. This involves converting node N into a leaf and labeling it with the most common class in D.
- ✓ There are no tuples for a given branch, that is, a partition D_j is empty. In this case, a leaf is created with the majority class in D.

2.2.2 Naïve Bayes

The well-known one of statistical method for classification is Naïve Bayes. The Bayes theorem determines how likely is that an event will happen given prior and posterior probabilities. Both theorems are based on a theory of probability. Given a hypothesis H and evidence E, Bayes' theorem states that the relationship between the probability of the hypothesis before getting the evidence $P(H)$ and the probability of the hypothesis after getting the evidence $P(E)$, $P(H|E)$ is defined as follows[3].

$$P(H|E) == \frac{P(E|H)P(H)}{P(E)} \quad \text{………………………….(2.2)}$$

From the above definitions and equations of empirical formula Bayes 'rule applicable for data mining to make group and classification based on given statistical information. By classification it is possible to predict group of objects that belong to specific instance based on a probabilistic model specification. The hypothesis or probability using Bayes' rule can predict a class.

Naïve Bayes Classifier is based on Bayes 'rule by assuming that all attributes are: 1) equally important and 2) independent of one another given the class. It is a probabilistic classifier. The following is the mathematical equation [3].

$P(A_1, A_2, \ldots, A_n|C) = P(A_1|C_j)\,P(A_2|C_j)\ldots P(A_n|C_j)$ ←→

$$C_{NaiveBayes} = \underset{j}{\operatorname{argmax}} P(C_j) \prod_i P(A_i \mid C_j) \quad \text{.................................... (2.3)}$$

Naive Bayesian is simple and easy to understand its mathematical formulae. The Naive Bayesian algorithm usually has the following steps [3].

1. A training dataset requires x_i attributes, C_k class values and w attribute values.
2. It calculates the probability of an instance having the class and the attribute value. The probability of attribute value x_i domain value $w_{i,t}$ in class C_k determines the probability such that $P(C_i|x) > P(C_j|x)$, x is in class C_i; else x is in class C_j. The Bayesian approach to classify the new instance is to assign the most probable target value, $P(C_i|x)$, given the attribute values $\{w_1, w_2, \ldots, w_n\}$ that describe the instance according the equation 2.3.

$$P(C\,i|x) = \frac{P(x|Ci)P(Ci)}{P(x)} \quad \text{.............................. (2.4)}$$

Since Naive Bayes classifier makes simplified assumption that the attribute values are conditionally independent given the target value according to the following equation:

$$P(x|C_i) = \prod_{k=1}^{n} P(x_k|C_i). \quad \text{.............................. (2.5)}$$

Step 3. All parties calculate the probability of each class, according to the following equation:

$$P(C\,i|x) = \frac{P(x|Ci)P(Ci)}{P(x)} \quad \text{.............................. (2.6)}$$

Step 4. It selects the maximal of the probability of each class according to the following equation:

$$C_{NaiveBayes} = \underset{j}{\arg\max} P(C_j) \prod_i P(A_i \mid C_j) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.7)}$$

In other words, the predicted class label is the class Cj for which P (Ai | Cj) P (Cj) is the maximum.

2.2.3 Neural network

Another popular supervised learning method for classification is Neural Network. The method of neural network model is unlike statistical. Neural Network or Artificial Neural network (ANN) is another important model of data mining to classify features. Even though Bayes, Naïve Bayes and Neural Network work on data mining tasks for classification, they are different.

ANN is a concept driven from neuron interconnection to compute and analyze logic. ANN is a mathematical model or computational model that is inspired by the structure or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase [20]. There are two types of neural network [1]. The first one is called feed forward and the second one is feedback loops called recurrent. In the case of recurrent networks data from the output feedback to the input to be again recursively as input and then will be an output.

The popular architecure of ANN is either single or multilayerd[20]. When ANN have no hidden layer it is called single layered where as if it has hidden layer it is multilayered[3].There are no clear rules as to the “best” number of hidden layer units.The computation of ANN considerd as a black box. Because the comlexity of ANN mathematical finding solution for a given problem is so much lengthy. Figure 2.2 shows the main framework of the ANN.

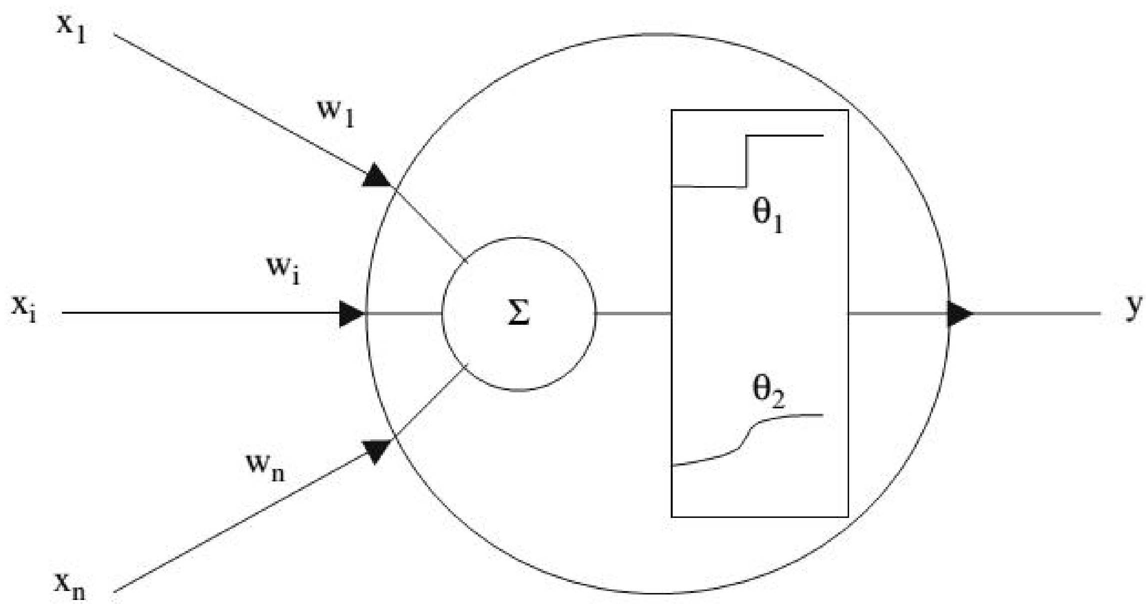

Figure 2.2 ANN model [1]

$$y = f\left(\sum_{i=1}^{n} w_i\ x_i - \theta_1\right)$$ ……………………………………………….(2.8)

Computing output involves calculating summation of the product of weights with input values that are pointing to a given ouput node, as shown in equation 2.9.

$$y=\sum_{j=1}^{m} w_j x_j$$ ……………………….. (2.9)

Another type of ANN backpropagation (the "backwards" direction, that is, from the output layer, through each hidden layer down to the first hidden layer (hence the name backpropagation))learning processis described as follows [3]:

- ✓ Initialize weights with random values(initialized to small random numbers (e.g., ranging from -1:0 to 1:0, or - 0:5 to 0:5)) and set other network parameters,
- ✓ Read in the inputs and the desired outputs,
- ✓ Compute the actual output (by working forward through the layers),
- ✓ Compute the error (difference between the actual and desired output),
- ✓ Change the weights by working backward through the hidden layers,
- ✓ Repeat steps until weights stabilize.

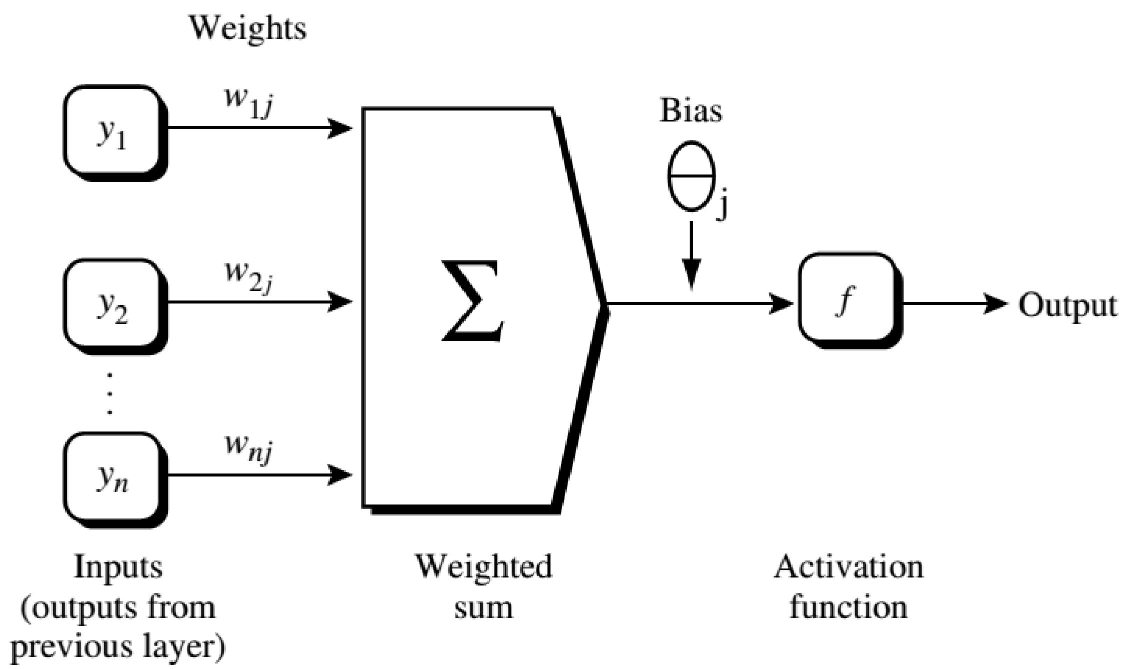

Figure 2.3 Backpropgation learning proceess [3]

AS decipted in figure 2.3, training Algorithm of Back Propagation with mathematical formulae [3]

- ✓ Initialize the weights and threshold to small random numbers.
- ✓ Present a vector x to the neuron inputs and calculate the output using the adder function.

$$y = \sum_{j=1}^{m} w_j x_j \qquad \text{.................................(2.10)}$$

- ✓ Apply the activation function (in this case step function) such that

$$y = \begin{cases} 0 & \text{if } y \le 0 \\ 1 & \text{if } y > 0 \end{cases} \qquad \text{.............................. (2. 11)}$$

- ✓ Update the weights according to the error.

$$W_j = W_j + \eta * (y_T - y) * x_j \qquad \text{..................... (2.12)}$$

Usually to limit the output an activation function will be considered. This function make boundary value between 0 and 1. There are so many activation function make boundry. The most used one is a sigmoid function[3], as shown in equation 2.8. Graphical representation of sigmoid function is presented in figure 2.4.

$a = 1/(1+e^{-x})$ ....(2.8)

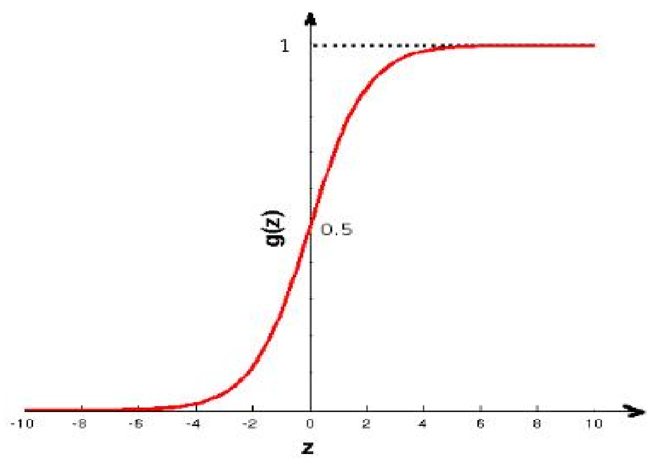

Figure 2. 4 Graphical representation of sigmoid function[3]

Notice consider when defined ANN topology before training can begin, decide on the number of units in the input layer, the number of hidden layers (if more than one), the number of units in each hidden layer,and the number of units in the output layer[3].

2.3 DM process models

An acceptable format for knowledge discovery process (KDP) within common frameworks is known as a process model [1]. A process model of data mining has its own framework. The DM process defines, as show in figure 2.5, a sequence of steps (with eventual feedback loops) that should be followed to discover knowledge (e.g., patterns) in data. Each step is usually realized with the help of available commercial or open-source software tools [3].

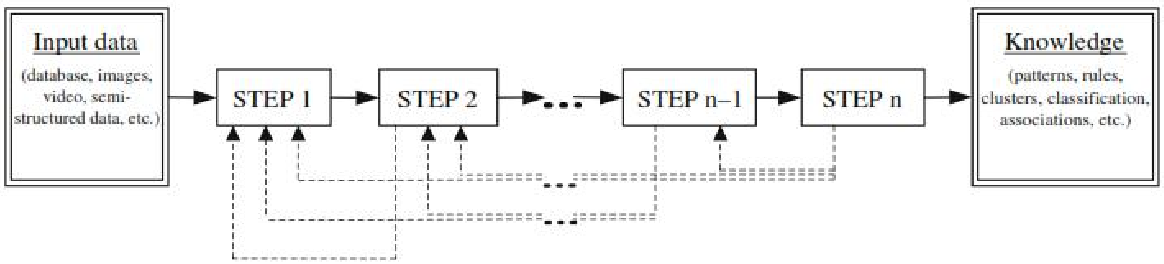

Figure 2.5 Sequential structure of the KDP model [1]

The followings are the three common Knowledge Discovery process models, academic research model, industrial model and hybrid model [1].

2.3.1 Academic Research Models

As Cios et al. [1] states; the academia model was created first in 1996 by Fayyad et al.[21]. It consists of nine steps in KDP which is the foundation for other models.

1) Understanding of the application domain and the final product value when passing through KDP.
2) Form a dataset which will produce valuable sample subset that will be input for KDP.
3) Data cleaning and preprocessing: - treatment of missing value, remove outliers and accounting for time-sequence information and known changes.
4) Data reduction and projection: - search and find determinant feature or attributes that align with the purpose of KDP by making data transformation to have representative of the dataset.
5) Make appropriate data mining task that realize the application domain. Select task whether it is predictive or descriptive. For example clustering, Association, and classification.

6) Select an algorithm to create a model that excels other models.

7) Data mining (find a pattern or knowledge): The knowledge representation can be in the form of rules such as decision tree, rule induction, etc.

8) Interpreting mined patterns: - the knowledge representation can be visualized in the form of graph or text to read based on the selected model.

9) Compile the acquired knowledge: - It include report for the concerned, document, deployment and make an appropriate action or be an input for other advanced research.

2.3.2 Industrial Model

According to Cios et al.[1] the two industrial models are the five-step model by Cabena et al. [27] with support from IBM and the six-step CRISP-DM model, developed by a large consortium of European companies. The fore runner of industrial model is CRISP-DM (Cross-Industry Standard Process for Data Mining).Figure 2.6show CRISP DM process model.

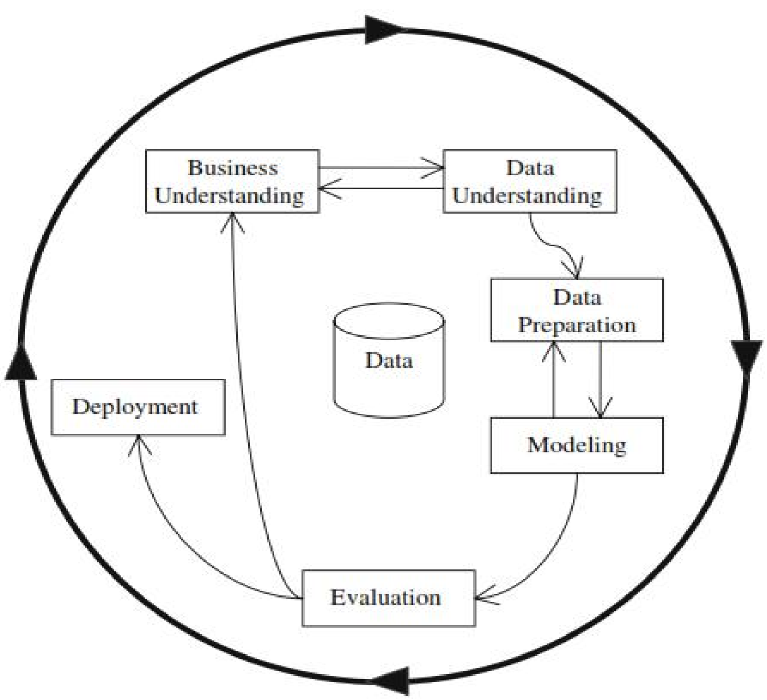

Figure 2.6 six steps of the CRISP-DM KDP [1]

1) Business understanding: - understanding of business goals and the desired input needed for that business. At this stage identified and known the business problem and or available resources accordingly to data mining problem definition. Also form a preliminary project plan which consists of details of each task that will be performed to achieve the objectives.
2) Data understanding: - startup with data collection, then know description of dataset, explore dataset to know what it contains inside, next verification of data quality, enumerate and know the placement of every feature.
3) Data preparation**: -** This is most time taking process and very crucial part of data mining. It includes Table, record, and attribute selection; integration data sets; data cleaning; construction of new attributes; and transformation of data.
4) Modeling: - Select the best algorithm and techniques that will be used for creating an applicable model. The default, calibrated and optimal parameter values tested and used to find best model. It is an iterative process.
5) Evaluation: - All the models created are evaluated according to business objectives criteria. At this step before determinant decision decided a review of all the previous processes required for the selected model to be a model.
6) Deployment: - The deliverable knowledge depend on application domain reported, presented, and submitted in such way easily to understand or it will be for another KDP .

2.3.3 Hybrid model

The hybrid model is the combination of academia and industrial models. This research uses the hybrid knowledge discovery process model because of the following reasons [1].

- ✓ This model has several feedback and detailed reasons why feedback.
- ✓ The extracted knowledge extended for another application domain.
- ✓ It contains research-oriented structure.
- ✓ Emphasize on data mining.

One such model is a six-step KDP model (see Figure 2.7 below) developed by Cios et al. [1].
The steps are discussed as follows,

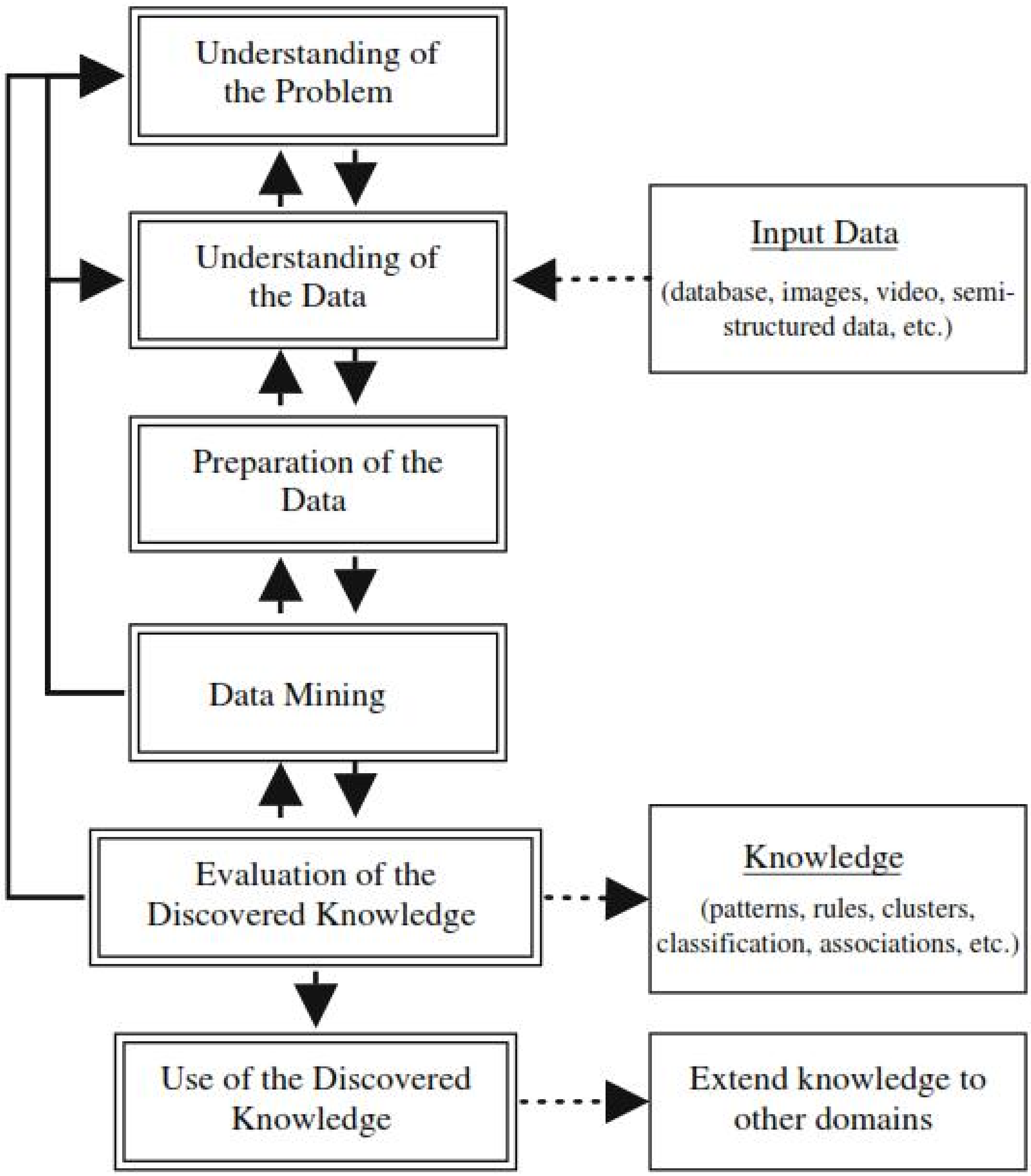

Figure 2.7: The six-step KDP model [1]

1) Understanding of the problem domain: - Kick off step is understanding of the data mining application domain, looking close at that specific domain, collaborate working with the domain expert to define clearly the problem and determine the project goals, identifying key people, and learning about current solutions to the problem. It is a key learning domain-specific terminology. This step includes the followings tasks.

   - ✓ A description of what, how, and why the problem happened and its restrictions are prepared.
   - ✓ The business application domain area goals are translated into DM goals.
   - ✓ Initial selection from many available commercial and open source DM tools to be used later in the process is performed.

2) Understanding of the data: - Upon the foundation of kick off step this phase builds the following tasks.

   - ✓ Data collection and sampling and deciding which data, including format and size, will be main task.
   - ✓ Data are checked for completeness, redundancy, missing values, believability of attribute values, etc.
   - ✓ The final task on this phase is verification of the usefulness of the data with respect to the DM goals.

3) Preparation of the data: - The task in this phase, upon the foundation and building of the previous two successive phases, is deciding which data will be used as input for DM methods in the consequent step. Data mining results highly depend upon data preparation. Incorrect results yield form poor data preparation. This step takes too much time to complete the followings tasks.

- ✓ Data cleaning which includes collecting data from different source or integration.
- ✓ Checking the completeness of data records which includes removing or correcting for noise or outliers and filling missing values by correct attribute values etc.
- ✓ Constructions of new attributes from the given ones.
- ✓ Data transformation by normalization (make attribute values with in specified boundaries) and aggregation (using concept hierarchy).
- ✓ Data reduction is removing irrelevant and duplicate attributes and reduces number of instances by sampling.
- ✓ Data preparation also includes suiting quality data for DM tool selected.

4) Data mining: - this step has quality data from the previous step to find the desired knowledge. There are different techniques and algorithms that will be applicable for extraction of knowledge. The followings are some of them.

   - ✓ Classification techniques - decision tree, rule induction, neural networks. Using algorithms such as J48 decision tree, PART rule induction, Multilayer perception neural network, Bayes…
   - ✓ Association Techniques – pattern discovery of items relationship for example in shopping items. Algorithms- Apriori and FP Growth

5) Evaluation: - At this step the extracted knowledge is checked for interestingness and applicability. Also domain experts are checking interpretation of the results and interestingness of the knowledge for retaining the model.

6) Use of Knowledge: - the final step will be documentation, deployment, and application in the current domain and extended to other domains and planning where and how to use the discovered knowledge.

2.4 Data mining applications

Application areas of data mining are enormous. According to Han and Kamber [3], DM applied for financial analysis, telecommunications, biomedicine and science, counterterrorism (including and beyond intrusion detection) and mobile (wireless) data. In business DM is used for both to increase revenues and to reduce costs [19].

Financial data collected in bank and financial industries are often are relatively completed, reliable, and of high quality, which facilitates systematic data analysis and data mining. Data mining in banks industry applied for loan payment prediction and customer credit policy analysis, detection of money laundering and other financial crimes, classification and clustering of customers for targeted marketing, and also to design and construct data warehouses for multidimensional data to find general properties of data [3].

According to Han and Kamber [3] the other application area is in retail industry. Many stores open their own website without any brick-and-mortar store location but exist solely online where their customers can purchase items. The data mining application in retail industry used to identify customer buying behaviors, discover customer shopping patterns and trends, improve the quality of customer service, achieve better customer retention and satisfaction, enhance goods consumption ratios, design more effective goods transportation and distribution policies, and reduce the cost of business. Some applications of DM in retail industries are design and construction of data warehouses, multidimensional analysis of sales, customers, products, time, and region, analysis of the effectiveness of sales campaigns, customer retention—analysis of customer loyalty, and product recommendation and cross-referencing of items.

The telecommunication industry also inclined to apply DM for understanding of the business involved, identifying telecommunication patterns, catching fraudulent activities, making better use of resources, and improving the quality of service [3]. The followings are lists of some applications:

- Multidimensional analysis of telecommunication data- to identify and compare the data traffic, system workload, resource usage, user group behavior, and profit.
- Fraudulent pattern analysis and the identification of unusual patterns: to (1) identify potentially fraudulent users and their atypical usage patterns; (2) detect attempts to gain fraudulent entry to customer accounts; and (3) discover unusual patterns that may need special attention, such as busy-hour frustrated call attempts, switch and route congestion patterns, and periodic calls from automatic dial-out equipment (like fax machines) that have been improperly programmed.
- Multidimensional association and sequential pattern analysis: This can help promote the sales of specific long-distance and cellular phone combinations and improve the availability of particular services in the region.
- Mobile telecommunication services: to design adaptive solutions enabling users to obtain useful information with relatively few keystrokes. And it used for telecommunication data analysis and visualization.

Han and Kmber [3] mentioned the application of DM powerfulness on intrusion detection. DM is the more precise on intrusion detection than the traditional intrusion detection system. Moreover, IDS needs highly qualified person to find the subtleties of anomaly signature detection but DM require far less manual processing and input from human experts. The following are areas in which data mining technology may be applied or further developed for intrusion detection [3]:

- Development of data mining algorithms for misuse detection and anomaly detection.
- Association and correlation analysis, and aggregation to help select and build discriminating attributes.
- Analysis of stream data for real-time intrusion detection.
- Distributed data mining to analyze network data from several network locations in order to detect these distributed attacks.
- Visualization and querying tools for viewing any anomalous patterns detected.

An empirical study by Farooqi et al. [28] describe the necessity of DM on historical data to extract useful information that would be the source of sound decision. Also presents DM techniques and its useful application in banking industry like marketing and retail management, CRM, Investment Banking, portfolio management, risk management and fraud detection.

Investment Banking

DM techniques are so supportive to select the best investment as per the clients' profile. Neural networks and linear regression could be applied to predict prices for stocks. Based on DM prediction the one selected ROI could be the maximum [28].

Portfolio Management

With DM techniques investors make allocation of budgeting appropriately in trading activities in order to have maximize profit and minimum risk [28].

2.5 Related works

Being predominant data mining has been applied in so many kinds of business or industries. One of these businesses that use data mining techniques for competitive advantage or business intelligence is financial industry like banks. The innovation of new technologies and software application in bank still continues. The emerging self-service systems or ATM's using a plastic card is going to contactless and video conferencing capabilities[22].On the other side expanding services, more sophisticated devices and the growing number of customers choosing self-service channel options are resulting in an explosion of ATM "Big Data". The electronic payment using ATM have vast transactional data that classified as Customer engagement, Payment and Cash management [23]. In this section based on these categories related works of data mining techniques applied on ATMs transactional data are reviewed and presented.

Not many years ago but recently the ATMs transactional data were considered to extract hidden pattern in certain journals. The goal of the analysis using data mining technology are to maximize profit, increase return on investment, business intelligence, satisfy customers in customers relationship management and stay alive and be forerunner in fierce competitive market.

The first reviewed article is construction of adaptive automated teller machines by Shaikh and Mahmood [11]. The ATMs transactional data was collected and preprocessed, data mining technology applied for construction of ATMs user interface. Data mining tool used was ProM, and then quantitative research method was an extended approach to reinforce the finding. The finding revealed that adaptive automated teller machine was the preference of most ATMs customers.

Whenever and everywhere quality of ATMs service has been desired for both customers and the service providers. This research and the related articles reviewed in this thesis concerned with improving ATM service based on historical data collected using data mining technology. These days the data mining attracts business and selected fields and because of this researches continue on ATMs transactional data to forecast the future business of ATM inclination.

Different types of users who have ATM plastic card access ATM at any time wherever ATM located to find different services. The time taken assuming normal condition for customer to access and use ATM depend on response time of thirty seconds. However the type of customer, the time of access, and the location of ATM can determine the span of time. It is common in very dense population area and peak hour of ATM transaction to see queue to get access.

The adaptive automated teller machine objective was development of adaptive ATM interfaces to minimize the ATM usage time for a population of customers particularly at heavy traffic ATMs [11]. For the achievement of the objective there were two approaches used. The first and most used was data mining technology. After preprocessing of the data interesting knowledge was extracted. The result identified that withdrawal is the most frequent operation performed by customers, followed by purchase and balance inquiry. Based on the above finding the authors develop interfaces that can minimize the time taken when ATM accessed.

The second approach to achieve the objective of adaptive automated teller machine was quantitative research method. The ATM interfaces of adaptive automated teller machine that was developed after knowledge discovery process were evaluated using online survey (questionnaire). The evaluation proofed that users' preference was the adaptive ATM interface or menu.

Indeed the data mining technology produce the required hidden knowledge that improve ATM service at dense area of population and pick ATM transaction hour. Not only enough improving wait time or queue on ATM but identifying the specific reason ATM out of service is the first step to increase and improve quality of service.

Madhavi et al. [13] conducted ATM service analysis using data mining. The ATMs transactional data collected and preprocessed, predictive data mining gave solution for finding in which time ATM used more frequently and identify peak time of an ATM in a day/month, and spot any ATM transaction, and data mining tool was Weka, the finding support decision makers to take the necessary actions.

The objective of the research was to provide the graphical visualization for easy identification of ATM usage level and monitor the ATM peak time. For the achievement of the objective predictive data mining technology was applied. After preprocessing of the data the extracted knowledge were visualized peak day of an ATM in a month, peak hour of an ATM in a day, the type of transaction which occurs regularly are recognized, the location of the ATM which provides the service to the customer is identified with their usage level, and the ATM usage for every location is calculated. Based on the finding business intelligence bank decision makers simply determine the business future direction.

The predictive data mining corrected ATM service to increase the Quality of Service. One of QoS replenish money be on timely manner and hence reduce the situation of out of stock in that ATM. The other uncovered hidden knowledge was peak level and idle level of the ATM to take appropriate action for decision makers.

The above researches opened door for more analysis on ATM transaction dataset because ATMs nowadays do not have more analysis [13].Both researches view and analyze ATM transaction dataset in their own way. The research at hand also in different dimension investigates the problem of out of service to identify the reasons for ATM out of service through designed model.

Gümüş et al.[12] attempted to analyze ultimate point in the service provided by the banks to their customers so as to determine customer satisfaction in the common uses of ATMs. The researcher pinpoints the necessity of standard measurement in bank industry for the provision of quality service of in dynamics of ATM usage. For business like banks customers care and customers relationship management to meet their expectations and determine how such expectations would be met is a key. For any business in order to have higher position and keep it up for long and to be competent it is required to find new customers or duly satisfy the already existing customer. According to Gümüş et al.[12] today, customer satisfaction has become one of the busiest segments of marketing because of that studied the expected service quality and the perceived service quality of common ATMs and thus determine the satisfaction level of ATM users.

The existence service provided for commonly use ATM users when perceived to what extent reached was not known. To know the satisfaction level of common ATM users the approach followed called screening model. The screening models based on demographic characteristics questionnaire were used to identify the difference between the expected service quality and the perceived service quality of common ATMs which indicates the satisfaction level of ATM users.

The finding were with respect to the demographic characteristics sample group divided in gender, age, educational status, marital status, income status, the number of banks/credit cards they are using, and the most frequently used credit cards. And the finding shown the measurements were statistically significant hence all most all perceived measurement score were less than the expected.

The research found out less satisfaction level provided by banks for their ATMs customers users' were because of unsatisfactory quality of service. And recommended to measure periodically their customer satisfaction levels through updated questionnaire screening operations. Further, the banks are recommended to improve their processes in order to provide services to customers on time and in a fast, flawless, enthusiastic and reliable manner. In respect of common ATM use, bank employees should improve their skills, should become equipped with the necessary know-how and foster a feeling of trust on the customers.

All the research reviewed initiates other researches typical on ATMs quality of service. As a matter of fact the research at hand investigates to identify the reason for ATMs out of service problem which is different dimension which is unlooked and untouched.

2.6 Related works of ATM Banking service

Customers' satisfaction with ATM banking in Malawi by Charles Mwatsika [29] studied the ATMs service quality and customer satisfaction. ATM SQ and customer satisfaction are coupled together. Well fitted SQ produce high level performance. It is a performance of the service that satisfy or dissatisfy customers. The researcher investigate the existing ATM banking service whether it satisfied customers or not.

The research methodology followed was importance-performance approach and referenced the commonly used five attributes models which are tangibles, reliability, responsiveness, empathy and assurance to measure SQ and customer satisfaction.

To develop the measurement scales referenced another known 25 valid ATM SQ attributes from different resources which comprised tangibles (6 items), reliability (6 items), responsiveness (6 items), assurance (3 items) and empathy (4 items). Likert scale was added for these 25 questionaries' and then 353 ATM card users administered through email to find their reply.

The finding was Overall 53% of the respondents were satisfied with ATM services and even though the referenced five SQ attributes significantly associate with customer satisfaction reliability is strongly correlates with ATM service satisfaction.

The study remarked banks responsiveness and empathy SQ in Malawi to be standard for competitive advantage. Because employee performance on ATM cards application, reconciliation processes and management functionality have been perceived not so good in performance.

The demographic characteristics pointed out was limited. Thus it is recommended ATM customers' satisfaction future research to include wide area demographic characteristics and different customers' satisfaction research on mobile and internet banking.

Modified automatic teller machine prototype for older adults: A case study of participative approach to inclusive design by Chan et al. [30] studied the existing ATM interface and aged 60 or above ATM card users' who have physical or cognitive limitations. Because the existing human– ATM interface didn't match with elderly people.

The research methodology followed was a user participative approach to adopt a universal design that can accommodate older adults. A total of 187 older adults, participated in two stages, 91 older adults were assigned to the existing human– ATM interface test group and 96 were assigned to the modified universal human– ATM interface prototype group.

The result present for participants who had a lower education level pointed that the universal design to include reduce amount of information to be recalled and processed, reduce the transaction time, present information more slowly, simplify the presentation of information on screen, use a single screen to complete one operation/transaction, and use graphics and visual effects.

The research notified the tradeoff of the universal design which is the modified ATM prototype reduction in functionality would create inconvenience to younger users. Hence it is remarked the future research workout on resolution to address optimum functionality. On the other hand the research gap was the participant. All the participant respondents were gathered from a certain elderly center. Also it is recommended on future work respondents to be global or from wide area different status people.

Analyzing and Investigating the Use of Electronic Payment Tools in Iran using Data Mining Techniques by Moslehi et al [31] investigated E-payment instruments –ATM and Pin Pad transactions. Firstly factors that affect the number and amount of transactions , second relationship between the period and the volume of the transaction, thirdly relationship between the bank and the province.

To address the problem approached followed up was CRISP-DM methodology. The techniques were clustering and classification. Data collected from Statistical Center of the Central Bank of Iran which is performance statistics of electronic payment tools ATM from 1986 to 1994 and 49, 425 records of 12 variables used for DM. The DM tool was Clementine 12. First K-Means algorithm was implemented to determine the target field categories. And then the CART decision tree algorithm was used to explore the factors affecting the average amount of ATM transactions and the average amount of Pin Pad transactions.

The finding from CART decision tree algorithm was ATM in seven banks and seven province in the years 1991 to 1994 in summer, autumn, and winter than in spring has increased significantly. And the other rule was increased ATM terminals had direct proportion with Pin Pad transactions. Additionally it is noted the research enhance E-banking services and E-banking future policy.

It is recommended future works to be done using telephone banking, internet banking, mobile banking, and POS for a comprehensive review of the bank performance in electronic payment.

A maintenance prediction system using data mining techniques by Bastos et al. [18] studied mitigation of industrial machine failure.

The methodology followed up was by demonstrating a new conceptual framework. Therefore introduces a decentralized predictive machines maintenance system based on the application of data mining techniques to forecast the possibility of breakdowns that may increase systems reliability and generate a set of schedules notifications for maintenance action.

The finding from this system using visualization techniques on ANN back propagation algorithm with an accuracy level of 72% can predict failure occurrence. And on future with the addition of monitoring data into the system suggested the possibility to predict the failure occurrence within a proper time and able to perform interventions on equipment before breakdowns to reduce maintenance effort and cost.

Thus the forwarded future work pointed that to predict new failures more features required particularly from monitored equipment database to understand the reason of all malfunction occurrences.

CHAPTER THREE

DATA PREPARATION

3.1 Understanding of the problem domain

To convert data to data mining goal it is vital to understand the problem domain at this initial step. Since the hybrid model is research oriented setup learning is the key issue to understand the problem area.

The Dashen bank external portal lists the following four main products and services [5]. Domestic banking, International banking, Dashen card, and E-banking.

Domestic banking contains three products and services. The first one is Current account which is a convenient medium to make and receive payments. It allows to access money with ease by using cheques or VISA Card. The other is loans that are offered in different kinds such as Agriculture, Manufacturing, Import/Export Loans, Trade and Services, Building and Construction, and Transport. The third is Money Transfer, Remittance of funds through one branch to another. Local common means of remitting are - Mail Transfers, Telegraphic or Telephone Transfers, Local Drafts, Cashier Payment Order (CPO). And the well-known from internationals are Western Union and Money Gram.

International banking products and services include mainly Foreign Exchange Permits and Import and Export. Approval process of foreign exchange permits requires presentation of different sets of documents for each transaction. The other one which is related with Foreign Exchange Permits Import and Export enable purchase of commodities, machineries, materials, etc. from abroad and allowed to enter Ethiopian territory.

Dashen card have different varieties. The first one is Debit card, it allows at any time accessing ATM/POS, Operate multiple accounts with a single card, Withdraw up to 5,000 Birr per day per card subject to the balance in account, purchase goods or services up to Birr 8000.00 per day per card at any of the Dashen Bank merchants, Check the balances of all accounts linked to the card, Obtain mini-statement that lists the last ten transactions in any of accounts linked to the card. The others are Salary Card which is useful for organization salary payments and Student Card for students.

E-banking services offered by the bank include ATM/POS, Internet Banking, Mobile Banking, and Agency banking [5].

Available services on Dashen Bank ATMs are Cash withdrawal, Balance Inquiry, Mini-statement, Fund transfer between accounts attached to a single card, PIN change, and PIN Unblock. And on POS allowed purchase of goods from Dashen merchants who have POS machines.

Internet banking is a service that enables the customer by accessing Internet Banking on all types of search engines like Mozilla fire fox, chrome etc… all over the world. The major services are Account information, Enquiries mini statement, full statement, Daily Exchange rate, Loan statement, Fund transfer within Dashen bank and To other local banks accounts, Salary and provident fund upload, Electronic bill payment(utility payment), Stop cheque payment, Cheque book order, password change and other service.

Mobile Banking services are Fund transfer within own Bank account and wallet account, Fund transfer through mobile phone for those who registered for mobile service, Fund transfer to others who have only mobile phone/No. for those who unregistered for mobile service, Mini Statement and checking of account history of wallet account, Balance Enquiry on bank account and Wallet account, PIN change, Fund transfer from Bank account to Bank account for those who registered for mobile service, Merchant payment, Bill payment and other services.

Agencies banking major services are Account information, E-wallet account opening /registration/, Cash deposit to wallet account, Cash withdrawal from wallet account, Fund transfer to others who have only mobile phone/No., Bill payment, Merchant payment, Facilitate Regular bank account opening and other services.

The ATM data collection studied on ProView monitoring console [16] with domain expert and conducted collaboration work to understand more the problem domain. In other words, on this step in order to properly understand the problem; we attempt to explore problem domain and found insight particularly focused on ATM data including the following issues. What are the variables? Which variables are making out of service ATM? What kind of data? How data collected? Where is the data? Why the data collected and data translation to achieve DM goals using a tool Weka [1].

For this reason the researcher in consultation with domain expert learn about Dashen bank S.C. ATMs monitoring system called ProView. ProView is an agent and PC-based event monitoring and incident management system for the monitoring and administration of ATMs[8].The agent from each terminal ATM or self-service application and the self-service hardware send all the collected events to the ProView Wincor Nixdorf's management system. For this purpose on the network operating system MS window 2013 installed and on this platform for relational database management system installed SQL Server 2008. The application of Wincor Nixdorf's ProView monitoring and administer all ATMs installed on win 7.

On this application administrator on real time can view cash status, mechanical problem, and others different status of ATMs to take remedial action and generate different kinds of report such as ATM uptime and down.

The main components of ATMs are: - Card reader, Keypad (EPP), cash dispenser, Display screen, Speaker and Receipt printer. The live communication between ATMs and ProView enable administrators to monitor the status of all Dashen ATMs. On the other side, B24remote host processor manages every customer withdrawal request and others found on ATM display menu. Every event on ATM interface is sent to ProView monitoring console which is the interesting part of this research. The event provides information described in table 3.1 below.

Table 3.1 event content and description

Event	Description
time stamp	includes month, date, year, hour, minute and seconds
event number	unique session identification number
event message	activities that going on when the ATM interfaces touched for different purposed based on menu
Server time stamp	a time like event stamp but when the events are arrived on ProView server
original message	messages come from ATMs activities. It is like event message but include the amount of transaction
ATM device name and ID	an ID of ATM, description of location and name
Component	ATM have two components; the upper one computer and dispenser(cash cassettes)

The ATM components based on event collected are hardware and software. The hardware components of ATM are card reader, cash dispenser, keypad, and screen buttons. And the components of ATM which are application and operating system considered as software. Supervisor activities and network are other independent determinant components of ATM.

Card reader is one component of an ATM that read from plastic card. The card reader captures the account information stored on the magnetic stripe on the back of an ATM/debit or credit card. The host processor uses this information to route the transaction to the cardholder's bank. Whenever the card reader has got a problem to read it will be impossible to process electronic payment and the ATM machine became down [32]. Some of card reader values when it is nonfunctional are read error, blank track, device disconnected, card jam and no smart card response [16].

Cash dispenser: It is the heart of an ATM which is the safe and cash-dispensing mechanism. The entire bottom portion of most ATMs is a safe that contains the cash. If this component of an ATM and its sub components find problem it will be impossible to electronic payment and the ATM machine became down [32]. Some of cash dispenser values when it is nonfunctional are device not in use, device not accessible, bill cassette is empty, bill cassette is missing, reject cassette removed, pick failure, presenter clamping mechanism failed, sensor failure, and currency jam [16].

Keypad: This component of ATM lets the cardholder tell the bank what kind of transaction is required (cash withdrawal, balance inquiry, etc.) and for what amount. Also, the bank requires the cardholder's personal identification number (PIN) for verification [32]. Keypad may also fail and make out of service ATM. If this keypad or EPP hardware failed the ATM became nonfunctional. The value of this keypad is invalid key or key doesn’t exist [16].

Application: This system is the one that make transaction or cash withdrawal impossible. Software found on ATMs is windows operating system and an application system. Both can affect electronic payment make an ATM down or unavailable. Some of the values are attempt to reboot via system, transaction failed unable to process transaction, and unable to dispense cash [16].

Network: This network means a communication between the end terminal ATM self-service machine and the remote server host which is manager and controller of transaction that connect to bank core system and database. The values of this independent ATM component are communication offline, TCP/IP address not accessible and device offline [16].

Supervisor activities are part of an ATM component. Whenever the supervisor made service and change the ATM will be out of service. The values of SOPs are terminal closed for customers and changed to supervisor mode [16].

3.2 Understanding of the data

This research considers ATMs data which are located in city area, upcountry area, hotels, shopping centers, branches and universities. The Dashen Bank ATMs are called NCR and Diebold. At present time there are a total of 305. Of which only 15% are Diebold. These ATM's found in Addis Ababa and upcountry. 66% of ATMs are found in the capital city Addis Ababa [6].

In this stage, a data collection activity that is done in this research is discussed. ProView Data Model 4.2/40(C) Wincor Nixdorf International 2015, the log event database for Dashen bank data ATMs monitoring have organized its data in many tables[24]. The researcher in collaboration with domain experts selected the portion of those datasets that are interesting for this particular research. The original data attributes available in the log database is presented in table 3.2.

Table 3.2 Event table from ProView Data Model 4.2/40 (C) Wincor Nixdorf International 2015

Name	Comment	Data Type	Mandatory	Primary	Foreign Key
deviceid	Device name	string	X		
timestamp	Time the event was created on the device ("YYYYMMDDhhmmss")	datetime	X		
messageno	ProView Agent event number (see table EVENTCONVERSION)	numeric	X		
orgmessage	Original device event text	string			
servertimestamp	Time the event arrived at the ProView Server ("YYYYMMDDhhmmss")	datetime			
devicestate	New device state	numeric			
eventno	ProView Server event number (see table EVENTBASE)	numeric			
eventcount	Unique event counter	numeric	X		
eventgroupid	event group id	numeric			

The most important are events tables that can be exported to MS Excel. The followings are some of the dataset from different tables that need refining to find complete, interesting subset and non-redundant data.

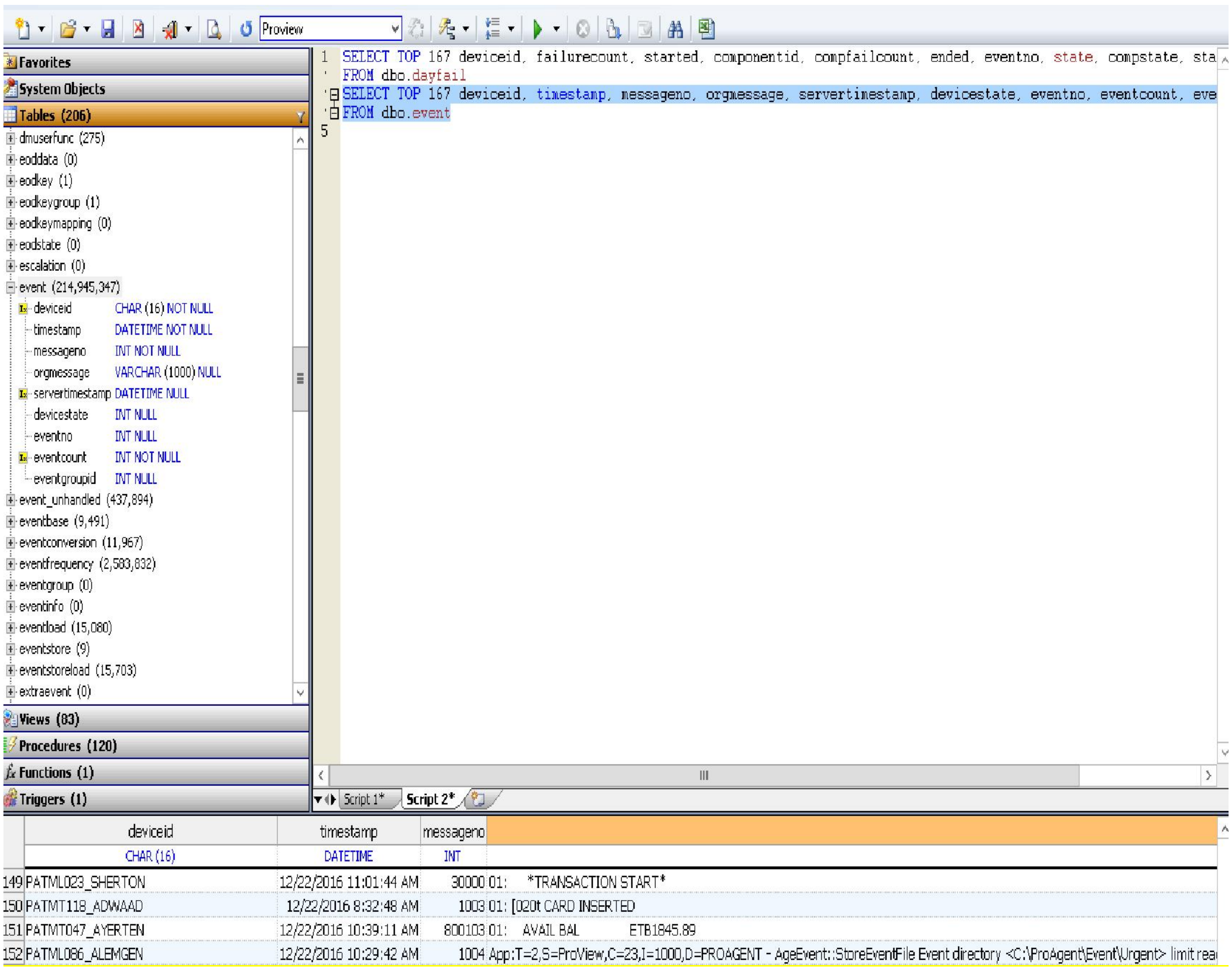

Figure 3.1 Event table on Database Server

The followings figure is screen shot of ProView.

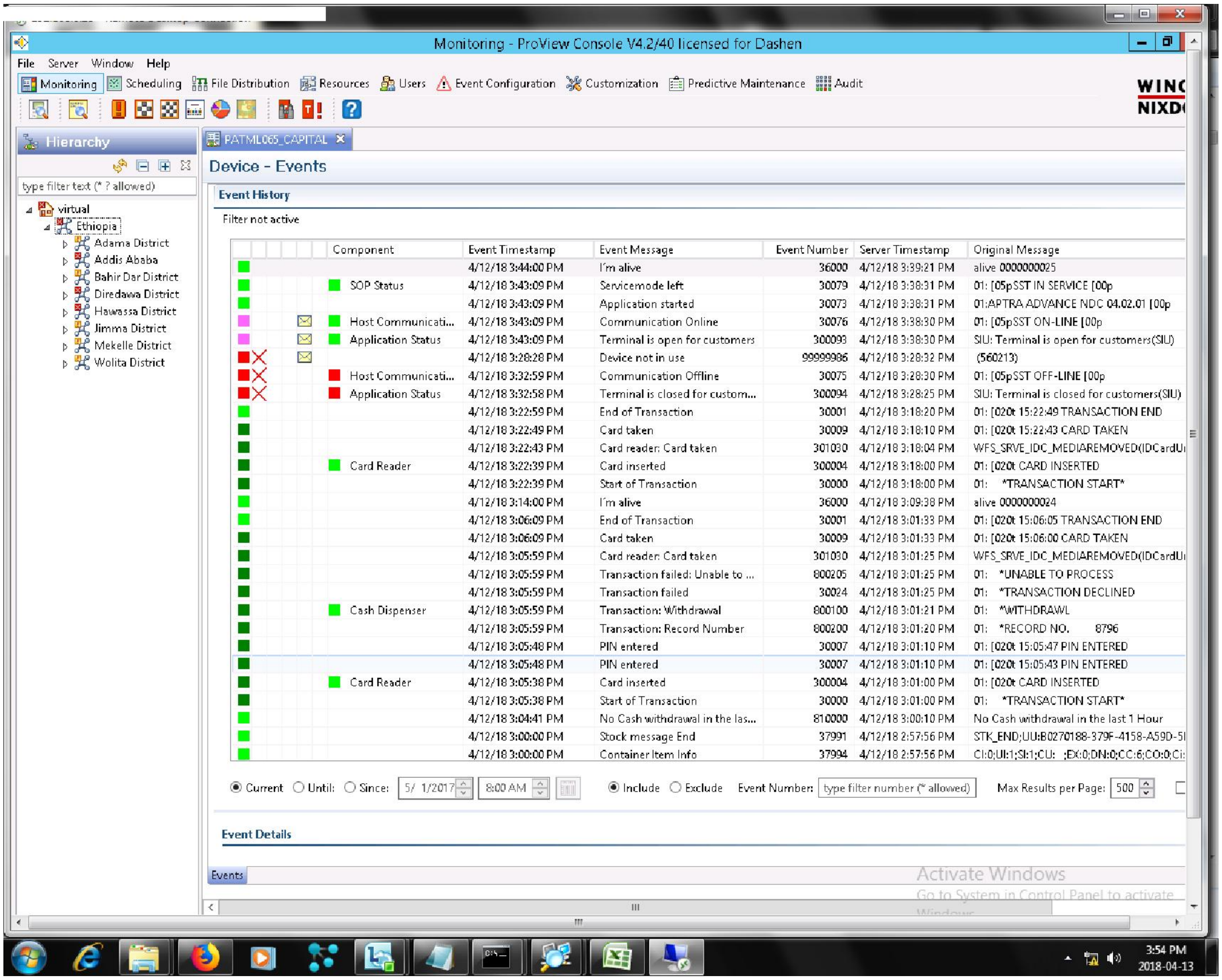

Figure 3.2 ProView Monitoring Consoles

The left side shows that all ATMs hierarchies and the right one is a single ATM events at Capital Hotel.

Table 3.3 Event table on ProView Monitoring Console

Device name and location	Event Number	Component	Event Timestamp	Event Message	Server Timestamp	Original Message
PATMT_043DILLA	800100	Cash Dispenser	4/27/18 2:45:16 PM	Transaction: Withdrawal	4/27/18 2:45:56 PM	01:WITHDRAWAL ETB200.00
PATMT_043DILLA	800200		4/27/18 2:45:16 PM	Transaction: Record Number	4/27/18 2:45:56 PM	01: RECORD NO. 2848
PATMT_043DILLA	30017	Status Retract Cassette	4/27/18 2:45:16 PM	Cash presented	4/27/18 2:45:56 PM	01: [020t 14:45:10 NOTES PRESENTED 0,0,0,2
PATMT_043DILLA	300506	Cash Dispenser	4/27/18 2:45:10 PM	The Money has been taken	4/27/18 2:45:50 PM	WFS_SRVE_CDM_ITEMSTAKEN (CurrencyDispenser1)
PATMT_043DILLA	30007		4/27/18 2:44:56 PM	PIN entered	4/27/18 2:45:35 PM	01: [020t 14:44:47 PIN ENTERED
PATMT_043DILLA	300004	Card Reader	4/27/18 2:44:46 PM	Card inserted	4/27/18 2:45:28 PM	01: [020t CARD INSERTED

As it is shown in table 3.3 ProView display the following attributes.

- ✓ Component
- ✓ Event time stamp
- ✓ Event message
- ✓ Event number
- ✓ Server time stamp
- ✓ Original message
- ✓ Device name and location

The numbers of attributes shown on table 3.3 ProView Monitoring Console are 7. According to [3] data quality can be measured in terms of accuracy, completeness and consistency. The Dashen bank S.C. ATMs data to be accurate complete and consistent the following section show what attributes represent and which value consists of.

Table 3.4 Description of event table on ProView Monitoring Console

Attributes	Data type	Description
Device name and location	Characters	ATMs Name and location
Event Number	Numeric -INT	Unique session ID
Component	Characters	Components of ATM
Event Timestamp	date/time	A specific time on happening
Event Message	Characters	Activities – from Started to end
Server Timestamp	date/time	Time stamp at ProView
Original Message	Characters	Activities – from Started to end and include the amount of transaction

The data collection has been made from 14 ATM from December 31, 2017 – May 04, 2018.

The following tables 3.5 depict every ATM together with the instances collected on MS Excel. The size of each ATM data varies because it depends on the transaction made. The combination of 14 independents ATMs data at this stage became one file of size 15.9MB with the sum of 365,522 instances.

Table 3.5 Size of ATM instances and location

Number	ATMs	Location of ATMs	Size of instance
1	Bole	City Area ATM	27,500
2	Lagar	City Area ATM	39,500
3	Bole premium	City Area ATM	17,500
4	RasDesta	City Area ATM	25,222
5	Adams Pavilion	shopping center ATM	16,000
6	Edna Mall	shopping center ATM	18,000
7	Filuha	Hotel ATM	8,500
8	Hilton	Hotel ATM	19,500
9	Shebell	Hotel ATM	17,500
10	Sheraton	Hotel ATM	23,500
11	Yoly	Hotel ATM	16,000
12	Awasssa	University ATM	66,000
13	Nekemete	Up country ATM	27,000
14	Woliso	Up country ATM	43,500
		Sum of records =	365,222

The data set attributes and values shown in Figure 3.2ProView Monitoring Consoles are valid and complete except ‘component’. Component attribute has 7% missing values.

Original message, device name and location and event number considered as irrelevant because they are not useful for the problem at hand for prediction of ATM out of service and both attributes are unused. It is too expensive to collect the whole ATMs data. Based on the domain expert consultancy 14 ATMs which are located in Addis Ababa city area (Bole, Lagar, Bole premium, and RasDesta); Shopping Center (Adams and Edna Mall); Hotels(Filuha, Hilton, Shebell, Sheraton, and Yolly);University -Hawasssa, and upcountry area (Nekemeteand

Woliso)were selected. These ATMs are selected because of their high transaction and the target data collections are more complete than the other ATMs.

The dataset at this stage after attributes selection that became an input as following table 3.4.

Table 3.6 Selected dataset attributes

Number	Attributes	Descriptions of attributes values
1	Event time stamp	Contented with date, month, year, hour and minutes
2	Event message	Activities on ATM interfaces indicating in service and out service

The following section 3.3 details about data preparation.

3.3 Data Preparation

As noted by Cios et al. [1] this step concerns deciding which data could be used as input for DM methods in the subsequent step. Major tasks in data preparation are Data Cleaning, Data Integration, Data Reduction, and Data Transformation. It also includes sampling dataset, derivation of new attributes (discretization), and summarization of data (data granularization).

The tasks applied in this study were data transformation and derivation of new attributes.

Driving new attributes

The following table 3.7 shows a new derived attributes. According to Han and Kamber [3] during attribute construction new attributes are constructed and added from the given set of attributes to help the mining process. Therefore new attributes which are components of ATM derived are CardReader, EPP, DispenserDevices, DispenserCurrencyCassette, DispenserPickCash, DispenserTransporter, SOP, Application, and NetworkConnectionB24. And they are derived from 'Event message' attribute.

These attributes are subset of event message attribute and they are derived according to Cios et al. [1] construction of new attributes.

Table 3.7 New derived attributes and descriptions.

Number	Attributes	Descriptions
1	CardReader	Hardware device that read ATM card
2	EPP	Hardware Encrypting PIN Pad
3	DispenserDevices	Dispenser devices
4	DispenserCurrencyCassette	Dispenser cash cassette
5	DispenserPickCash	Dispenser pick cash
6	DispenserTransporter	Dispenser cash transporter
7	SOP	Supervisor of ProView
8	Application	An application and operating system on ATM
9	NetworkConnectionB24	Communication between ATM and the manager base 24 server

The following is a snapshot of event message frequency on weka preprocess.

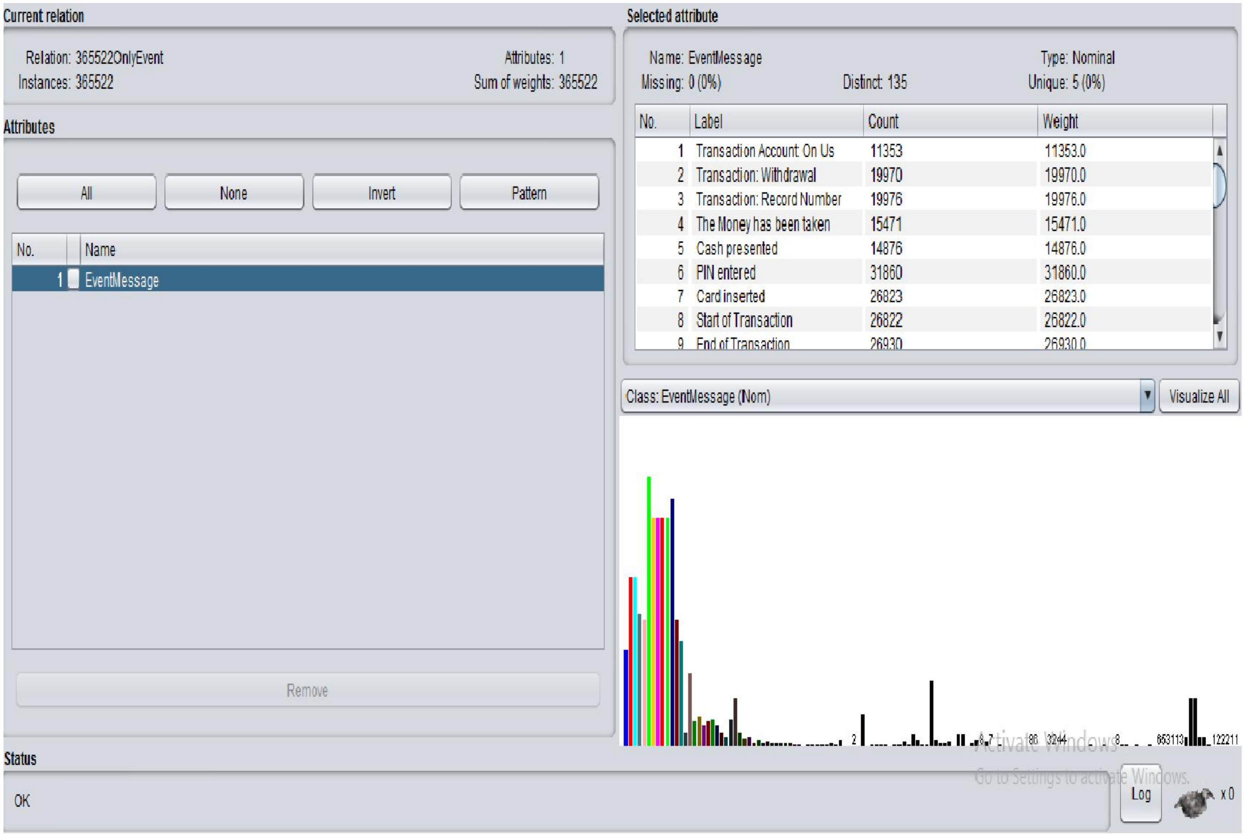

Figure 3.3 Event message count

As shown in figure 3.3 there were a total of 135 distinct event message values count inside 365,522 instances. After removing all the in service values, which are not the concern of the current study, the out of service event values are organized to prepare data set for experimentation. The selected event message out of service is shown in figure 3.4.

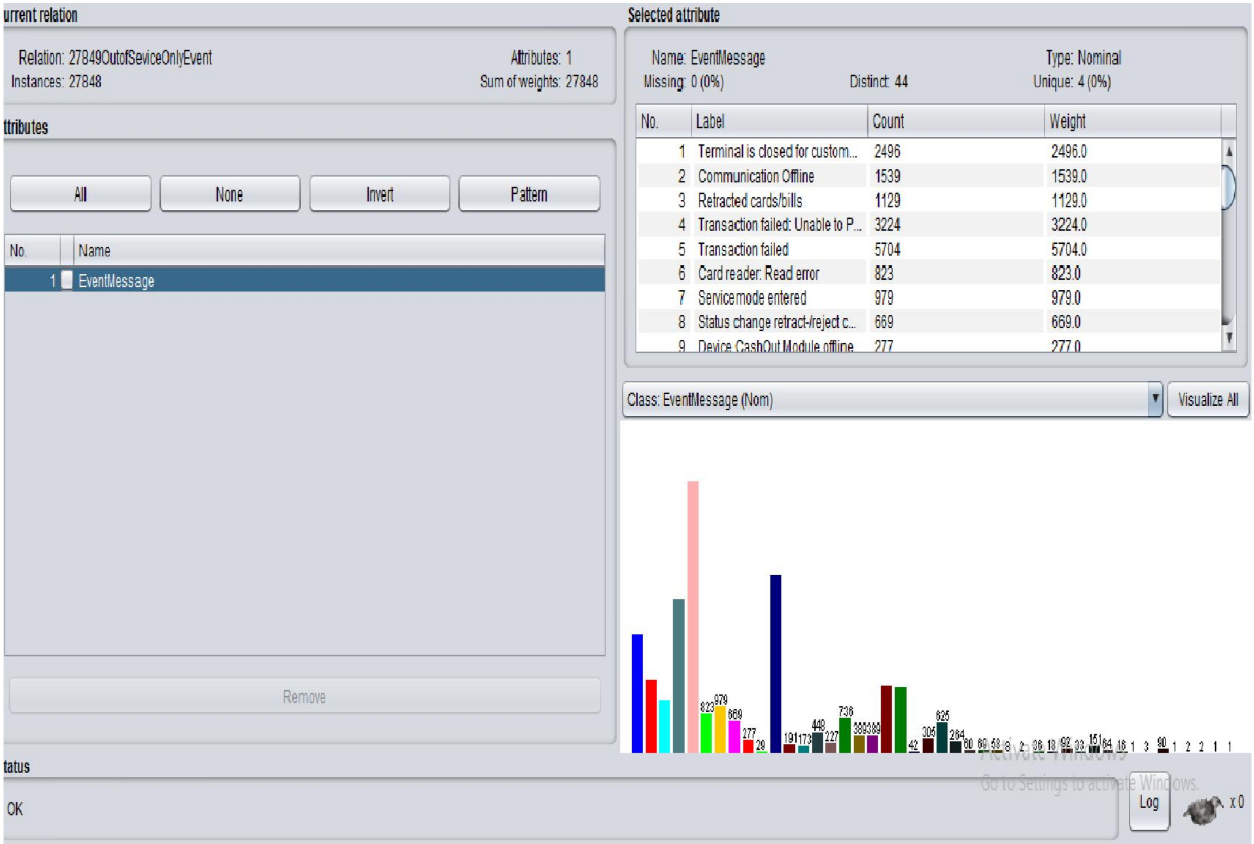

Figure 3.4 Event message out of service

Data transformation

According to Han and Kamber [3] discretization, concept hierarchy, and generation are where raw data values for attributes are replaced by ranges or higher conceptual levels. Time stamp attribute after aggregation became three distinct class values as shown below in table 3.8.

Table 3.8 Data transformation of Time stamp

Attribute time stamp	Time stamp values	Aggregated values
Time stamp	January	Jan 1-31 2018
	March	March 1-31 2018
	April	April 1-30 2018

The following table 3.9 shows attributes and their values used for this research together with their data type.

Table 3.9 List of attribute used for model building

No.	Attribute name	Data Type	Attribute values
1	CardReader	Nominal	Card Reader Read error, Blank track , No smart card response , Card Reader disconnected, Shutter jammed open , Device still inoperative , Card jam during capture, Card jam
2	EPP	Nominal	PIN/EPP: Invalid key, key does not exist
3	DispenserDevices	Nominal	Device not in use , disconnected, not accessible, , offline
4	DispenserCurrencyCassette	Nominal	Retracted cards/bills, Device CashOut Module offline, Bill cassette Slot 4 is inoperative, Reject cassette removed, Bill cassette Slot 4 is missing, Bill cassette Slot 4 is empty, Bill cassette 4 is empty
5	DispenserPickCash	Nominal	Pick failure, Pick failure - out of bills, Presenter clamping mechanism failed or jammed, Purge bin not present, Too many bills rejected

6	DispenserTransporter	Nominal	Currency jam in presenter transport or transport sensor failure, Sensor failure or currency jam in main transport
7	SOP	Nominal	Operator switch changed to supervisor mode, Terminal is closed for customers
8	Application	Nominal	Attempt to reboot via special electronic, Attempt to reboot via system, Transaction failed, Transaction failed: Unable to dispense cash, Transaction failed: Unable to Process Transaction
9	NetworkConnectionB24	Nominal	Communication Offline, Device offline, TCP/IP address not accessible
10	Eventime_Timestamp_2018	Nominal	January, march, April

The combined 365,522 instances after preprocessing became 20,880 Out of Service event quality dataset that had been input for data mining tool weka. MS Excel and VB were used for data cleaning purpose. This quality dataset file converted to comma separated value and attribute relation file format to make it suitable for data mining tool weka.

As Cios et al. [1] a classifier is a model of data used for a classification purpose: given a new input, it assigns that input to one of the classes it was designed/trained to recognize. The dependent classifier attribute was even time stamp. It classifies to three different instances.

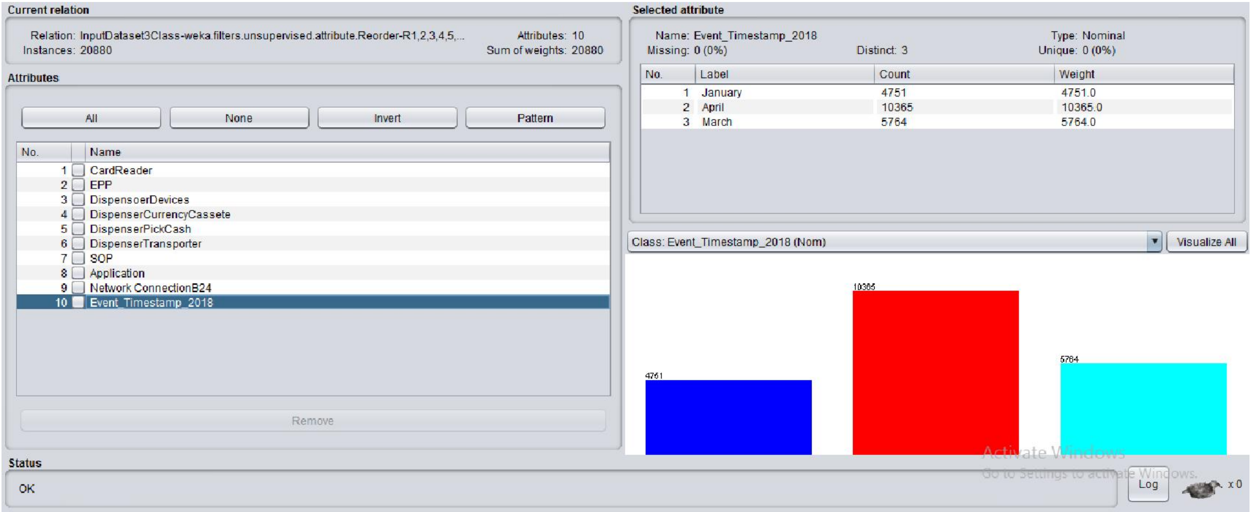

Figure 3.5the class event time stamp 2018 and its values

CHAPTER FOUR

Modeling

4.1 Building the model

Here the data miner uses various DM methods to derive knowledge from preprocessed data [1]. In this study classification algorithms are used patterns describing the reasons for ATM out of service. The tool for data mining task used was weka. Weka contains varieties of machine learning algorithms and hence the selected predictive models algorithms were PART, J48, Naiev Bayes, and multi-layer perception on weka version 3.8.2 knowledge analyzer.

For test design purpose default weka test option 10 folds cross-validation was used for all experiment. It is partitioning a data set randomly into 10 folds. Then all combined partitioned dataset except a single subset data set used to train and produce model to have the statistical result. That single partitioned subset dataset used for test set to evaluate the model. This training and test repeated 10 times. The cross validation in weka is one of the option of test design to evaluate predictive model.

The following sections were experiments result achieved in each algorithm when the models built.

4.2 Experimental result using J48 decision tree

In this experiment the parameters binary split and unpruned of J48 decision tree are calibrated by changing their default values into true or false whereas the rest of the parameter were kept as their default value. Summary of experimental results are presented in table 4.1.

Table 4.1 Experimental result of J48 decision tree algorithm

Experiments	Un Pruned	Binary Split	Correctly Classified Instances	Incorrectly Classified Instances	Time taken to build model in seconds
1	True	True	52.4808%	47.5192%	0.23
2	True	False	52.4808%	47.5192%	0.07
3	False	True	**52.7059%**	47.2941%	1.46
4	False	False	52.3707%	47.6293%	0.29

The Experiment results of J48 accuracy as shown in table 4.1 on cross validation test mode when unpruned false and binary split true; **52.7059%**accuracy greater than all others results That means J48 algorithm correctly classified about **52.7059%**and 47.2941% incorrectly.

The following table 4.2 shows the confusion matrix for pruned and binary split.

Table 4.2 Confusion matrix for the result ofJ48 decision tree

a	b	c	<===Classified as
1208	3386	157	a= January
668	9563	134	b = April
795	4735	234	c = March

The above confusion matrix shown that out of 20,880instances10,976 were classified correctly (**52.7059%**) which is the diagonal partition and 3 of them were classified incorrectly (47.2941%).

4.3 Experiment result using PART

In this experiment the parameters binary split and unpruned of PART rule induction are calibrated by changing their default values into true or false whereas the rest of the parameter were kept as their default value. Summary of experimental results are depicted in table 4.3 below.

Table 4.3 Experimental result of PART algorithm

Experiments	Un Pruned	Binary Split	Correctly Classified Instances	Incorrectly Classified Instances	Time taken to build model in seconds
1	True	True	52.4761%	47.5239%	0.98
2	True	False	52.48.08%	47.5192%	0.32
3	False	True	**52.591%**	47.409%	0.3
4	False	False	52.3515%	47.6485%	0.28

The Experiment results of PART accuracy as shown in table 4.3 on cross validation test mode. The accuracy **52.591%**is greater than all the other. That means PART algorithm correctly classified about **52.591%**and 47.409% incorrectly.

The following table shows confusion matrix for pruned binary split.

Table 4.4Confusion matrix for the result of PART rule induction

a	b	c	<====Classified as
1340	3230	181	a= January
791	9283	291	b = April
897	4509	358	c = March

The above confusion matrix shown that out of 20,880 instances 10,951were classified correctly (**52.591%)** which is the diagonal partition and three of them were classified incorrectly (47.409%).

4.4 Experimental results of Naïve Bayes

In the case of Naïve Bayes algorithm the parameters calibrated to change default values are kernel estimator and use of supervised discretization; the rest of the parameter value were kept as their default value. The experiment done by changing their value into true or false but both parameters cannot be true at the same time. The results were similar as shown in table 4.5.

Table 4.5 the result of Naïve Bayes algorithm accuracy

Experiments	Use Kernel Estimator	Use Supervised Discretization	Correctly Classified Instances	Incorrectly Classified Instances	Time taken to build model
1	True/False Or False	False/ True Or False	52.6868 %	47.3132 %	0.05 seconds

The Experiment results of Naïve Bayes accuracy as shown in table 4.5 on cross validation test mode whether it is default value or changes calibrated parameters Use Kernel Estimator and Use Supervised Discretization are all similar. The accuracy is 52.6868 %. That means Naïve Bayes algorithm correctly classified about **52.6868 %**and 47.3132 %incorrectly.

The following table 4.6 shows the confusion matrix of Naïve Bayes which is alike J48 and PART.

Table 4.6 confusion matrix result of Naïve Bayes

a	b	c	<===Classified as
1320	3218	213	a= January
775	9309	281	b = April
874	4518	372	c = March

The above confusion matrix shown that out of 20,880 instances 10,977were classified correctly (**52.6868 %**) which is the diagonal partition and three of them were classified incorrectly (47.3132 %). It is clear J48, PART and Naïve Bayes confusion matrix are similar.

4.5 Experimental result of multilayer perception

The last experiment was done using neural network multilayer perception. The calibrated parameters were hidden layers and learning rate with a 10-fold cross validation. Hidden layer is one of metrics of the multilayer perception. The default value of this parameter is ‘a’ which stores = (Number of attributes + classes)/2, which is in this case=> (9+3)/2= 6.This default value has been used and changed to see the ANN classification accuracy. Learning rate is another Multilayer perception parameter which is defined as the amount the weights are updated and its default value is 0.3.The result of the neural network model with default parameter and calibrated values is shown in table 4.6.

Table 4.7 Experimental result of multilayer perception

Experiments	Correctly Classified Instances	Incorrectly Classified Instances	Time taken to build model
1) Used default parameters	51.7912 %	48.20.88 %	494.86 seconds
2)when hidden layers is 6 or ‘a’ and learning rate were 0.4	51.8199 %	48.1801 %	490.93 seconds
3) when hidden layers is 6 and learning rate were 0.5	**52.2701 %**	47.7299 %	495.64 seconds
4) when hidden layers is 6 and learning rate were 0.6	51.0967 %	48.9033 %	494.49 seconds
5) when hidden layers is 7 and learning rate were 0.6	51.2644%	48.7356%	157.05seconds

The Experiment results of multilayer perception accuracy as shown in table 4.7 on cross validation test mode. The accuracy **52.2701 %** greater than all the other. That means multilayer perception algorithm correctly classified about **52.2701 %**and 47.7299 % incorrectly. Notice the maximum time taken to build modelwas495.64 seconds when default parameters used and the minimum was 157.05 seconds when hidden layers were 7 and learning rate 0.6.

The confusion matrix of multilayer perception is alike all the above others algorithm.

Table 4.8 confusion matrix result of multilayer perception

a	b	c	Classified as
1093	3378	280	a= January
630	9388	347	b = April
724	4607	433	c = March

The above confusion matrix shown that out of 20, 880 instances 10,914 were classified correctly (**52.2701 %**) which is the diagonal partition and three of them were classified incorrectly (47.7299 %). It is clear J48, PART, Naïve Bayes and multilayer perception confusion matrix are competent but J48 performance is best.

4.6 Evaluation

Evaluation includes understanding the results, checking whether the discovered knowledge is novel and interesting, interpretation of the results by domain experts, and checking the impact of the discovered knowledge [1]. This research classification models were developed to determine the reason for ATMs out of service of Dashen bank S.C. J48 decision tree exhibited model performance matched with business objective. Because to extend the discovered knowledge according to hybrid KDP model.

The following table 4.9 is the summarized classifier output. Looking closely at each of the classifier output they have their own unique presentation. Additionally the weka preprocess tab have feature to visualize and counting instances that can be easily observed.

Table 4.9 summarized classifier output

Name of the algorithm	Tree : J48	Rule: PART	Bayes: Naive Bayes	Function: Multilayer Perception
Correctly Classified Instances	**52.7059 %**	52.591 %	52.6868 %	52.2701%
Incorrectly Classified Instances	47.2941 %	47.4808 %	47.4282 %	47.7299 %
Time taken to build model in seconds	1.46	0.3	0.05	495.64

Additionally weka have feature to visualize data mining metrics that is easy to understand. The other selected metrics that prove the experiment done as accuracy were precision, recall, and ROC. The following figures snapshot taken from weka. The first one figure 4.1 which is precision-recall curve.

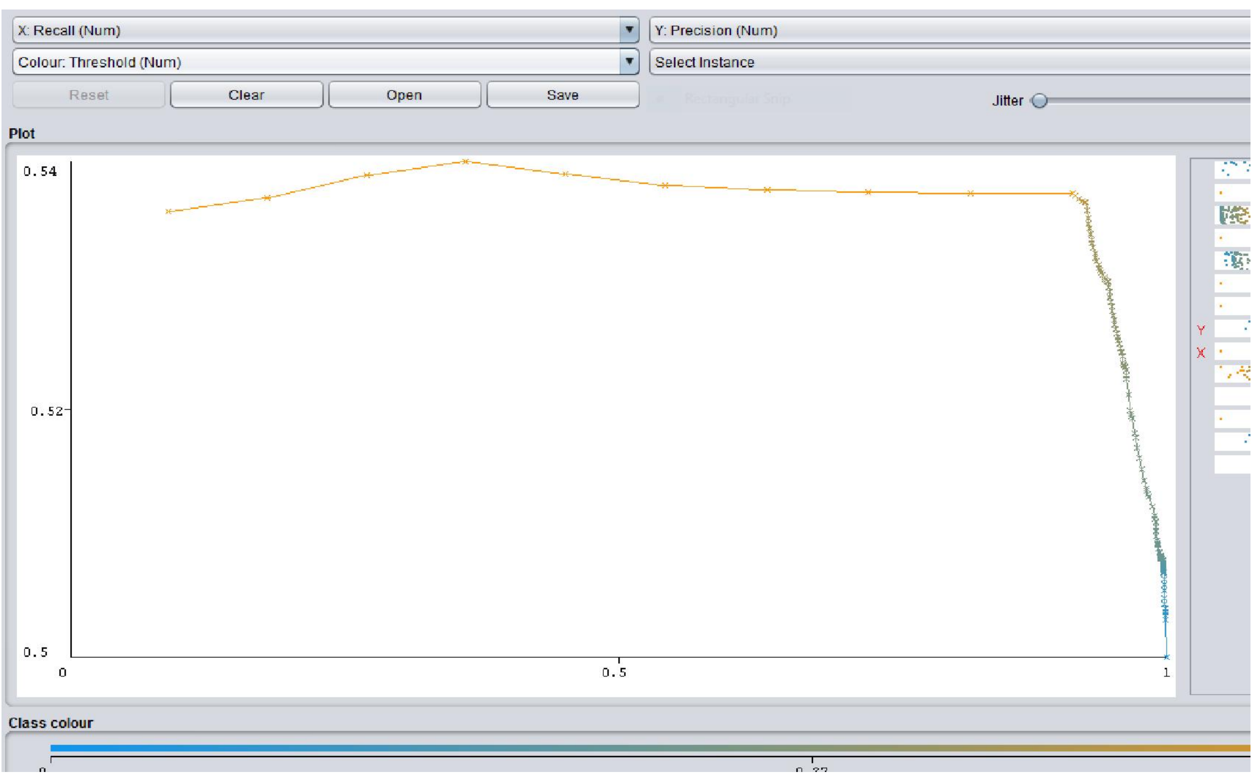

Figure 4.1 precision-recall curve of class April

Precision-recall curves are important to visualize the classifier performances as accuracy. The aim is to observe whether precision-recall curve is towards the upper right corner of the chart. The P-R curve displayed with respect to class value April and x-axis is recall (true Positive Rate) and y a-axis precision.

The second one figure 4.2 is ROC curve.

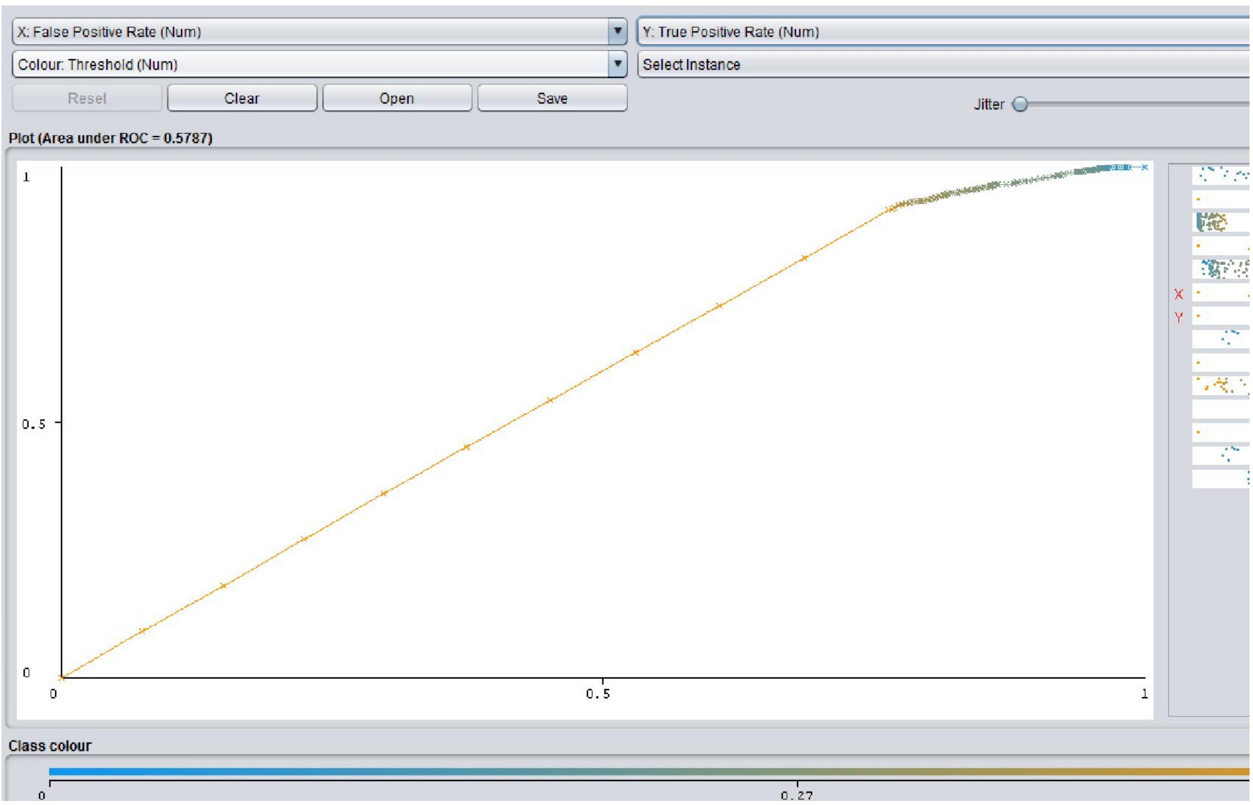

Figure 4.2 ROC curve of class value April

As accuracy and P-R the other important measurement of model performance is ROC. ROC curve displayed on figure 4.2 with respect to class value of April. The aim of producing ROC curve is to have the curve close to upper left corner on y-axis which is one. The other different interpretation is the given area under ROC as shown on figure 4.2. The AUROC is a comparison of two operating characteristics (TPR y-axis and FPR x-axis). And the AUROC curve measured describes the performances of the model if it is greater than 0.5 and less than 1.

On this research the J48 decision tree classifier based on evaluation metrics discussed above performed better so it is selected to use the discovered knowledge. The following chapter had shown the implementation of J48 model to produce prototype.

The following is J48 pruned tree

DispensoerDevices = Device disconnected: January (86.0)

DispensoerDevices != Device disconnected

| CardReader = Card Reader disconnected: January (34.0)

| CardReader != Card Reader disconnected

| | DispensoerDevices = Device offline: January (13.0)

| | DispensoerDevices != Device offline

| | | Network ConnectionB24 = Device offline: January (13.0)

| | | Network ConnectionB24 != Device offline

| | | | DispenserPickCash = Dispenser: Presenter clamping mechanism failed or jammed: March (66.0/10.0)

| | | | DispenserPickCash != Dispenser: Presenter clamping mechanism failed or jammed

| | | | | DispenserPickCash = Dispenser: Too many bills rejected: January (36.0/12.0)

| | | | | DispenserPickCash != Dispenser: Too many bills rejected

| | | | | | DispenserCurrencyCassete = Bill cassette Slot 4 is empty: January (54.0/23.0)

| | | | | | DispenserCurrencyCassete != Bill cassette Slot 4 is empty

| | | | | | | DispenserCurrencyCassete = Retracted cards/bills: January (822.0/479.0)

| | | | | | | DispenserCurrencyCassete != Retracted cards/bills

| | | | | | | | Application = Transaction failed: Unable to dispense cash: March (209.0/119.0)

| | | | | | | | Application != Transaction failed: Unable to dispense cash

| | | | | | | | | Application = Attempt to reboot via system: January (294.0/179.0)

| | | | | | | | | Application != Attempt to reboot via system

| | | | | | | | | | Application = Attempt to reboot via special electronic: January (294.0/179.0)

| | | | | | | | | | Application != Attempt to reboot via special electronic

| | | | | | | | | | | DispenserCurrencyCassete = Bill cassette 4 is empty: January (64.0/38.0)

| | | | | | | | | | | DispenserCurrencyCassete != Bill cassette 4 is empty

| | | | | | | | | | | | SOP = Operator switch changed to supervisor mode: January (406.0/238.0)

| | | | | | | | | | | | SOP != Operator switch changed to supervisor mode

| | | | | | | | | | | | | DispenserCurrencyCassete = Device CashOut Module offline: January (236.0/139.0)

| | | | | | | | | | | | | DispenserCurrencyCassete != Device CashOut Module offline

| | | | | | | | | | | | | | CardReader = Card reader: Shutter jammed open: March (3.0)

| | | | | | | | | | | | | | CardReader != Card reader: Shutter jammed open

| | | | | | | | | | | | | | | CardReader = Card reader: Blank track: January (228.0/108.0)

| | | | | | | | | | | | | | | CardReader != Card reader: Blank track

| | | | | | | | | | | | | | | | DispenserPickCash = Dispenser: Purge bin not present: March (8.0/2.0)

| | | | | | | | | | | | | | | | DispenserPickCash != Dispenser: Purge bin not present

| | | | | | | | | | | | | | | | | DispenserPickCash = Dispenser: Pick failure - out of bills: March (246.0/153.0)

| | | | | | | | | | | | | | | | | DispenserPickCash != Dispenser: Pick failure - out of bills: April (17768.0/8163.0)

Number of Leaves : 19

Size of the tree : 37

Time taken to build model: 1.3 seconds

CHAPTER FIVE

Research model, Use of the Discovered Knowledge, Implementation and Evaluation

5.1 Research Model

The research is conducted on experimentation. According to the world book encyclopedia [15] experimentation is a method used to discover facts and to test ideas. On this study to identify the reason ATM out of service the four classifier algorithms J48, PART, NB, and MLP with the default cross validation test design after sixteen experimentation produce models. The selected J48 model was used for the extended use of discovered knowledge. Thus the discovered knowledge revealed the desired reasons for ATM out of service in this thesis which are the following components of ATMs.

DispensoerDevices: - 1) Device disconnected 2) Device offline

DispenserCurrencyCassete: - 1) Bill cassette Slot 4 is empty 2) Retracted cards/bills 3) Bill cassette 4 is empty 4) Device CashOut Module offline

DispenserPickCash: - 1) Presenter clamping mechanism failed or jammed 2) Too many bills rejected 3) Purge bin not present 4) Pick failure - out of bills

CardReader: - 1) Card Reader disconnected 2) Shutter jammed open 3) Blank track

Application: - 1) Transaction failed: Unable to dispense cash 2) Attempt to reboot via system 3) Attempt to reboot via special electronic

SOP: - 1) Operator switch changed to supervisor mode, and

Network ConnectionB24:- 1) Device offline were hidden in the timestamp of ATMs events. The following figure 5.1 is the model of this research.

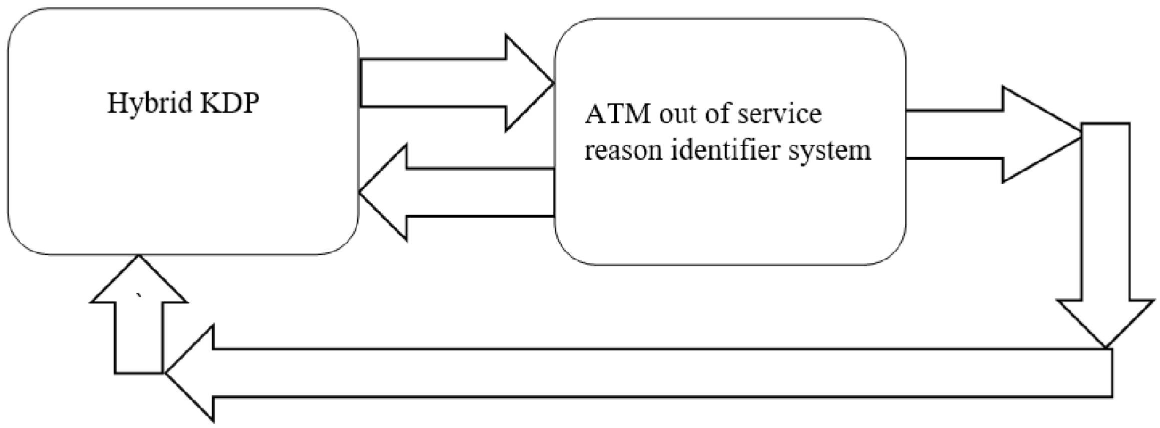

Figure 5.1 Research model for design the reason ATM out of service

5.2 The System Development

For the implementation of graphical user interface that enables the use of discovered knowledge to identify the reason for ATM out of service a desktop application development tool NetBeans IDE 8.2 was used. NetBeans is an open-source integrated development environment (IDE) for developing with Java, PHP, C++, and other programming languages. NetBeans is also referred to as a platform of modular components used for developing Java desktop applications [26].

5.3 The Prototype

The prototype is designed based on hidden rules identified by classification algorithm, J48 decision tree. The prototype has attempts to identify reasons for ATM out of service based on the given J48 classifier output.

Figure 5.1 shows snapshot of the user interface through which displayed one of the class label time stamp January and its frequency and reasons for ATMs out of service.

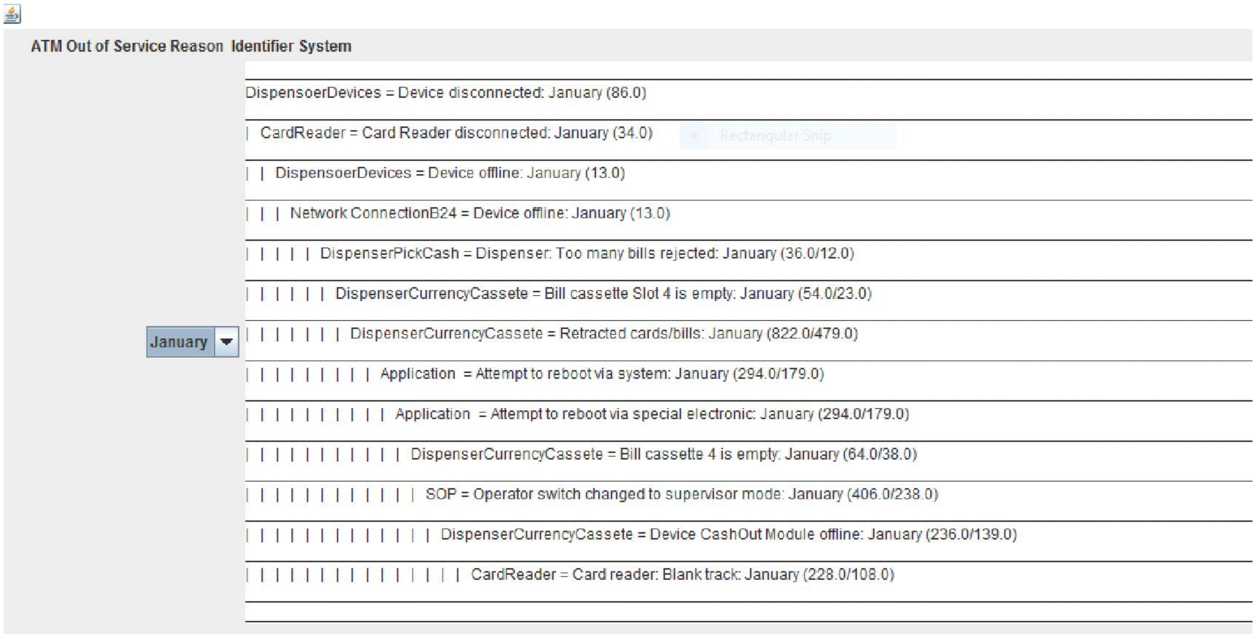

Figure 5.1 ATM out of service reason identifier system: - Prototype

The input for ATM out of service reason identifier system came from weka J48 classifier output which is the designed model. In other words, the model have been input for the prototype.

5.4 Evaluation

For conducting usability testing test, seven ATM system administrators were involved; to evaluate the prototype done on NetBeans IDE 8.2 from the point of effectiveness, efficiency and their satisfaction accordingly the ISO 9241-11 usability testing features [25]. Out of the seven system administrators, five of them are seniors in the area. The system administrators section is the one who is responsible to follow-up any incidents on ATM. Before conducting the evaluation process description of the prototype has been given for these evaluators.

Guiding questionnaires with two parts has been prepared (see APPENDIX A), for facilitating experts response. The first part of the questionaries' was supportive in identifying their experience on ATM out of service reasons. And the second part was five level likert scale (strongly agree (5), agree (4), neutral (3), disagree (2) and strongly disagree (1)) is used for the reply of the usability testing test given questions.

The below table 5.1 summarizes the responses of system administrators.

Table 5.1: Detailed summary of questionnaire result

Question No.	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean Value
1	7	0	0	0	0	5
2	5	2	0	0	0	4.7
3	7	0	0	0	0	5
4	3	4	0	0	0	4.4
5	7	0	0	0	0	5
6	7	0	0	0	0	5
7	7	0	0	0	0	5
8	7	0	0	0	0	5
9	7	0	0	0	0	5
10	7	0	0	0	0	5
11	7	0	0	0	0	5
Overall system usability (%)						98%

5.5 Analysis and interpretation

The guiding questionnaires part two based on ISO 9241-11 usability testing features [25] questions are classified into three. The first one effectiveness has one questions out of eleven; the second efficiency has three and the third one user satisfaction have seven. From the questionnaires analysis concluded that 98% of respondents agreed the system is as an effective, efficient and satisfactory and accepts as a prototype.

CHAPTER SIX

Conclusions and Recommendation

6.1 Conclusions

The ATM service is not far from us in our day to day life. Most selected areas such as hotels, shops, branch bank, universities, hospitals, etc. have a placement for ATMs. These ATMs intended to provide service 24 hours a day, seven days week, and all the time. But customers of ATMs service observe commonly out of service on these self-service machine display. This study was to find the reason for ATM out of service.

The researcher consider Dashen bank S.C. ATMs to answer why ATMs are out of service. Approach followed up to investigate was data mining technology and the six steps of hybrid knowledge discovery process model was applied. One of the crucial step in KDP is DM which enables to design a model so the researcher used weka knowledge discovery tool to identify the causes for ATM out of service. The method to accomplish DM objective was by 16 experimental analysis followed evaluation using appropriate metrics accuracy, PR, ROC, and AUROC and proof the experiments were worthy.

Firstly the researcher together with domain expert particularly studied the event data to understand and prepare a dataset for data mining task. To identify out of service event data 14 ATMs were purposely selected within periods, December 31, 2017 – May 04, 2018. From the collected dataset of ProView console as per the objective of this research 44 events of which hardware problem were 73 % and software 27% describing out of service happening were identified. Next was preparing dataset that is suitable for DM. Preparation of data set includes constructions of new attributes from the existing dataset, removing unnecessary attributes and inconsistence values, and aggregation of attribute values.

After the completion of DM it was found that the basic reasons for ATM out of service were the non-functionality ATM components which are

DispensoerDevices: - 1) Device disconnected 2) Device offline

DispenserCurrencyCassete: - 1) Bill cassette Slot 4 is empty 2) Retracted cards/bills 3) Bill cassette 4 is empty 4) Device CashOut Module offline

DispenserPickCash: - 1) Presenter clamping mechanism failed or jammed 2) Too many bills rejected 3) Purge bin not present 4) Pick failure - out of bills

CardReader: - 1) Card Reader disconnected 2) Shutter jammed open 3) Blank track

Application: - 1) Transaction failed: Unable to dispense cash 2) Attempt to reboot via system 3) Attempt to reboot via special electronic

SOP: - 1) Operator switch changed to supervisor mode, and

Network ConnectionB24:- 1) Device offline were hidden in the timestamp of ATMs events.

The finding shows that 87 % ATMs out of service were in April, 10.7 % January, and 2.2 % March. The major problem 87 % was on hardware DispenserPickCash Dispenser: Pick failure - out of bills. And next the remaining were CardReader. Application, SOP and Network ConnectionB24.

The final step of hybrid KDP is use of the discovered knowledge. To use this discovered knowledge the finding J48 model used to produce a prototype and the implementation done using Java on NetBeans IDE 8.2 platform. The Extended knowledge to this result is ATM out of service reason identifier system that make users easily identify the reasons for ATM out of service.

The best selected classification algorithm was J48. The selected DM measurements metric accuracy was **52.7059 %**, PR curve shown a good performance which is a recall x axis 1 and y axis 0.5 at start. ROC have the curve like bow and its peak reached to one to one where as the area ROC is 0.6161 which is worthy.

The designed model found in this study identify the reasons for ATM out of service and made classification. Classified ATM out of service reasons support ATM supervisors and increase the availability and improve the service. To have higher availability on ATMs components and service it needs further research.

6.2 Recommendation

Quality of ATM service is desired at most for customer satisfaction and to gain more on return investment. Bank industry is responsible to make maximum in service of ATMs. This study looks at closely Dashen bank ATMs in order to identify the reasons for ATMs out of service. Based on the findings of the study the following recommendations are forwarded.

- ✓ In this study, an attempt is made to identify the causes of ATMs out of service using scarce data captured by ProView. However preparing enough quality data needs to be considered for future study to simplify the data mining task.
- ✓ In this study an attempt is made to use the knowledge discovered for identifying the reasons for ATM out of service. We recommend to integrate data mining result with the ProView so as to detect the reasons automatically for taking immediate corrective action.
- ✓ To enhance the accuracy of predictive model further study needs to be conducted using other classification algorithms.
- ✓ One of the research on ATM is the hardware parts card reader, dispenser and all its sub components time to failure prediction in order to classify ATM out of service by time.
- ✓ If currency cassettes are not empty it increases the availability of ATM; therefore, how to make ATM not run empty of a cash proactively needs to construct a predictive model which is left for further research.

Reference

[1] Cios et al., Data Mining A Knowledge Discovery Approach, New York: Springer, 2007.

[2] W. Ian H and F. Eibe, Data Mining: Practical machine learning tools and techniques, San Francisco: Morgan Kaufmann, 2016.

[3] J. Han and M. Kamber, Data mining: concepts and techniques, San Francisco: Morgan Kaufmann, 2006.

[4] M. H. Dunham, Data mining: Introductory and advanced topics, NJ: Pearson Education, 2006.

[5] Dashen Bank, "Company profile," Dashen Bank, 4 September 2018. [Online]. Available: https://dashenbanksc.com. [Accessed 4 September 2018].

[6] Dashen Bank, "21st Annual Report for the year," Dashen Bank, Addis Ababa, 2017.

[7] W. Gardachew, "Electronic-banking in Ethiopia-practices, opportunities and challenges," Journal of internet Banking and commerce, vol. 15, no. 2, pp. 1-8, 2010.

[8] Wincor Nixdorf, Administration & System Management ProView Reporting API, Paderborn: Wincor Nixdorf, 2015.

[9] Dashen Bank, Risk Management policy Manual, Addis Ababa: Dashen Bank S.C., 2017.

[10] Dashen Bank, "Internal Audit Policy," Internal Audit Policy, pp. 10-15, 15 Feburary 2017.

[11] T. Mahmood and G. M. Shaikh, "Adaptive Automated Teller Machines," Expert Systems with Applications, vol. 40, pp. 1152-1169, 2013.

[12] Gümüş et al., "Ultimate Point in the Service Provided by the Banks to Their Customers: Customer Satisfaction in the Common Use of ATMs," Social and Behavioral Sciences, vol. 207, pp. 98-110, 2015.

[13] S. Madhavi, S. Abirami, C. Bharathi, B. Ekambaram, T. Krishna Sankar, A. Nattudurai, N. Vijayarangan, "ATM Service Analysis Using Predictive Data Mining," International Journal of Computer, Information, Systems and Control Engineering, vol. 8, no. 2, 2014.

[14] WordWeb software, "WordWeb 8.03a," Princeton University, 2016.

[15] Field enterprises Education Corporation, The world book encyclopedia Volume 6, USA FGA: Field enterprises Education Corporation, 1967.

[16] Wincor Nixdorf, ProView Console 4.2/40, Paderborn: Wincor Nixdorf, 2015.

[17] Wincor Nixdorf, ProView Data Model 4.2/40(C), Paderborn: Wincor Nixdorf, 2015.

[18] P. Bastos et al, "A Maintenance Prediction System using Data Mining Techniques," Proceedings of the World Congress on Engineering , vol. III, pp. 1148-1453, 2012.

[19] Two Crows Corporation, Introduction to data mining and knowledge, Potomac: Two Crows Corporation, 2005.

[20] G. Tewary, "Data Mining Through Neural Networks Using Recurrent Network," itccma, pp. 57-74, 2015.

[21] Fayyad et al., "From Data Mining to Knowledge Discovery in Databases," AI Magazine, vol. 17, no. 3, 1996.

[22] Transaction Network Services, What Payments Trends Should You follow in 2018?, Virginia: Transaction Network Services, 2017.

[23] INETCO, Unlocking Your ATM “Big Data”: Understanding the, Burnaby: INETCO, 2015.

[24] Wincor Nixdorf, ProView Data Model 4.2/40(C), Paderborn: Wincor Nixdorf, 2015.

[25] ISO, "ISO Online Browsing platform," The International Organization for Standardization, 26 January 2018. [Online]. Available: https://www.iso.org/obp/ui/#search. [Accessed 26 January 2018].

[26] NetBeans, "NetBeans," NetBeans, 26 January 2018. [Online]. Available: https://netbeans.org/. [Accessed 26 January 2018].

[27] Cabena et al, Data Mining:From Concepts to Implementation, New Jersey: Prentice Hall Saddle River, 1998.

[28] Farooqi et al, "Effectiveness of Data mining in Banking Industry: An empirical study," International Journal of Advanced Research in Computer Science, vol. 8, no. 5, pp. 827-830, 2017.

[29] C. Mwatsika, "Customers’ satisfaction with ATM banking in Malawi," African Journal of Business Management, pp. 218-227, 2014.

[30] Chan et al., "Modified automatic teller machine prototype for older adults: A case study of," Applied Ergonomics, no. 40, pp. 151-160, 2009.

[31] Moslehi et al, "Analyzing and Investigating the Use of Electronic Payment Tools in Iran," Journal of AI and Data Mining, pp. 417-437, 2018.

[32] Electro Magnetic Components Inc. , "ATMs: How They Work and Basic ATM Parts," Electro Magnetic Components Inc. , 2015. [Online]. Available: http://www.atmparts.net/atm-parts/. [Accessed 28 February 2019].

APPENDIX

ATM OUT OF SERVICE REASON IDENTIFIER SYSTEM

Usability Testing Questionnaire (Users: - System Administrator)

This questionnaire is intended to know admins knowledge related to ATM out of service reasons based on existing system ProView, B24, and NetMon and others.

I. Background Information about the company and the user

1. Name of the company ________________________________
2. Your position ________________________
3. On which ATM monitoring system tool you have experience for identifying status?

   ____

4. Are you familiar with the ATM out of service reasons? ☐ Yes ☐ No
5. How many reasons out did you identify as out of service?
6. List the reasons of out of service?
7. Do you know or your company proactively ATM out of service? ☐Yes ☐ No
8. If your answer for question number 7 is Yes, please describe in detail

   ____

9. If your answer for question number 7 is No, please describe in detail

   ____

II. Prototype

The following items are related to usability testing test of ATM out of service reason identifier system. Please indicate your agreement by making "✓ "in the boxes

No.	Question	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
1	Do you think classifying ATM out of service with respect to timestamp of months in the prototype is essential?					
2	Are you satisfied when events are labeled or classified with time stamp of the three months (January, March and April)					
3	Do you think the ATM out of service reason identifier system prototype can be used easily?					
4	Do you think the system is good enough product?					
5	Do you think the response time for most operations is fast enough?					
6	Do you think the cost of ATM out of service reason identifier system is lower than any real time monitoring system?					
7	Do you think the system can be used by any user with basic knowledge of using computers?					
8	Do you think the text which appears on the pages is clearly readable throughout operating on the system?					
9	Do you think the interaction to accomplish tasks is simple and complete with a few seconds?					
10	Do you think the menu items are consistently located and work without failure?					
11	Is ATM out of service reason identifier system easy to use to view, edit, and copy?					

Please write any other comment about the ATM out of service reason identifier system:

____

____

________ ____