A Predictive Model to Determine Mobile Banking Customers: The Case of United Bank

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Abstract

In Ethiopia Mobile banking (M-banking) has been offered by various financial institutions, including private and public banks. However, M-banking in Ethiopia is not widely used and accepted as in other African countries. Accordingly, the study of M-banking in Ethiopia focuses on factors affecting adoption of E-banking in Ethiopia. Different factors are mentioned and discussed with different researchers. This paper aims to build a model to predict potential M-banking customers in the case of United Bank, identify significant attributes based on the bank's historical data using data mining techniques with various classification algorithms such as BayesNet, Naïve Bayes, IBK, KStar, PART, J48, and RandomForest and to recommend appropriate actions to be taken to promote Mobile Banking in Ethiopia. These algorithms are selected based on literature review and discussion with experts. Data are collected from two disparate databases on M-banking to identify registered customers and core banking to identify non registered customers and different transactions provided by the bank. The Mobile transaction attribute is used for the domain knowledge or class label. Stratified random sampling was used to collect unregistered and registered but not use the service from 109 branches of the bank since this sampling technique is more precise and represents the data. A total of 3000 customers are identified with 14 attributes. A total of 7870 instances or datasets was prepared and fed into the WEKA tool for experimentation. The experiment was done in two phases, the first with 10 fold cross validation and the second one with 75/25 percentage. Model evaluation was done by accuracy rate and ROC. According to the comparison made on the classification algorithms, seven algorithms are selected to build the model. Among those algorithms, PART from Rule is the best and has value of 79.75% accuracy and ROC Area 0.837. Account to account is a significant attribute. This is followed by loan repayment and telegraphic transfer. Then a prototype is developed. Based on the prediction model, the bank can easily identify customers that are potential users of mobile banking services.

Keywords: Mobile Banking; Electronic Banking; Data Mining; Classification; Model; Prototype

1. Introduction

Recently banks have developed innovative products and offered a wider range of services in an effort to increase customer satisfaction and efficiency. Therefore, banking services are being presented through electronic delivery channels. Electronic-banking offers banking services via various electronic channels. Electronic banking is becoming the main tool for bank services without needing the physical presence of customers. E-Banking is a means of banking service where funds are transferred through electronic devices between financial institutions and individuals instead of cash exchange, checks, or other negotiable instruments E-banking, also known as electronic funds transfer, uses electronic media to transfer funds directly from one account to another. The term E-banking often refers to online banking or Internet banking which is the use of the Internet as a remote delivery channel for banking services. With the help of the Internet, bank services are available anywhere, customers all over the world can access

bank services 24 hours a day, seven days a week. E-banking can be also defined as a diversity of platforms such as Internet banking, TV-based banking, mobile phone banking, and PC (personal computer) banking whereby customers access these services using an intelligent electronic device, like PC, ATM (automated teller machine), and POS (point of sale) [11]. The most important channels are: the Internet, wireless connection systems, ATM (Automated Teller Machine), telephone, etc. [2].

When we see the history of E-Banking, it started in the use of ATMs. Finland is the first country in the world to use E-Banking [4].

Among various E-banking channels, due to its convenience, familiarity among the society, and easy to use, mobile banking is a powerful channel to deliver banking services to billions of people.

Mobile banking also means performing banking activities which primarily consist of opening and maintaining mobile/regular accounts and accepting deposits. Furthermore, it includes performing fund transfer or cash-in and cash-out services using mobile devices [12].

Mobile banking is classified into two. The first is transformational mobile banking, which is the provision of banking services using a mobile phone to reach the population that do not have a bank account instead use a phone as an account. The second is additive Mobile banking, in which the mobile phone is simply an additional channel that is used to provide banking services to those who have bank accounts [13].

According to [7] through mobile banking a customer can operate his/her account from office or home. The need for going to the bank in person for every single banking activity is reduced. It eliminates the need to wait long queues for the reason of bill payment, most, if not all, services that are usually accessible from the local bank can be found in a single handset, sharp growth in credit card or debit card usage can be credited to Mobile banking. A customer can shop globally without any need for moving paper currency. In M-banking, banks are available 24 hours a day and 7 days a week and are just a finger click away.

For the banks, the main advantage of the mobile phone lies in its capabilities to reach everywhere. Its influence is transforming the economics of service delivery, especially by reducing the costs of financial transactions worldwide. In addition, it has the potential to significantly increase people's access to finance. In South Africa, the Democratic Republic of Congo, Zambia and Kenya, for instance, mobile banking is taking services to remote areas where conventional banks have been physically absent. People can now open accounts, check their balances, pay their bills, and transfer money [1].

Despite its expansion around the globe, specifically in Africa, the services provided by Ethiopian banks are not attractive and the penetration is not fast as in neighboring countries.

Since 2009 United Bank started M-banking services such as SMS and telephone banking, but the service was not successful due to user unfriendly and complex commands in the case of SMS banking. Since July 2013, due to the innovation of new mobile banking technologies like USSD (Unstructured Supplementary Services Data), the bank replaced its previous version with the new one. The innovation of new technologies came with additional features of SMS notification for each transaction, fund transfer, Forex rate and min statement inquiry.

However, we observed some problems with the services provided by the bank. M-banking is the main service having more registered customers following ATM users. Despite the number of registered customers, the service is accessed by few. Thus, this research tries to explore and predict potential customers of M-banking based on data mining techniques and various classification algorithms with the bank's historical data [4].

2. Related Work

When we see related works on the challenges of E-banking, different researchers mentioned challenges

in the adoption of E-Banking in Ethiopia. These are chances of risk, lack of trained and efficient staff in e-banking, lack of appropriate legal and regulatory framework, absence of financial networks that link different banks, low level Internet penetration and poorly established telecommunication infrastructure, high cost of Internet, and security issues. In addition, lack of customer awareness regarding the service is another challenge in order to provide the service [3].

The work in [8] investigated E-Banking customers using data mining techniques and under clustering they used K-means algorithm. The objective of was to find valuable customers and their usage behaviors in order to add new products or services to meet customers' needs. According to the findings, daily E-banking concurrent access increased between 12.00 - 17.59 PM that impact the system to serve all resulting with slow response.

Data collected from September and October 1999 in University of Michigan's Survey of consumers also found that age and education have an effect on the use of electronic banking products [6]. The study of 1,000 US households evaluated attitudes toward electronic banking. The paper concludes that positive attitudes to e-banking services matter more than demographic factors in determining whether such services are used.

The work in [9] investigated the extent of the adoption and usage of M-banking services among banking customers in Nigeria and the associated problems. The finding shows that M-banking was more established than Internet banking and ATM services, but ATM services have a wider reach.

Research on the effect of e-banking service on deposit mobilization was conducted by Hailu Biza [10]. The paper concluded that mobile credit and card credit transactions have a great impact on deposit mobilization.

There have been a number of valuable studies in the area of mobile banking over the years. Almost all focused on finding the challenges of adoption of E-banking in Ethiopia. No one investigated or predicted potential M-banking customers so far. The existing research in Ethiopia included mobile banking in electronic banking challenges and barriers [3, 5, 10]. To the best of our knowledge, there is no study conducted with regards to potential M-banking customers in Ethiopia. This study, therefore, aims at predicting potential M-banking customers in order to increase usage of M-banking services and to create an understanding of this new technology in the banking sector as well as the society.

3. The Proposed Solution

According to the work in [7], there are no security and dysfunctional issues mentioned by commercial banks in Ethiopia. In this paper we tried to predict potential M-banking customers of the bank based on historical transaction with the help of data mining techniques and classification algorithms. Then a prototype is developed. The overall objective of this study is to design a model to predict M-banking potential customers, identify the core attributes of transactions using data mining techniques and identify the best model. To do this 7870 instances and 14 attributes including the target class were input into WEKA tool. After using InfoGain Attribute EvalAttributes we found 7 Account to account, 8 Loan-repayment, 6 Telegraphic-transfer, 12 Inhouse-cheque Deposit, 11 CPO, 3 Cheque-Withdrawal, 10 Inward-Clearance, 5 Fund transfer-Incoming, 13 Other Bank-RTGS, 4 Fund transfer-outgoing, 1 outgoing-RTGS, 2 Cash-Withdrawal, and Time-Deposit.

Seven algorithms were used for experimentation namely, BayesNet, NaiveBayes, IBK, KStar, PART, J48, and RandomForest. Accuracy, ROC and Confusion matrices were used to choose the best model. Finally, to help the bank to predict customer potential, a prototype is developed. The prototype has a database connection that helps to maintain attributes and rules revealed from the best model.

In general, the bank can use the prototype to predict mobile banking customers and take appropriate measures regarding M-banking service provision.

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To achieve the main and specific objectives of this paper, the significant transaction attributes or parameters collected from the bank are used to build the predictive models based on data mining technique and different classification algorithms. We achieved an accuracy rate of 79.75%. The research questions and the findings are the following.

a. *What type of transaction is most important to predict Mobile banking potential customers?*

'Account to Account' transaction is the most important to predict customer potential. Loan repayment and telegraphic transfer transactions come next. These three are the main transactions that can be accessed by mobile channels. Customers also want to know their loan status, monthly repayment amount, loan repayment date, outstanding loan, and transferring money from one account to another. To perform the above mentioned activities, Mobile banking services are more suitable.

b. *Which data mining algorithms can best classify customers based on the transaction data?*

Based on the comparison made on classification algorithms, seven algorithms are selected to build the model. Among those algorithms, PART from rule classifier is the best and has accuracy of 79.75% and ROC Area of 0.837 followed by RandomForest with accuracy of 79.63% and ROC Area of 0.84, then J48 with accuracy of 79.61% and ROC 0.818. We are unable to compare the result with similar works done by other researchers, since there are no researches done on potential customers using historical data with data mining techniques. The result shows that rule and decision tree classifiers predict customer potentiality better than other classification algorithms in terms of accuracy and ROC area.

c. *How can a best predictive model be designed to predict potential e-banking c*ustomers?

Predicting customer potentiality is applied based on data collected and data mining techniques. In addition to this, a prototype is developed to predict customer potentiality. Based on this prediction model, The organization can easily identify potential customers. It helps to identify target customers in order to set quotas for each branch based on those identified significant attributes rather than newly opened accounts to build strategic follow up techniques to follow the status of service activities. For example, Account to account transfer, loan repayment, and telegraphic transfers are the most significant attributes to identify potential customers so that they can identify such customers from the core banking database and check whether all those potential customers are registered and use services actively or not and should take appropriate measures in order to address them.

Figures 1 to 3 show screenshots of the developed prototype.

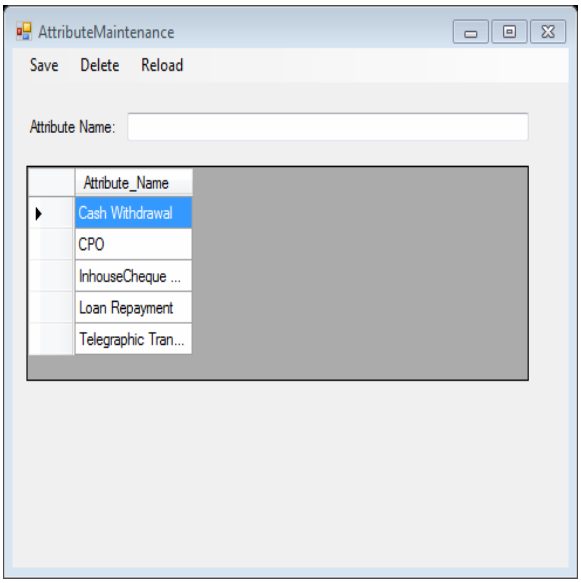

Figure 1: Attribute Maintenance Interface

This interface is used to maintain, modify, and remove new and existing attributes, since attributes may increase in number or changes in type.

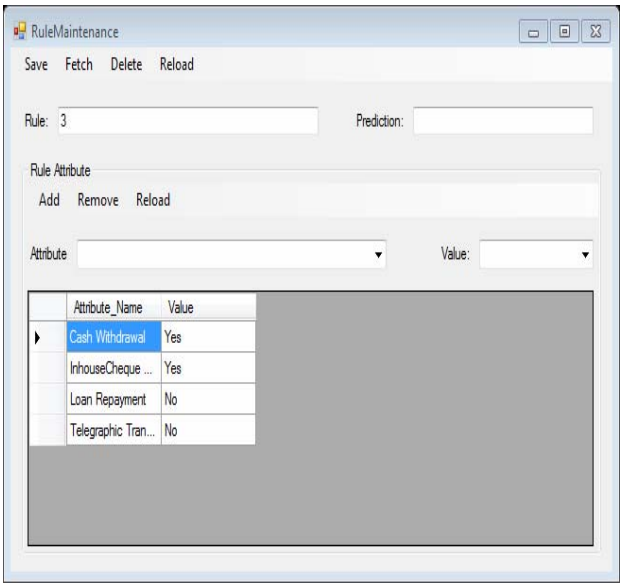

Figure 2: Rule Maintenance Interface

The interface shown in Figure 2 is used to maintain each rule in the database. A new rule can be maintained and the existing ones can be modified and deleted using this interface.

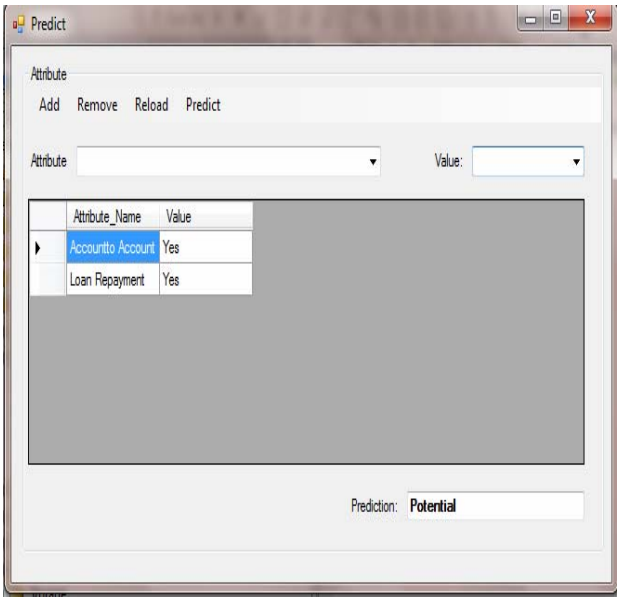

Figure 3: Rule Prediction Interface

Rule prediction will be done by selecting attributes with the corresponding value in the Gridview then click the Predict main menu, then the system automatically displays a Customer Potentiality on the prediction text box as shown in Figure 3.

5. Conclusion and Recommendations

In this paper, we tried to see unseen or predict potential M-banking customers of the bank based on historical transaction with the help of data mining techniques and classification model. In addition to this, a prototype is developed.

7870 instances and 14 attributes including class label are input to WEKA tool. The algorithms used for experimentation were BayesNet, NaiveBayes, IBK, KStar, PART, J48, and RandomForest. The attributes are selected based on expert decision and branch transaction observation. Accuracy, ROC and Confusion matrices were used to select the best model. PART was selected as the best model with accuracy of 79.75% and 0. 837 ROC.

Based on the result, account to account has significant contribution to predict customer potentiality. Moreover, loan repayment and telegraphic have significant impact for the service following account to account.

Finally, in order to achieve the bank's objective of customer retention, the bank should work with potential customers. To help the bank to predict potential customers, a prototype is developed. This prototype has a database connection that helps to maintain attributes and rules.

In general the bank can use this prototype to predict potential customers and take appropriate measures regarding M-banking service provision.

We recommend the following:

- Employees of the bank have to understand the benefits of the M-banking product and work more on awareness creation.
- Employess of the bank should identify potential customers based on the developed interfaces, then address each customer to promote the services and to make customers more aware of M-banking services.
- Bank Association, NBE and all financial institutions should work together for awareness creation of the society regarding M-banking services.

- The bank should make capable internal staffs by enforcing them to use the services in order to make a good support to customers.
- To make research based on personal information data, the bank should incorporate appropriate information on the application forms since current registration techniques lack personal detailed information.
- The bank should identify the most used channels and services accessed by customers to plan accordingly.

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