Study on Mobile wallet preference in times of the COVID-19 pandemic with special reference to Pondicherry state

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Abstract -In the last decade, ownership and use of mobile phone has increased dramatically in India promoting the use of mobile wallet service, especially among the adults. Mobile wallet adoption and usage is poised for major growth in the next few years, and thereby displace traditional payments such as cash and cards. The COVID-19 pandemic has accelerated the trend to use mobile payment. During this study, the essential variables of technology accepted model (TAM), viz. perceived security, social influence, and perceived innovativeness, have been identified through the survey. These variables area unit expected to own associate influence on the mobile services adoption intention. The goal of this paper is to predict the adoption of mobile wallet using 5 different classifiers namely Logistic Regression (LR), Multilayer Perceptron (MLP), Random Forest (RF), Naïve Bayesian and Logistic Model Tree (LMT) classification algorithm. We assessed the classifiers of the samples collected from 100 respondents from Puducherry India.. For experimentation, WEKA is used as a simulation tool; the results reveal that the RF achieves better performance when compared to other classifiers. LR attains the classification accuracy of 78.11%, Naive Bayes 63.88%, LMT 81.5% and MLP 82.66% for the dataset respectively.

Key Words*:Mobile wallet service, traditional payments, TAM, social influence, perceived security, innovativeness.*

1. INTRODUCTION

India has forwarded a step closer towards becoming a cashless economy with the new method of Unified Payment Interface (UPI). With this new payment method, smart phones are increasing as like virtual debit cards and we can send or receive money instantly. Using QR code, it can take over the wallet all together.

The best alternative for cash and card transactions are the Mobile wallets. In the year 2016, because of demonetization the use of Mobile wallets increased. It includes Google Pay, Amazon Pay, Paytm, Phonepe, Mobiwiketc. People started using mobile wallets in big malls and in online shopping. Basically, Mobile wallets assumed to be ordinary wallets, where money would be stored in the wallet the consumer could use whenever needed. Later Mobile wallets are connected with bank accounts. The availability of Smartphone's, vibrant usage of the internet determined the usage of mobile wallets.

Mobile wallets are a progressive mode of payment. Mobile wallets pave the method for cashless transactions.Mobile wallets in the smart phone apps help us to store our debit and credit cards and a convenient way to pay for transactions The convenience, speed and added security, this mobile wallet payment option has gain its popularity, in the market estimated to rise to $1.35 trillion in 2017.

During COVID times people started using the mobile wallet for day today transactions at Supermarkets, street vendors, retail shops, fuel stations restaurants etc.

The reasons mobile wallets are gaining popularity are:

- They help to reduce fraud - Mobile wallets use random payment codes and the data stored is encrypted such that the original account numbers are not sent while making a payment.
- Time saving - Using mobile wallet, payment can be done quickly over the payment terminal verifying the purchase, in just a few seconds.
- Wallet contents are trimmed - Without putting a bulge in the wallet, in addition to credit and debit cards, certain mobile wallets also can store loyalty cards and gift cards, allowing to have them on hand at all times.
- Rewards- If the card offers cash back or other rewards, it can be stored in a mobile wallet.
- Online shopping on the go - Purchases with the mobile wallet can be done, instead of typing in card numbers when shopping online.

In this age of digital world and use of mobile wallet and digital payment is increased day by day. Large volume of data is generated by electronic devices from various activities. Data is stored in data repositories. In order to extract and to identify patterns, trends, and useful data and to take the data-driven decision from huge sets of data is called Data Mining. Data mining is a branch of computer science that deals with this problem. There are many data mining tools like WEKA, KNIME, ORANGE and IBM SPSS.

In this paper, WEKA data mining tool is analyzed by using some classification algorithms in the context of the mobile wallet dataset. Machine learning algorithmsareanalyzedusingthemobile wallet dataset. We have tried to find the best algorithm of classification out of following: Logistic regression, MLP, Random Forest, Naïve Bayes classifier and LMT.

Here, all implementations have been done byusingdataminingtooli.e.WEKA.Thebasicfunctionalityof WEKAtool canbe seen as:

- Data pre-processing – processing of format ARFF3 and support of various other formats, filters;
- Classification - more than 100 classification methods, interface for classifiers implemented;
- Clustering - unsupervised learning is supported by several clustering schemes;
- Attribute selection - the set of attributes used is essential for classification performance;
- Data visualization (tree viewer, Bayes network

viewer with automatic layout, and a dendrogram, viewer for hierarchical clustering, 2D, 3D).

WEKA (Waikato Environment for Knowledge Analysis) is a popular data processing tool that enables information pre-processing process.Attribute selection is very interesting feature of WEKA. It enhances the effectiveness and accuracy of selected data.One of the aims of the study is to analyze the use of the proposed WEKA software for data mining through feature selection and classification methods. It will look to identify patterns, reoccurrence of events as regard to the sample data and this will then be further analyzed and discussed.

1.2 Significance of the study

India's flagship digital payment platform, Unified Payments Interface (UPI), has started this year financial year 2023 on a positive note, with 5.58 billon transactions amounting to Rs 9.83 trillion processed in April. This can be a record high for the payment platform, each in terms of volume and price of transactions since its beginning. In March 2022, UPIbreached 5 billion transactions in a month for the first time. Compared to March 2022, volume of transactions was up 3.33 per cent and value of transactions was up 2.36 per cent. In March, UPIprocessed 5.4 billion transactions amounting to Rs 9.6 trillion.

However, on a year-on-year basis, the degree of transactions jumped 111 per cent andprice of transactions accumulated by nearly one hundred percent. In April 2021, UPI had processed 2.64 billion transactions worth Rs 4.93 trillion. Initially in financial year 2022, transactions had dipped slightly due to the second of the wave of the pandemic. But, since then, UPI transactions have been on an upward trajectory, mirroring the recovery in the broader economy.Further, since the pandemic began, UPI's dealing volume and price has gone up by over 350 per cent, whereas at first UPI was thought-about as a most well-liked payment mode for peer-to-peer (P2P) transactions.

1.1 Contribution of the paper

The contribution of this paper is summarized below.

- To know the consumer preference of Mobile wallets in times of COVID-19 pandemic
- To know the various factors affecting the usage of Mobile wallet in times of COVIDpandemic.
- Initially, a sample (N=100) were collected from the Puducherry state inIndia.
- The samples are processed the mobile wallet usage are identified by employing 5 different classifiers namely LR, MLP, Random Forest, Naïve Bayesian and LMT.
- The performance of 5 classifiers is analyzed based on the classification accuracy, kappa value, precision, recall, F-score and ROC.
- The experimentation shows that the Random Forest achieves better results and classifies accurately than the existing methods.

1.3Limitations of the study

This study is not free from limitations. Primary data has been collected through questionnaires and the result of the study suffers from the limitation of data collection. The study was limited to 100 consumers.

1.4 Formulation of the paper

The rest of the further paper is as follows: Section 2 explains the existing methodologies of Mobile Wallets. Section 3 is about the mobile wallet data set that is used for implementation of algorithms, Section 4 describes some machine learning algorithms and finally section 5 deals with the performance evaluation among all the algorithms.

2. RELATEDWORK

K.M Siby (2021) in his study" A study on consumer perception of Digital payments method in times of COVID pandemic" Their intention was to review the perception of the buyer in digital payment ways. Through statistical tools like Correlation and ANOVA the researcher found that there is no significant variance in consumer perception of digital payments technique even within the time of COVID pandemic.

Dr C..Revathy and Dr. P.Balaji(2020)have done their analysis on the subject "Determinants of Behavioural intention on E Wallet usage An empirical examination in AMID of COVID 19 Lockdown period" .The main objective of their study was to review the consumer preference and importance of e Wallet usage .and to explore the significant predictors of consumer intention and behavior on e- wallet usage in a middle of COVID Lockdown period. The statistical tools used in the study were frequency distribution, reverse weighted average mean, ranking correlation and multiple linear regression analysis. The results of the study were that college students principally use the e-wallet payment as they use mobile phones and the internet in an abundant manner, because it is very convenient for them to access.

Nidhi Singh,ShaliniShrivatsava, and Neena Sinha(2017) had their analysis article in the topic "A consumer preference and satisfaction on Mobile Wallet: a study on North Indian consumers" The purpose of the research was to know the consumer intention and satisfaction level towards mobile wallets. With statistical tools like ANOVA, Regression analysis, and descriptive analysis the researcher found out that there was a major association between consumer perception, preference, usage and satisfaction. Additional variables like security, trust and hedonism were different influencing variables.

Sanuja Shree et.al, (2019)conducted an empirical study to look at the the youth behavior towards mobile banking usage intention in Chennai, Tamil Nadu. The researchers has adopted survey methodology and structured questionnaire to collect the perception of youth towards mobile banking usage intention. The result illustrates that convenience factor, benefits factor, deliberation factor, safety factor and trust factor are the most significant factors influencing the usage intention of the youth towards mobile banking in their day-today life.

Sujeet Kumar Sharma et.al, (2019)conducted an empirical study to develop a hybrid model with the assistance of SEM-Neural Network Model to know significant predictors of mobile payment services in Middle Eastern Country, Oman. The researchers have adopted empirical research design and survey methodology to develop a hybrid model for the usage of mobile payment services. The results of the structural equation model proves that perceived trust, perceived usefulness and perceived security have significant and positive influence on intention to utilize mobile payment services whereas, perceived ease of use do not have structural influence on intention to utilize mobile payment services among Oman customers. Further, researchers suggested the service suppliers to use social media platforms to create awareness among users to increase good time spent on these mobile payment platform services.

Tamil Selvi and Balaji (2019)carried an explorative study to know the role of demographic profiles of the respondents towards behavioral intention towards mobile banking adoption in Chennai city and Hyderabad City. The primary data were collected with the assistance of structured questionnaire from private and public sector bank customers towards their perception on mobile banking adoption. The result justifies that performance expectancy, effort expectancy; hedonic motivation, trust and loyalty are significantly influencing the behavioral intention of the customers towards mobile banking adoption within the study area.

Suma Vally and Hema Divya (2018) performed their study with the perspective of consumer's adoption in using digital payment. In their study they observed the effect of adopting digital payments impact on consumers of the banking sector of India. The paved way to show the important policy direction towards what can enable the country to increase cashless payments .The outcome of the study revealed that the deployment of technology for digital payments have increased the performance of banking sector and able to achieve the motive cash less country. It also emphasized the awareness on maximum utilization of technology.

3. DATASET DESCRIPTION

The survey was helpful in finding out the different modes of digital payments people have been using during the lockdown and will continue to use post lockdown. While it will take time for normalcy to resume, people will continue using contactless payments. The lockdown has also brought many people who were not very tech-savvy and much aware of digital payments closer to the ecosystem.

To validate the effective results of the proposed method, it is validated using a dataset, which comprises of 15 items with 100 instances. There are about 8 attributes like name, age, sex, Smartphone usage, digital payment mode, acceptance level, easiest to use, offers and discounts. With the help of this survey, we can measure whether customers are satisfied with their mobile wallet usage online, offline or both. Its goal is to find out whether customers would recommend mobile wallet service to their friends and colleagues.

4. COMPARISON OF VARIOUS CLASSIFIERS

Five candidate classifiers are considered in this study: WEKA classifiers functions LR (Logistic Regression), Neural Network MLP (Multilayer Perceptron), Decision Tree (Random Forest), Naïve Bayes and Decision Tree LMT (Logistic Model Trees).

Logistic Regression (LR)

Logistic regression is a conventional statistical analysis method. In order to identify the target class, it employs the logits (score).This is a linear classifier that determines the relation between categorical dependent variable and one or more independent variables by calculating probabilities. It uses a black box testing known as Softmax function. The logit model with its distribution function is equated in Eq. (1).

$$F(Xi\beta)=\exp\ (Xi\beta)1+exp(Xi\beta) \qquad (1)$$

The density function is given in Eq. (2).

$$F(Xi\beta)=\exp\ (Xi\beta)[1+exp(Xi\beta)]2 \qquad (2)$$

Multilayer Perceptron (MLP)

MLP is the famous neural network based method which activated through the process of loading the input layer with the input vector and propagating actions in a feed forward manner via weighted connections in the complete network. For an input wk, the state of ith neuron (si) is computed as

$$si = f(wi,0+\Sigma wi,j\times sjj\in Pi) \qquad (3)$$

where $\boldsymbol{f}$ is the activation function, $\boldsymbol{Pi}$ is the group of nodes reaching node $\boldsymbol{i}$,$\boldsymbol{wi}$,$\boldsymbol{j}$ is the weight of the connection between node $\boldsymbol{i}$ and $\boldsymbol{j}$. MLP employs an iterative function for learning process which begins from random weights. A training algorithm is also utilized to manage the weights to an intended target values. The training will be stopped only when the error slope comes to zero.

Random Forest (RF)

RF is a new and powerful statistical classifier that is well established in other disciplines but is relatively unknown in ecology. Advantages of RF compared to other statistical classifiers include (1) very high classification accuracy; (2) a

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 05 | May - 2022 Impact Factor: 7.185 ISSN: 2582-3930

novel method of determining variable importance; (3) ability to model complex interactions among predictor variables; (4) flexibility to perform several types of statistical data analysis, including regression, classification, survival analysis, and unsupervised learning; and (5) an algorithm for imputing missing values.

Naive Bayes

Naive Bayes implements the probabilistic Naïve Bayes classifier. Naïve Bayes Simple uses the normal distribution to model numeric attributes. Naïve Bayes can use kernel density estimators, which develop performance if the normality assumption if grossly correct; it can also handle numeric attributes using supervised discretization. Naïve Bayes Updateable is an incremental version that processes one request at a time. It can use a kernel estimator but not discretization.

Logistic Model Tree (LMT)

A Logistic Model tree essentially consists of a typical standard decision tree structure with logistic regression functions at the leaves, very similar like a normal binary tree it could be a regression tree with regression functions at the leaves. For a nominal (enumerated) attribute with k values, the node has k child nodes, and instances area unit sorted down one in all the k branches looking on their value of the attribute. LMT consists of a tree structure that is made up of a set of inner or non-terminal nodes N and a set of leaves or terminal nodes T. Let S denote the whole instance space, the tree structure gives a disjoint subdivision of S into regions St, and every region is represented by a leaf in the tree The root node N has training data T and one of its sons N′ has a subset of the training data T ′ ⊂ T. Following the classical approach, there would be a logistic regression model M at node N trained on T and a logistic regression model M′ at N′ trained on T ′. For classification, the class probability estimates of M and M′ would be averaged to form the final model for N'.

5. PERFORMANCEEVALUATION

In this section, the 100 were collected from Puducherry, India using questionnaire to assess the mobile wallet usage. The dataset consists of a total of 10 instances. For experimentation, WEKA is used as a simulation tool. The same dataset is applied to all the above mentioned 5 classifiers. The results are analyzed based on some metrics such as classification accuracy, kappa value, precision, recall, F-score and ROC.

The experimental results of various classifiers to inspect usage are tabulated in Table I. The comparison results are also pictorially represented in Figure I. From Table I, it is clear that NaiveBayes attains the poor performance with a 63.88% accuracy whereas MLP achieves better accuracy of 82.66% but lesser than RF with a accuracy 93.01%.The discussion reveals that RF is the best classifier to identify the mobile wallet usage using the questionnaire.

Table -1: Comparison on Mobile wallet dataset with various classifiers

Classifier	**Accuracy**	**Kappa**	**Precision**	**Recall**	**F-score**	**ROC**
LR	78.11	67.33	78.9	78	66.3	91.5
MLP	82.66	73.05	86.66	82	82	96.6
RF	93.01	89.64	93.2	93	93	99.3
NaiveBayes	63.88	46.49	70.23	63	63.8	48.6
LMT	81.5	71.74	81.9	81	81.1	91.5

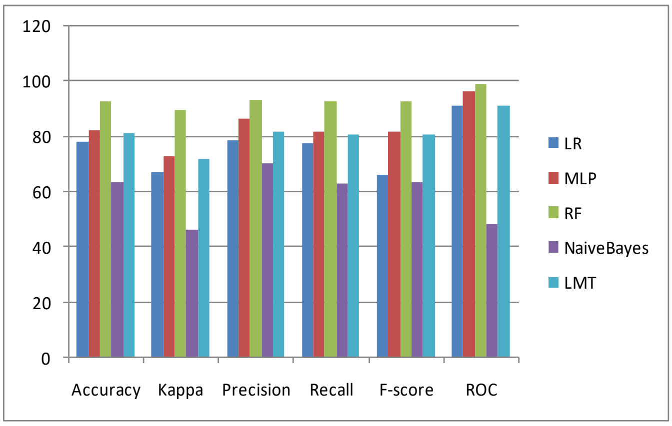

Fig -1: Comparison on Mobile dataset with various classifiers

6. CONCLUSION

In this paper, 5 different classifiers namely Logistic Regression (LR), Multilayer Perceptron (MLP), RF, NaiveBayes and LMT algorithm are applied to assess the level of usage of Mobile wallet using the questionnaire. The major contribution of this study is to compare the performance of these 5 classifiers based on classification accuracy, kappa value, precision, recall, F-score and ROC. We assessed the classifiers the samples collected from 100 respondents from Puducherry, India. For experimentation, WEKA is used as simulation tool and the results reveal that the RF achieves better performance when compared to other classifiers.
From the above study it is concluded that there are many positive factors like safe and secure payment, easy accessibility, risk free transaction confidentiality in financial data of the customer and non-contact payment. To avoid direct payment method during this pandemic time non-contact payment mode is highly recommended and people also started to use mobile wallets in the pandemic situation.

7. LIMITATIONS AND FUTURE DIRECTIONS

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