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ENHANCED DIGITAL MARKETING STRATEGIES USING PREDICTIVE DATA MINING TECHNIQUES

Jatinder Singh, Research Scholar, Om Sterling Global University, Hisar jatindercse192@osgu.ac.in
Dr. Parveen Sehgal Professor, Om Sterling Global University, Hisar drparveensehgal@osgu.ac.in

ABSTRACT
The research paper entitled "Utilizing Predictive Data Mining Techniques to Enhance Digital Marketing Strategies" investigates the incorporation of predictive data mining methods in order to enhance and optimize digital marketing tactics. In a contemporary period characterized by the significance of data-driven decision-making, this study explores the utilization of sophisticated predictive analytics techniques to unravel intricate patterns, emerging trends, and customer behaviors inside extensive datasets. Through the utilization of advanced methodologies, the study seeks to provide marketers with valuable knowledge that surpasses conventional methods. This will enable them to predict customer preferences, refine campaign targeting, and improve the overall efficacy of their marketing strategies. This article explores the theoretical underpinnings of predictive data mining and provides practical applications and case studies to illustrate its concrete effects on digital marketing results. The primary objective of this research is to provide significant contributions to the dynamic field of digital marketing by emphasizing the revolutionary capabilities of predictive data mining. This study aims to demonstrate how predictive data mining can be utilized to develop more accurate, adaptable, and effective marketing tactics.

KEYWORDS:
Association Rule Mining, Apriori, Digital Market, Consumer Behavior, Machine Learning.

1. INTRODUCTION
Predictive data mining stands at the forefront of modern analytics, offering organizations the ability to extract valuable insights from vast datasets to anticipate future trends and outcomes. As an integral subset of data mining, predictive analytics leverages advanced statistical and machine learning techniques to uncover hidden patterns, relationships, and predictive models. In essence, it empowers businesses to move beyond descriptive analytics and embark on a proactive journey, foreseeing potential scenarios and making informed decisions. This comprehensive exploration delves into the core components, classification, and diverse applications of predictive data mining, highlighting its pivotal role in shaping contemporary data-driven landscapes.

1.1 Main Components of Predictive Data Mining
The predictive analytics process commences with the initial stage of Data Collection and Integration. This phase involves the gathering and merging of various datasets, encompassing historical records and pertinent variables. These collected datasets serve as the foundation for further studies in the workflow. The subsequent step involves the undertaking of Data Cleaning and Preprocessing, wherein the focus is on rectifying missing values and outliers in order to adequately prepare the data for the modelling phase. Feature selection and engineering are important steps in the modelling process, with a focus on identifying key factors that can improve the accuracy of the model.
The crux of the procedure is in the phase of Model Building, whereby a selection is made among different predictive models such as regression or neural networks, contingent upon the characteristics of the situation at hand. The incorporation of training and validation processes in model development serves to enhance the model's robustness, allowing for iterative refinement to achieve optimal performance. Evaluation and testing procedures are employed to gauge the efficacy of the model by

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utilising criteria such as accuracy and precision. Ultimately, successful models progress towards the stages of Deployment and Monitoring, when they are implemented in production and subjected to ongoing monitoring to ensure their continued effectiveness in light of emerging data. The implementation of a structured methodology guarantees a thorough and efficient progression from the gathering of data to the deployment of models in the field of predictive analytics.

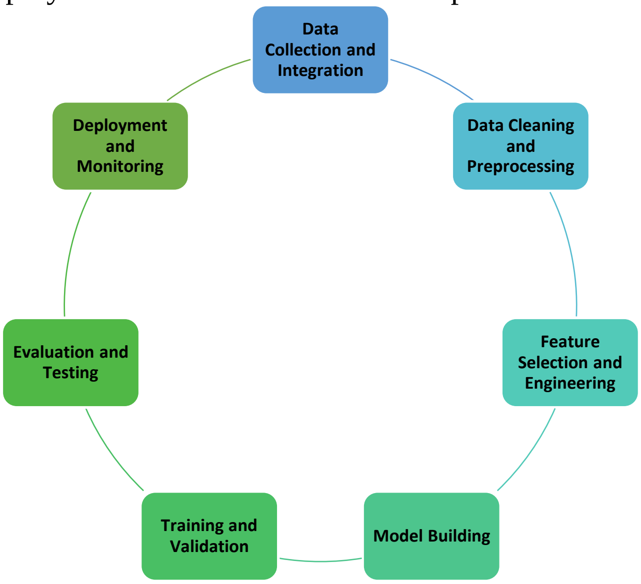

Figure 1. Cyclic Presentation of Datamining Processes

1.2 Classification of Predictive Data Mining

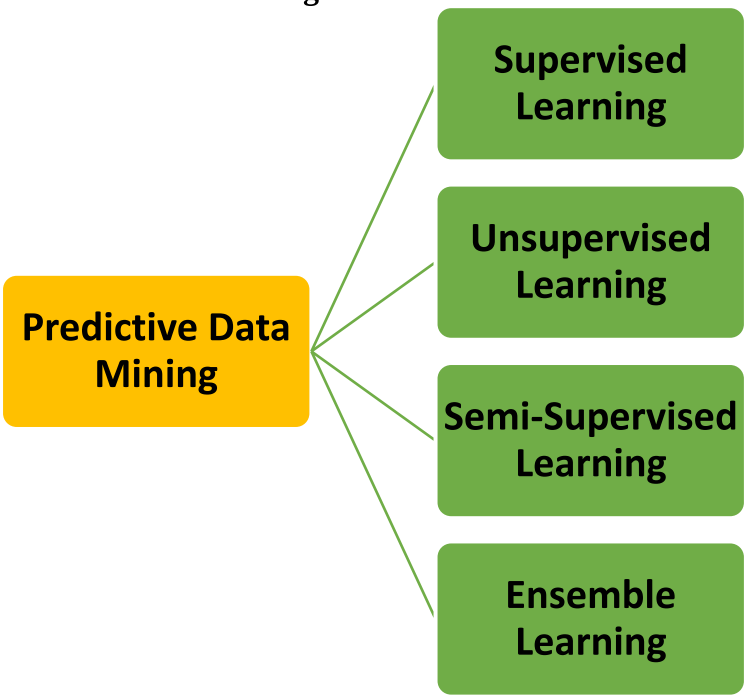

Figure 2. Classification of Predictive data Mining

Predictive data mining techniques encompass various categories tailored to different data scenarios:

- **Supervised Learning:**

- Supervised learning involves training models on labeled datasets where the outcome variable is known. The model learns to predict the target variable based on input features and can subsequently make predictions on new, unseen data.

- **Unsupervised Learning:**

Unsupervised learning analyzes datasets without labeled outcomes. Common techniques include clustering, which groups similar data points, and association, which identifies patterns and relationships within the data without predefined targets.

- **Semi-Supervised Learning:**

Semi-supervised learning combines aspects of both supervised and unsupervised approaches. It typically utilizes a small amount of labeled data along with a larger pool of unlabeled data to enhance model performance.

- **Ensemble Learning:**

Ensemble learning techniques, such as bagging and boosting, amalgamate the strengths of multiple models to improve predictive accuracy. By leveraging the diversity of individual models, ensemble methods create a more robust and reliable predictive system.

1.3 Predictive Data Mining Algorithms

Predictive data mining employs a variety of algorithms to analyze data, make predictions, and uncover patterns. Here are some key types of algorithms commonly used in predictive data mining:

- Regression Algorithms
- Decision Tree Algorithms
- Neural Network Algorithms
- Support Vector Machines (SVM)
- Clustering Algorithms
- Ensemble Learning Algorithms

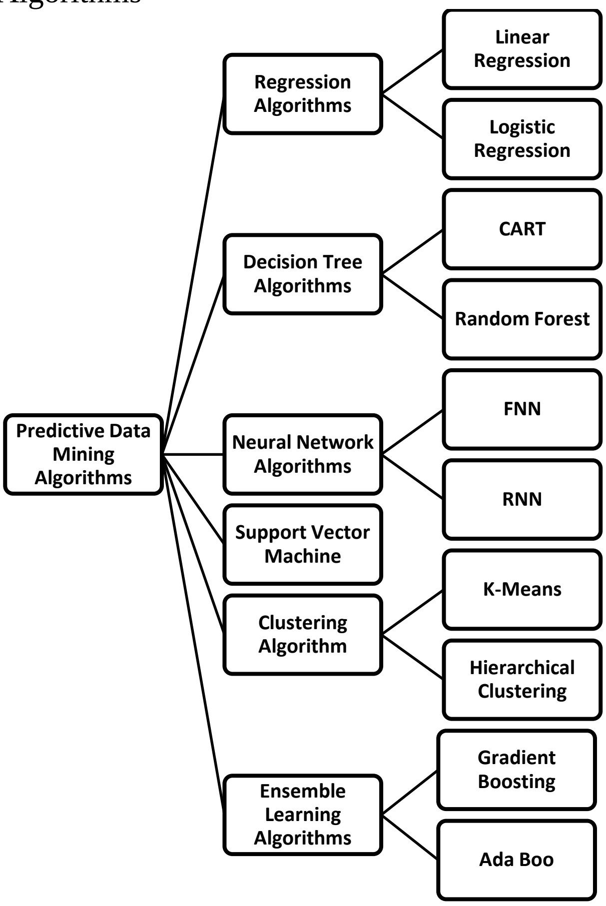

Figure 3. Predictive Data Mining Algorithms

2. LITERATURE REVIEW

The study conducted by Hewage et al. (2023) examines privacy-preserving data mining techniques and their influence on the accuracy of data mining processes, particularly in data stream mining. The authors conduct a systematic literature review to assess the impact of privacy-preserving mechanisms on the accuracy of data mining tasks. They explore how techniques designed to protect privacy in data mining processes affect the precision and reliability of the mined information. The review provides insights into the trade-offs between privacy preservation and the accuracy of data mining outcomes, offering valuable considerations for practitioners and researchers in the field of artificial intelligence.
Ordoñez-Avila et al. (2023) delve into the realm of data mining techniques specifically aimed at predicting teacher evaluation within higher education settings. Their systematic literature review investigates various data mining methodologies employed to forecast teacher performance evaluations in higher educational institutions. This review aims to analyze the effectiveness of diverse data mining techniques in predicting and assessing teacher evaluations. The study provides a comprehensive overview of the state-of-the-art methodologies and their applicability in enhancing the evaluation processes within higher education, contributing significant insights for educators and administrators.
Rastogi and Bansal (2023) study focuses on developing a diabetes prediction model employing data mining techniques. Published in Measurement: Sensors, the research aims to create an effective predictive model for diabetes utilizing various data mining methodologies. The article delves into the application of machine learning and data mining techniques to predict the likelihood of diabetes occurrence. It offers insights into the effectiveness of different modeling approaches in medical prediction, specifically in diabetes prognosis, which holds significant implications for healthcare practitioners and patients.
Alizargar, Chang, and Tan (2023) research, published in Bioengineering, focuses on comparing the performance of different machine learning approaches for predicting Hepatitis C using data mining techniques. The study aims to evaluate the efficacy of various machine learning methodologies in predicting Hepatitis C, a critical health concern globally. By employing data mining techniques, the research assesses and compares the performance of these approaches, providing insights into their effectiveness and applicability in medical prediction tasks related to Hepatitis C diagnosis and prognosis.

3. METHODOLOGY

The dataset is a structured transnational data set which contains all the online customer transactions occurring between 01/12/2010 and 09/12/2011 for an international based and registered non-store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers. The online retail purchase data has customer behaviour data with 8 attributes that have both continuous and symbolic attributes. The first attribute invoice number holds nominal value, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation. The second attribute is stock code describing the product (item) code. It holds nominal value, a 5-digit integral number uniquely assigned to each distinct product. The third gives the description of product (item) name while the fourth is the quantity of purchase of each item per transaction. The fifth attribute is the invoice date and time of each transaction. Unit price: which is the product price per unit price is the sixth attribute. The seventh attribute is the Customer ID or Customer number, a 5-digit integral number uniquely assigned to each customer. The last attribute holds the name of Country where customer resides.

Table 1 shows the different behavioral features

S/N	Name of features	Description
1	InvoiceNo	a 6-digit integralnumber uniquelyassigned to each transaction
2	StockCode	a 5-digit integralnumber uniquelyassigned to each distinct product

3	Description	Product (item) name
4	Quantity	The quantities of eachproduct (item) per Transaction
5	InvoiceDate	The day and time when each transactionwas generated
6	UnitPrice	Product price per unit Currency
7	CustomerID	a 5-digit integralnumber uniquelyassigned to each customer
8	Country	the name of the country where each customer performs a transaction

Network data that describes the behaviour of customers on an online retail store purchases are sourced for this paper.They include but not limited to; invoice number, stock code, item description, quantity, invoice date, unit price, customer ID and country of purchase and sourced from UCI repository and studied. The online retail store dataset contains eight (8)attributes and about 500,000 rows. These customer behaviour attributes are the input variables to the proposed model.The approach used involves the use of association analysis in mining customer behaviour purchase rules. The technique is implemented using Apriori algorithm. Figure 4 shows the architecture framework for customer behaviour prediction using association rule based approach.

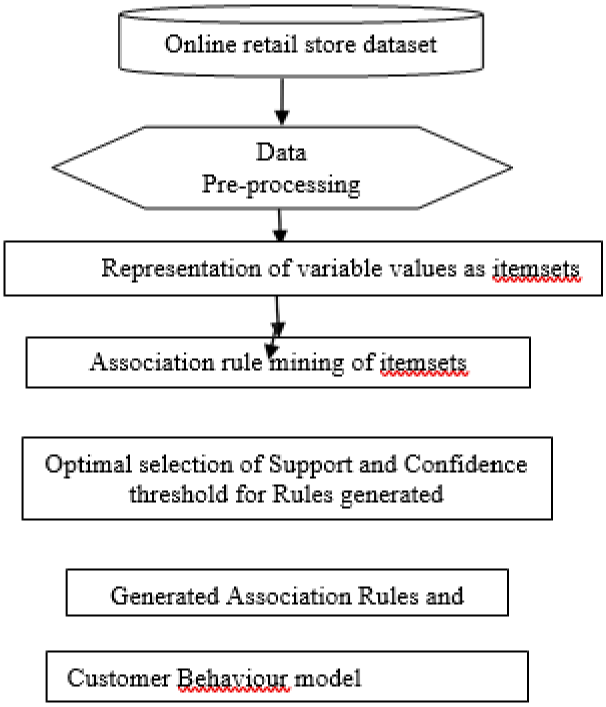

Figure 4. Customer behaviour prediction model using rule mining approach architecture.

In the realm of digital marketing, predictive data mining (DM) holds a pivotal role in leveraging large datasets to extract valuable insights. Different definitions and approaches to predictive data mining exist, reflecting its multifaceted nature within the field. Hand et al. describe it as the analysis of substantial observational datasets to uncover unexpected relationships and present data in innovative and practical ways, beneficial to the data owner. Another perspective, such as that from Teradata Corporation, emphasizes the process of discovering and interpreting patterns within data to address business problems. This definition encompasses three primary stages: identifying patterns, interpreting their significance, and utilizing these insights to solve business challenges. Notably, predictive data mining has become synonymous with handling vast datasets, often containing hundreds of thousands to millions of records, particularly prevalent in industries like finance, retail, manufacturing, telecommunications, travel, transportation, and the public sector. These sectors involve large customer bases with frequent transactions, necessitating advanced tools for uncovering meaningful patterns amidst the immense volume of potential relationships.

Table 2. Phase of Predictive Data Mining

Phase	Description
Business Understanding	Focuses on understanding project objectives, converting them into a data mining problem definition, and devising a preliminary plan.
Data Understanding	Involves initial data collection, exploring data to identify quality issues, gaining initial insights, and forming hypotheses for analysis.
Data Preparation	Involves constructing the final dataset for modeling by selecting, transforming, and cleaning data, often performed iteratively.
Modelling	Selecting and applying various modeling techniques and calibrating their parameters to achieve optimal results.
Evaluation	Thoroughly evaluating the model's quality, reviewing steps taken, and ensuring alignment with business objectives before finalizing.
Deployment	Creating a model is not the end; deploying results in a way the end-client can utilize, which might involve reports or complex processes.

In recent years, a broader scope of activities known as 'Advanced Analytics' has emerged. According to Forrester Research, Inc., advanced analytics involves solutions that facilitate the identification of meaningful correlations among variables in intricate, structured, and unstructured datasets, including historical and future data. These solutions aim to predict future events and evaluate various courses of action. Advanced analytics encompasses functionalities such as predictive data mining, descriptive modeling, econometrics, forecasting, operations research optimization, predictive modeling, simulations, statistics, and text analytics. This expanded approach broadens the application of sophisticated analytics beyond traditional predictive data mining. It includes techniques like text mining, which involves analyzing unstructured text data, and social network analysis (SNA), focusing on extracting relationships between records. These methods contribute significantly to enhancing the value of data and amplifying the benefits derived from data mining processes in digital marketing and other domains.

3.1 Data Mining Model

Digital marketing, predictive data mining involves the process of uncovering patterns within a dataset, which is often referred to as analytical modeling. This activity aims to create data mining models by identifying significant relationships between variables in the data and utilizing these relationships to develop predictive or descriptive models. Analytical modeling entails finding meaningful connections among variables in the dataset and leveraging these connections to create models that can predict specific outcomes or provide a better understanding of the data. The models generated from this process are expressed in the form of formulas or algorithms, enabling the calculation of scores (such as predicted values or probabilities) for individual records. For instance, these scores might predict responses from customers, defection rates, or probabilities of repeat sales based on the data associated with each record.

There are two primary types of predictive predictive data mining models:

1. Predictive Model: This type of model is designed to forecast a particular outcome or target variable. Common techniques used in predictive modeling include multiple regression (for predicting numerical

values), logistic regression (for predicting responses), and decision trees (for creating rule-based models predicting values or responses).
2. Descriptive Model: These models aim to provide a better understanding of the data without focusing on a single specific target variable. Techniques used for descriptive modeling include factor analysis (which extracts underlying dimensions from multivariate data), cluster analysis (for segmenting a customer database into distinct groups), and association analysis (for identifying relationships between items, such as products in retail).
To create these models, a diverse range of analytical techniques is available, sourced from the realms of statistics and machine learning. According to a 2009 survey by Rexer Analytics, some of the core techniques most frequently employed by data miners include regression analysis, decision trees, and cluster analysis. These techniques serve as fundamental tools for extracting insights, making predictions, and gaining a deeper understanding of data, particularly in the context of digital marketing and customer behavior analysis.

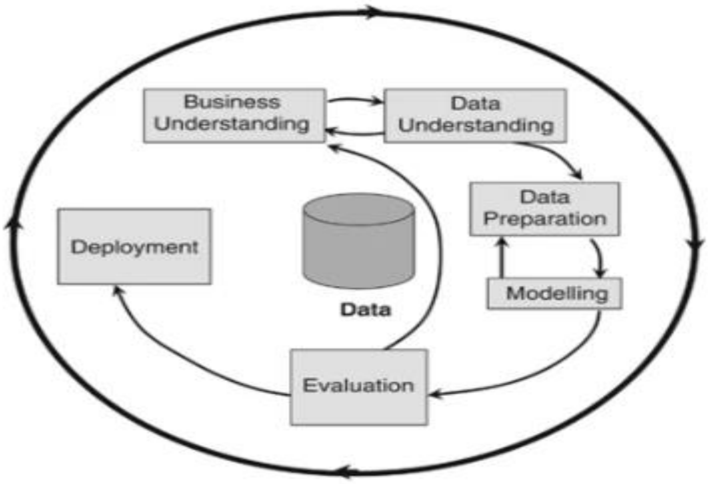

Figure 5. Standard Process for Predictive Data Mining

Table 3. Some Software for Data Mining

Product	Supplier	Notes
FICO Model Builder	FICO	
IBM Smart Analytics System	IBM	For use with IBM databases
IBM SPSS Modeler	IBM (SPSS)	Formerly SPSS Clementine
KnowledgeSTUDIO	Angoss	
KXEN Analytic Framework	KXEN	Employs structured risk Minimization for model reliability and automation
Oracle Data Mining	Oracle	For use with Oracle databases
Portrait Customer Analytics	Portrait Software	
RapidMiner	Rapid-I	Open source
SAS Enterprise Miner	SAS	
SQL Server Analysis Services	Microsoft	
Teradata Warehouse Miner	Teradata	For use with Teradata databases
TIBCO Spotfire Miner	TIBCO Software	

Apart from predictive predictive data mining toolsets, several statistical packages prove valuable for data analysis, manipulation, and intricate modeling. These tools typically demand higher statistical

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proficiency and often lack automated functionalities or comprehensive model management features. Table 4 presents a few instances of such statistics packages.

Table 4. Some of statistics packages for Data Mining

Product	Supplier	Notes
IBM SPSS Statistics	IBM (SPSS)	Formerly SPSS Statistics
R	Free Software Foundation	Open source
SAS	SAS	
Statistica	StatSoft	
TIBCO Spotfire S+	TIBCO Software	

4. RESULT

Finding interesting and rare patterns in the dataset is based on association analysis. Association analysis is a set of tools used to find valuable relationships in a large set of data. This analysis is based on Apriori principle which states that ―if an itemset is frequent, then all of its subsets are frequent‖. Association rules suggest that a strong relationship exists between two items. An illustration is shown with an example in table extracted from the raw data. The rule states that if the set of customer behaviour feature(s) on the antecedent part (X) occurs, then the behaviour states on the consequent part (Y) does happen. In general, a set of behaviour feature items, such as X or Y, which are disjoint, is the behavior feature item set. In table 2,a hypothetical six rows table of 7 features is shown.

In this research, three evaluation criteria are used due to their widespread relevance in most related literature. They include number of frequent itemsets, rules generated, and execution time (in seconds).

Table 5. shows the chart of number of frequent itemsets against minimum support.

S/N	Behavior Features item set													
0	11	21	37	148	112	122	132	141	153	161	171	181	171	241
1	11	23	35	148	112	121	132	143	153	161	171	181	172	241
2	11	21	33	141	111	123	131	141	152	162	171	181	173	242
3	11	23	34	137	113	121	132	142	152	161	171	181	172	241
4	11	22	33	134	112	123	131	142	154	161	172	182	173	242
5	11	22	33	134	113	121	132	143	153	162	171	181	171	241

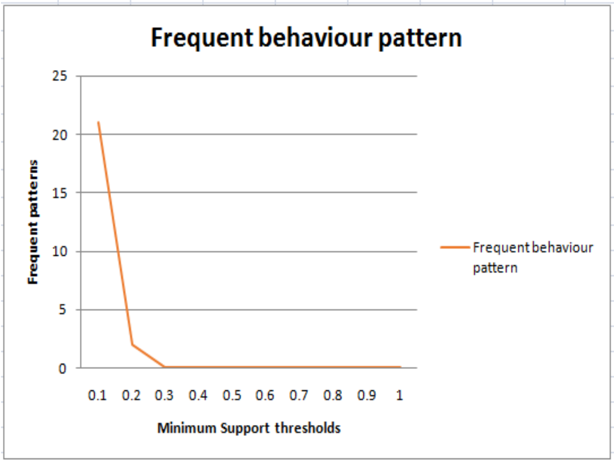

Table 5: Sample table of processed online store dataset

Figure 6. Plot of number of frequent patterns generated based on minimum support levels

The chart in Figure 6 shows a decrease in total number of frequent itemsets mined as minimum support threshold is increased. A sharp decline was recorded from a support of 0.1 to 0.2 and gradually declined up to 0.3 threshold. The curve almost ran parallel to the horizontal axis from a support of 0.4 to 1. Figure 3 shows a chart of number of association rules mined based on minimum confidence thresholds (from 10% to 100%) respectively.

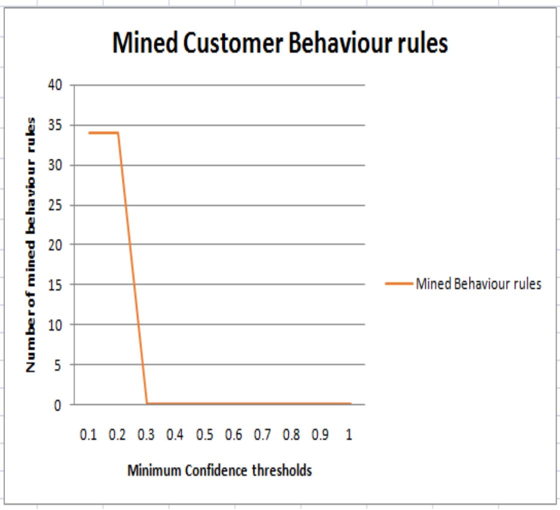

Figure 7. Chart showing number of customer behavioural rules mined based on minimum confidence thresholds

It can be observed that the mined rules trend is a negatively sharp declining slope curve. At confidence threshold of 30%to 100%, no mined rule was recorded. Highest number of rules mined is generated at minimum confidence threshold of 10% to 20%. This shows that as the confidence level is increased, optimal rule mining occurs thereby producing strong rules with efficient confidence. The strongest rules have rule confidence of approximately 100%.

Storing instructions for creating and updating analytic datasets, often in the form of a sequence of interconnected SQL programs. Managing and structuring model scoring code, incorporating version control mechanisms and basic descriptions for clarity. Automating the execution of processes for generating analytic datasets or performing model scoring runs based on predetermined schedules. Monitoring and presenting reports on model performance, including notifying users about performance updates. Several tools are currently available for effective model management in the context of digital marketing for rural areas. Some of these tools include:

- IBM (SPSS) Predictive Enterprise Services
- KXEN Modelling Factory
- SAS Model Manager
- Teradata Model Manager

These tools offer functionalities aimed at efficiently handling model-related tasks, facilitating the creation, deployment, and monitoring of models within the specific domain of digital marketing targeted at rural areas.

Table 6. Tools for Model Management

Tool	Description
IBM (SPSS) Predictive Enterprise Services	Offers model management and deployment capabilities within the SPSS ecosystem.
KXEN Modelling Factory	Provides functionalities for managing models, including deployment and automation in model development and execution.
SAS Model Manager	SAS software offering model management features, aiding in model development, deployment, and performance monitoring.
Teradata Model Manager	Teradata's toolset designed for managing models, enabling the tracking and deployment of analytic models efficiently.

The progression of data mining (DM) within the digital marketing domain has experienced substantial advancements in both sophistication and capabilities during the past decade within computer science projects. These strides owe much to various developments, including in-database processing, improved mechanisms for transmitting model algorithms, and the capability to analyze non-structured data, significantly enhancing DM and its associated software products. Diverse viewpoints on data mining exist, underscoring its multifaceted nature within the field. According to Hand et al., it entails analyzing vast observational datasets to unveil unforeseen relationships and presenting data in innovative and practical ways beneficial to the data owner. Conversely, Teradata Corporation emphasizes the process of discerning and interpreting patterns in data to tackle business challenges, delineating three critical stages: pattern identification, interpretation of their significance, and leveraging these insights to address business issues.

Industries spanning finance, retail, manufacturing, telecommunications, travel, transportation, and the public sector have embraced data mining due to their expansive customer bases and high-frequency transactions. The management of substantial datasets containing hundreds of thousands to millions of records necessitates sophisticated tools to unearth meaningful patterns amidst the multitude of potential relationships. The advent of 'Advanced Analytics' has broadened the horizons of sophisticated analytics beyond conventional data mining within computer science projects. This inclusive approach incorporates techniques like text mining and social network analysis (SNA), substantially amplifying the value extracted from data mining processes across digital marketing and various other domains.

5. DISCUSSION

The comprehensive landscape of data mining involves a series of sequential phases, as highlighted in Table 1, ranging from understanding business objectives, collecting and preparing data, modeling, evaluating models, and finally deploying them to facilitate decision-making. The process of creating data mining models involves uncovering patterns within datasets, known as analytical modeling, which aims to develop predictive or descriptive models. Predictive models forecast specific outcomes or target variables, whereas descriptive models provide a deeper understanding of the data without focusing on a single specific target variable. A myriad of software products is available for data mining purposes, as illustrated in Table 2. These tools cater to various needs and industries, offering diverse functionalities and compatibility with different database systems.

Additionally, Table 3 showcases several statistical packages that supplement data analysis, manipulation, and complex modeling. These packages often demand higher statistical expertise and may lack automated features, but they provide intricate capabilities for in-depth data exploration and modeling. The deployment of data mining models as part of a continuous process, encompassing monitoring, evaluation, learning, and refinement, is critical to deriving tangible business value in digital marketing and other sectors. The evolving nature of data mining tools and methodologies necessitates a strategic approach wherein different tools and techniques are synergized to optimize insights and drive business outcomes.

6. CONCLUSION

This paper was able to identify frequent itemsets customer behaviour features patterns and mining association rules between frequent purchase behaviour on an online store.The results from the frequent pattern mining shows that optimum rule generation occurred at minimum support and confidence thresholds of 0.1 and 0.2. This paper was able to design and implement a of association rule mining model for customer behaviour prediction. It discovered interesting frequent customer behaviour purchasing patterns that occurred in the online retail store dataset and mined strong association rules. The performance of this model is greatly affected by the quality and dimensionalityof the dataset used and nature of feature set. Overall optimum performance of the model is peaked at minimum support and confidence thresholds of 0.1 and 0.2 respectively.

In the realm of data mining for digital marketing, the landscape of DM and its associated software products has seen remarkable advancements in both potency and intricacy within the last decade. These advancements stem from various innovations, including in-database processing, facilitating the communication of model algorithms across tools, and the evolution of systems capable of analyzing non-structured data. When it comes to selecting a DM toolset, it's paramount to maintain a focus on business requirements and the method of deploying models. Potential purchasers of software should conscientiously assess the products they shortlist before arriving at purchase decisions. It's crucial to note that there isn't a one-size-fits-all solution in all scenarios or market sectors. Therefore, users should be willing to employ a strategy of 'mixing and matching' between toolsets, ensuring seamless communication and compatibility among them as needed. The actual generation of business value happens when models are put into operation within a process framework. This includes not only deploying models but also continuously monitoring, evaluating, learning from, and refining them. The integration of these models into an ongoing, adaptive process is fundamental for maximizing their impact and relevance in the dynamic landscape of digital marketing.

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