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THE ROLE OF DECISION SUPPORT SYSTEM IN ENHANCING CUSTOMER RELATION MANAGEMENT IN THE EGYPTIAN TELECOMMUNICATION SECTOR

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ABSTRCT

A Decision Support System (DSS) is a computer-based information system that assists human decision makers in exercising judgment but does not make the decision itself. DSS helps management by identifying negative trends, allocating business resources more effectively, and presenting information in the form of charts and graphs, i.e. in a summarized format. The telecom industry generates a large volume of data on a daily basis due to its large client base. Decision-makers and business analysts stressed that acquiring new customers is more expensive than retaining existing ones. Business analysts and Customer Relationship Management (CRM) analysts must comprehend the causes of customer churn, as well as the behavioral patterns revealed by data from existing churn customers.

Models were applied to a 3333-record telecommunications dataset. The results of the experiments revealed that the ***Logistic Model Tree (LMT)*** method and JRip are the best methods for this dataset; with a 96 percent accuracy improved using neural networks from previous research. Multilayer Perceptron is recommended because it has a 94 percent accuracy rate. J48 and PART accuracy was 95%, while naive Bayesian accuracy was 90%.

Keywords: Decision Support System (DSS) Customer Relationship Management (CRM); Decision Makers (DM); Telecommunications; Logistic Model Tree (LMT)

1. INTRODUCTION

Today, the global telecommunications market is suffering from severe revenue losses as a result of fierce competition and the loss of potential customers. To maintain competitive advantages and acquire as many customers as possible, most operators invest a significant amount of revenue in the early stages of their business (Yu, 2009).

Decision support systems (DSS) are useful business intelligence (BI) tools because they assist managers in large organizations in making the best decisions out of a large number of options. Decisions are made using a variety of raw data, models, documents, knowledge, and previous experiences.

The acceptance of this terminology has most likely influenced the ownership of the term Customer Relationship Management (CRM) (Dutt et al., 2019) in recent years and years. While some use the terminology as a suggestion for relationship advertising, for example, defining it as “a management strategy that allows businesses to identify, appeal to, and boost retention of lucrative clients by controlling connections by them,” others incorporate it to using Information Technology (IT) in relationship promotion tactics(Ghazaleh et al., 2020).

The telecom industry is technologically advanced in terms of implementing certain CRM technologies. This is clearly due to the state's high market demand for the service. Egypt's mobile services industry is a highly competitive one. Organizations in this industry are attempting to attract and retain clients in this difficult environment. CRM has become a necessity for organizations to survive in recent years as a means of gaining a competitive advantage. As markets become more competitive, developing relationships that can be maintained in the face of numerous inducements to switch service providers is viewed as a method of gaining a sustainable competitive advantage.

1.2 DECISION SUPPORT SYSTEMS (DSS)

A decision support system assists decision makers in solving unstructured and semi-structured problems by combining human judgment and computer technology. Less structured problems necessitate the involvement of multiple individuals from various divisions, organizational levels, and, in some cases, different organizations. This emphasizes the significance of decision support systems. Multi criteria decision-making (MCDM) decision support systems are designed to channel expert judgment and form educated opinions in order to make decisions (Hwang and Yoon, 1981; Mahdi et al., 2017).

A DSS is a computerized information system that assists organizations in making effective business and organizational decisions (Huber, 2008). A DSS system assists decision makers in gathering all relevant and useful information from documents, raw data, personal knowledge, and business models in order to identify and solve organizational problems and make business decisions (Power and Heavin, 2017). Such systems provide critical information for middle management to make unstructured and semi-structured decisions.
A variety of DSS categories can all add value to business processes:

1.2.1 DATA DRIVEN DSSs

Data-driven DSSs grant access to and authority over a large database containing structured data and primarily time-series of internal organizational data and, at times, external data (Leeflang et al., 2014). Management report and file drawer systems, data warehousing and analysis systems, Executive Information Systems (EIS), and Geographic Information Systems (GIS) are all part of it (GIS). This enables retailers to determine the demand for a product based on various characteristics such as customer age and cultural background

1.2.2 KNOWLEDGE DRIVEN DSS

The knowledge-driven DSS category offers suggestions and recommendations to managers in order for them to take appropriate actions. These are person-computer systems with specialized problem-solving expertise, such as knowledge about a specific domain, knowledge of problems within that domain, or skill in solving some of those problems (Leeflang et al., 2014). Data mining is widely used in the retail industry because it allows organizations to draw conclusions from daily sales and purchasing behavior of consumers to identify products in demand, provide knowledge about the efficiency of supply chain and suppliers, and identify key processes that contribute to enhancing business performance (Hemalatha, 2011).

1.3 ADVANTAGES OF DECISION SUPPORT SYSTEM

The Decision Support System can provide users with a benefit or advantage. The benefit is that it contains (Risawandi & Rahim, 2016 ; Jasri, 2017).

1. Decision Support System extends decision makers' capabilities in processing data/information for the wearer.
2. Decision Support System to assist decision-makers in reducing the time required to solve problems, particularly complex and unstructured problems.
3. Decision Support System can produce more reliable and timely results.
4. Although a Decision Support System cannot solve the problems that decision-makers face, it can help policymakers understand the problem.
5. The Decision Support System can provide additional evidence to justify decisions, thereby strengthening decision-making positions.

1.4 CUSTOMER RELATIONSHIP MANAGEMENT (CRM)

A customer relationship management system (CRM) is a continuous process that allows businesses to improve their core competitiveness, strengthen communication with customers, and continuously improve products and services to meet customer needs. Its content is that enterprises use information technology (IT) and Internet technology to collect and analyses multidimensional customer information, assisting enterprises in identifying, developing, maintaining, and serving customers, improving customer satisfaction, and ultimately increasing enterprise income and value. Customer relationship management focuses on customer communication; business is customer-centric rather than product- or market-centric. Customer relationship management can provide customers with a variety of communication channels in order to facilitate communication.

CRM is typically classified into three types: analytic CRM, operational CRM, and collaborative CRM. (Charoensukmongkol & Sasatanun, 2017):

1.4.1 ANALYTICAL CRM

Customer knowledge and segmentation analysis, dashboard development to analyses profitability, customer value measurement, and life calculation are all part of analytical CRM. Analytical CRM provides tools for decision-makers and managers to assess the performance of marketing, sales, and customer service departments. It also provides statisticians with tools to improve their department's operational capacity.

1.4.2 OPERATIONALCRM

Operational CRM focuses on the day-to-day management of the customer relationship through all points of contact (remote contact center via phone or internet, sales force tools). By synchronizing information for marketing, sales, and all services, management can coordinate the various channels of interaction between the company and its customers.

1.4.3 COLLABORATIVE CRM

The collaborative synthesis approach is intended to improve communication between the company and its customers, as well as integration with other departments such as logistics, finance, and distribution.

1.5 The CRM in the telecommunications sector

The CRM system plays an important role in the telecommunications industry by assisting organizations in gaining insight into their customer database in order to compete in the following sector. It contributes to the development of its business strategy by retaining customers, cross-selling, attrition, and customer loyalty. The CRM assists businesses in understanding their customers' behaviors, allowing them to create loyalty programmers for their most valuable customers. The system also assists organizations in understanding why their customers prefer them over the competition, allowing the company's marketing team to launch appropriate marketing promotions and counter the competitors' promotions (Bahri-Ammari et al., 2019; Viriri et al., 2017).

The telecommunications industry is going through a difficult period. Market saturation leaves little room for maneuvering, and debts capital investment is stifled, and launching new services is frequently prohibitively expensive. However, delivering on new Profitability, lower churn, higher customer satisfaction, lower costs, and a competitive edge are all strategic goals. Are required the following areas must be considered by the company as a whole in the competitive business arena. CRM implementation is a part of that.

1.5.1 CUSTOMER SERVICE:

CRM solutions provide the functionality and integration required by the company to meet the demands of its customers and other stakeholders. It will assist the organization in becoming more customer-centric, providing the type of individual care and attention that today's consumers expect. Simultaneously, it enables the company to achieve strategic business goals such as lower costs through process automation and optimization, increased productivity of front- and back-office staff, lower churn, and increased profitability.

1.5.2 CUSTOMER CARE AND BILLING:

CRM provides a wide range of capabilities for the center of interaction for organizations as well as for customer self-care via Websites of organizations As a result; customer service centers can resolve issues more quickly and efficiently. Detailed customer profiles provide service providers with the facts and figures they need to effectively manage their customers. Phone, e-mail, fax, or letter interactions complete integration with financial, billing, and order and service systems. Management systems enable them to investigate and close inquiries in a timely, professional, and point-and-click fashion. Simplicity with a click Customer service providers or agents can gain access to and modify customer information. Billing information; view invoices, account balances, and complete customer histories; accept payments; generate credit notes and reestablish services Furthermore, they can respond quickly to information requests and send out messages. Product brochures and contract information With the CRM systems of today, all types of customer expectations are met. Customer information from CRM databases is verified, and automated billing systems are provided for customers within the shortest unit of time.

1.5.3 MARKETING:

CRM can help organizations improve the efficiency, effectiveness, and profitability of their marketing campaigns and promotions. Real-time information can be used by organizations at any level to plan, budget, execute, and analyses their activities: enterprise, regional, field, product, or brand. CRM systems enable highly personalized campaigns to be launched, targeting products to customers who are most likely to be interested, increasing profitability and reducing waste, which is critical for the telecom industry.

1.5.4 SALES AND CONTRACT MANAGEMENT

CRM provides the functionality required by the telecom industry to shorten sales cycles, increase revenues, maximize productivity, and optimize direct, indirect, or online channels. Organizations can more accurately plan and forecast sales activities and organize territories based on a variety of criteria such as size, revenue, product lines, or strategic accounts. Organizations must create and implement sophisticated incentive programmers to have a direct motivational impact on their sales representatives.

1.5.5 PARTNER RELATIONSHIP MANAGEMENT

CRM enables partners to share critical information on sales forecasts, order flow, and delivery schedules outside of the company's walls. The System also provides a wide range of self-service capabilities and tools via an Internet portal, as well as completes access to the information and processes that assist dealers in selling more of their companies' products and services. With their agreed-upon contract, businesses can also keep all types of information about dealers, agents, and partners.

1.6 LITERATURE REVIEW

Potential research work on various techniques for churn prediction in various fields such as e-commerce, telecom, and banking, among others, has been discussed in the following paragraphs. In this paper, GA, PSO, NB, SVM, DT, RF, LR, NN stand for genetic algorithm, particle swarm optimization, naive Bayes, support vector machine, decision tree, random forest, linear regression, and neural network.

1. (**Berger and Kompan, 2019)** created a prediction model for user churn based on the user's web-ased interaction. The model's performance was predicted by predicting churn from real data from an online retailer. They came to the conclusion that the proposed model outperforms baseline models for predicting churn. The authors proposed that the developed methodology be used in e-commerce applications.
2. **(Sivasankar et al., 2019; Viriri et al., 2017)** The CRM system boosts the overall response rate of direct marketing campaigns. Companies create promotions based on accurate customer data gathered by the system and set the correct prices for their customers. Companies, for example, use phone calls on a regular basis to provide customers with information about the company's

offerings and to stay in touch with them to ensure their satisfaction. Through consistent monitoring and customer care, such a systematic approach improves the relationship between the company and its customers. Furthermore, the CRM system assists businesses in targeting their most valuable customers. Furthermore, the CRM system assists businesses in targeting their most valuable customers. For example, a company can introduce new services to some residential areas by providing inclusive call allowances and free phone or Internet services.

3. **(Esteves, 2016)** Esteves reports on a churn analysis study that used KNN, Nave Bayes, C4.5, Random Forest, AdaBoost, and ANN on a dataset provided by WeDo Telecom Company of 100,000 calls from 160 clients between 30 June 2012 and 31 January 2013 of 14 variables. Several methods for predicting customer churn are compared. The models were validated using 10-fold cross validation with three repetitions. To balance the data set, a hybrid sampling method (SMOTE) was used. Among all models, the random forest model with the highest ROC value of 0.9915 and Sensitivity value of 0.9110 performed the best**.**
4. **(Kim et al., 2019)** addressed the following research gap: a lack of work in the area of customer welfare and bundle subscription, based on the pros and cons that lead to the customer subscription, subscription switching cost, and customer retention They came to the conclusion that switching costs are typically higher for subscribers than for stand-alone users, and bundle subscription is influenced by lock-in, performance, and economic benefits.
5. **(Alwin, 2018)** Expressed that when the reason behind customer churning is known to the service providers, it is possible for them to enhance their services to accomplish the demands of the customers. Churns could be considerably lessened by investigating the earlier history of the potential users analytically. The framework has been developed using algorithms known as logistic regression and the neural network. Finally, a comparative analysis is performed to determine the most advantageous model and analyses the model with precise and consistent results. For churn management, the study recommended a model such as the C5.0 algorithm of the decision tree. And the above-mentioned model has been shown to be the best among the models, with an accuracy level of 85 percent and an AUC value of 0.888.
6. **(Azeem et al., 2017)** used fuzzy classifiers, NN, LR, SVM, AdaBoost, and RF techniques to predict an accurate set of churners on a real-time dataset of prepaid telecom customers from South Asia. The model was used to consider and improve parameters such as TP rate and AUC. The authors proposed that using a large data volume could improve prediction accuracy. It was also suggested that churn prediction models be developed for other applications such as e-commerce.
7. **(Essam et al., 2012)** have introduced a simple data mining-based model to track customers and their behavior in relation to churn. A dataset of 500 instances with 23 attributes was used to test and train the model using three different techniques: decision trees, support vector machines (SVM), and neural networks for classification, and the k-means algorithm for clustering. According to the findings, SVM is the most appropriate scheme for predicting churn in the telecom industry.

8. **(Saad et al., 2013)** To identify customers who can switch and active customers, we used machine learning algorithms such as linear and logistic regression, ANN (Artificial Neural Network), K-means clustering, and Decision Tree. The best results were obtained using exhaustive CHAID, a decision tree variant.
9. **(Andrews et al., 2019)** Various classifying algorithms are seen to be used in customer churn prediction. Customer churn prediction studies in telecommunications have been successfully performed using Random Forest and KNN algorithms, among others.
10. **(Lee et al., 2017)** proposed a customer churn prediction model in the mobile industry based on the influence of words in Korean online news. NN, DT, and LR were used to predict churn based on the effect of text within advertisements in online news. The authors concluded that the prediction is based on web data. They also mentioned that surveys could be included for better prediction. Other markets, such as the online market, have a larger scope and should be investigated. The authors took a macro perspective, so they ignored churn factors of individual tendencies, which can be studied further.
11. **(Bahari and Eloyidom, 2015)** for the prediction of customer behavior in banking, a CRM framework based on neural networks and data mining was proposed. The UCI dataset was used, which contained direct bank marketing campaigns from Portuguese banks. It was determined that the NN algorithm was superior to the NB algorithm in terms of accuracy and specificity, while the NB algorithm was superior in terms of sensitivity, TPR, FPR, and ROC area. The neural network classified 4007/514 instances correctly/incorrectly, while the Naive Bayes algorithm classified 3977/544 instances correctly/incorrectly. The authors suggested that the time required to build a model is excessive and should be reduced. Furthermore, improved algorithms for banking and e-commerce model building can be created.

1.7 TECHNOLOGY USED

1.7.1 DECISION TREE ALGORITHM (DT)

DTs are simple, popular (Sahar, 2018), fast to train, and easy to interpret models that learn features from data using a comparison or if-then-else method. They can be applied to both categorical and continuous data, and their predictions are reasonably accurate, but they are prone to over fitting. Their effectiveness can be improved by increasing their workload (Mohri & Talwalkar, 2018). The C4.5 algorithm is a well-known tree-based classifier in which a tree is formed; the algorithm searches for an attribute with the highest information gain and partitions data into classes based on the attribute's value; recursive partitioning continues on each sub-tree until a leaf node is reached (Huang & Kechadi, 2013).

1.7.2 K-NEAREST NEIGHBORS ALGORITHM (KNN)

This algorithm can predict and classify objects based on the feature space and the closest training samples. A prediction based on the nearest neighbour is given with a percentage of confidence; this prediction result is obtained first by inspecting the feature space; this is how the KNN algorithm method works (Deng, Zhu, Cheng, Zong, & Zhang, 2016).
The KNN algorithm is considered lazy learning because it relies on predictions from only a subset of instanc es that are most similar to the test set instance, (Gongde, Hui, David, & Yaxin, 2004; Sonia & Maheshwar

2019). Aside from that, it is the most basic method or algorithm for data mining and machine language, (Mohammad et al., 2016).

1.7.3 EXTREME GRADIENT BOOSTING (XGBOOST)

XGBoost is a recently dominant algorithm in applied machine learning and Kaggle competitions for structured or tabular data. XGBoost is a gradient-boosted decision tree implementation optimized for speed and performance. The name xgboost, on the other hand, refers to the engineering goal of pushing the computational resources limit for boosted tree algorithms. As a result, many researchers employ XGBoost. The algorithm's implementation was designed to maximize compute time and memory resources. One of the design goals was to make the best use of available resources when training the model. On classification and regression predictive modeling problems, XGBoost dominates structured or tabular datasets (Brownlee, 2016). The AdaBoost (Adaptive Boost) and Stochastic Gradient Boosting algorithms are both ensemble-based on the concept of boosting. They attempt to convert a group of weak learners into a group of stronger learners (Sahar, 2018).

1.7.4 NAIVE BAYES (NB)

A Bayes classifier is a simple probabilistic classifier that is based on the Bayes theorem and strong (naive) independence assumptions. The underlying probability model would be better described as an independent feature model. A Naive Bayes (NB) classifier, in simple terms, assumes that the presence (or absence) of a specific feature of a class (i.e., customer churn) is unrelated to the presence (or absence) of any other feature. The NB classifier performed well on the churn prediction problem for the wireless telecommunications industry (Nath & Behara, 2003), and it can also outperform other widely used algorithms, such as DT-C4.5 (Kirui et al., 2013).

1.7.5 REGRESSION ANALYSIS -LOGISTIC REGRESSION ANALYSIS

This is a strong and well-known statistical technique for estimating the probabilities of the target categories. It's similar to simple linear regression, but with categorical outcomes. It employs the generalized linear model to compute regression coefficients that represent the effect of predictors on the probabilities of the target field's categories (Balaji, 2013).

1.7.6 RANDOM FOREST CLASSIFIER (RF)

The Random Forest is a collection of classification trees that have not been pruned. It generates a large number of classification trees, each of which is built from a different sample of the original data using a tree classification algorithm. Following the formation of the forest, a new object that needs to be classified is placed beneath each tree in the forest for classification. Each tree casts a vote to indicate its preference for the object's class. The forest then selects the class with the most votes for the object (Al Mehedi , Nasser, Pal, & Shamim, 2014).

1.7.7 LOGISTIC MODEL TREE (LMT)

The Logistic Model Tree (LMT) is a popular classification model. LMT is a data mining algorithm that combines two classification algorithms, Decision Tree (DT) and Logistic Regression (LR) (LR). In practice, LMT produces more accurate results than comparable algorithms such as C4.5, CART, and LE (Colkesen and Kavzoglu 2017; Ghosh and Kumar 2013; Widodo, Handayanto, and Herlawati 2013).

1.8 EVOLUTION METRICS

This study will evaluate the performance of the classifiers in churn prediction using the different evaluation metrics which are derived from the result of confusion matrix. There are four (4) possible outcomes in the matrix namely. A confusion matrix similar to the one shown in table 1 is generated.

Table. 1 Confusion matrix

		Prediction Class	
		CHURN	ACTIVE
Actual Class	CHURN	TP	FN
	ACTIVE	FP	TN

- True Positive *(TP):* Number of positive cases correctly predicted.
- False Negative *(FN):* Number of positive cases wrongly predicted as negative.
- False Positive *(FP):* Number of negative cases wrongly predicted as positive
- True Negative *(TN):* Number of negative cases correctly predicted.

Accuracy is the percentage of correctly classified instance over the total number of instances. See eq. (1).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \qquad (1)$$

Precision is computed by dividing the number of true positives to the number of true positives and false positives. See eq. (2).

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

Recall is computed by dividing the number of true positives to the number of true positives and the number of false negatives. See eq. (3).

$$Recall = \frac{TP}{TP+FN} \qquad (3)$$

F-Measure (or F1 Score) carries the balance between precision and recall. See eq. (4).

$$F\text{-}score = \frac{2 \times precision \times Recall}{Precision+Recall} \qquad (4)$$

1.9 IMPLEMENTATION AND PERFORMANEE ANALYSIS

1.9.1 CHURN PREDICTION FOR FEATURE SELECTION

Data were collected for validation from an online available telecom sector of cell 2 cell dataset. All information about a customer's services, as well as convention details, are included in customer data.

Customer ID
Monthly Minutes

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Roaming Calls
Blocked Calls
Customer Care Calls
Received Calls
Outbound Calls
Inbound Calls
Call Forwarding
Months in Service
Service Area
Some of the data has been attached here and is shown in table 2.

TABLE 2 : DATASET PARAMETERS OF TELECOM CUSTOMER

Customer ID	Monthly Minutes	Roaming Calls	Blocked Calls	Customer Care Calls	Received Calls	Outbound Calls	Inbound Calls	Call Forwarding Calls	Months In Service	Service Area
5000008	480	0	1	1.7	55.3	46.3	6.3	0	56	MILMIL414
5000020	570	0	0.7	8.7	106.3	14.7	0.7	0	57	NNYSYR315
5000034	1093	0	3	11.3	213.9	103.3	0.3	0	55	MILMIL414
5000071	153	0	0.7	0	33.1	8	4.7	0	59	SLCSLC801
5000074	1213	1.3	6	4.3	490.1	50.7	8.3	0	52	OKCTUL918
5000088	1424	0	0	0.3	939.3	7.7	39	0	54	SEAPOR503
5000097	300	0	0.7	1	77.5	6.3	5	0	52	SLCSLC801
5000120	972	0	0	0	244.6	20	8	0	58	PITHOM412
5000248	406	0	1.7	0	47.7	6.3	4.3	0	50	SANMCA210
5000255	2961	62.3	9.3	0	871.5	210.7	96.3	2.3	52	NSHNSH615
5000259	244	0	2.7	0	48.8	13	1	0	54	KCYKCK913
5000271	380	0	0.7	0	76.2	21.7	4.7	0	56	DENDEN303
5000333	1088	0	1	3.7	335.1	11	6	0	54	OKCLRK501
5000335	1348	1.9	7.3	0	436.5	59.3	2.3	0	56	SANAUS512
5000336	1804	0	11	0	742.4	133	31.7	0	50	NSHNSH615
5000367	365	0	7	3.3	99.9	9.3	2	0	50	KCYWIC316
5000370	1306	0	1	1.7	809.1	25.3	0	0	52	KCYKCM816
5000435	1656	0	9.7	9.3	197.9	42.7	0.3	0	52	DALSHR903
5000450	25	0	0	0	1.6	0	0	0	50	NSHNSH615

Many things can go wrong with a brand, from complicated onboarding in which customers aren't given simple information about product usage and capabilities to poor communication, such as a lack of feedback or delayed responses to inquiries. Another possibility is that long-term clients feel unappreciated because they do not receive as many bonuses as new clients. Customers who have been with the company for a long time may be dissatisfied with customer service support calls. In this study, churn analysis is used to determine why customers switch service providers based on data such as customer call data. Obtaining access to customer data is the first step in developing a churn analysis application. Table 2 displays the customer data that was used to process or identify churn. After that, the factors are classified to determine which factor or factors influence customer churn decisions.

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Overall customer experience shapes brand perception and influences how customers recognise the value of the products or services they use.

TABLE 3: CHURN IDENTIFICATION OF DATASET THROUGH CUSTOMER CARE CALLS

Customer ID	**Total Recurring charge**	**Customer Care Calls**	**Director Assisted Calls**	**Unanswered Calls**	**Not respond Calls**	**Un satisfied customer**	**Unique Subs**	**Active Subs**	**Service Area**	**Credit Rating**
5000002	22	6.3	0.25	0.7	0.7	0	2	1	SEAPOR503	5- satisfied
5000010	17	2.7	0	0.3	0	0	1	1	PITHOM412	5- satisfied
5000014	38	0	0	0	0	0	1	1	MILMIL414	3- Good
5000022	75	76	1.24	52	7.7	4.3	2	2	PITHOM412	4- Medium
5000026	17	0	0	0	0	0	2	2	OKCTUL918	1-Highest
5000030	52	13	0.25	9	1.7	0.7	1	1	OKCTUL918	3- Good
5000038	30	2.3	0.25	0	1	0	2	2	OKCTUL918	5- satisfied
5000042	66	4	2.48	0	0.3	4	2	2	OKCOkC405	0-Dissatisfied
5000046	35	1	0	0	0	0	3	3	SANMCA210	5- satisfied
5000050	75	0	0	0	0	0	1	1	PITHOM412	3- Good
5000054	25	0.3	0	0	0	0	2	2	SANMCA210	5- satisfied
5000058	85	43.7	2.23	9	0	0.3	5	1	SLCSLC801	5- satisfied
5000062	37	7.7	0.25	3.3	1.7	1	2	2	OKCOkC405	3- Good
5000066	60	17.3	0	5	0	3.7	1	1	SLCSLC801	3- Good
5000078	70	9	0	1.7	0.3	0.3	1	1	MILMIL414	3- Good
5000082	100	114.3	0	7.3	18	4	2	1	LOULOU502	0-Dissatisfied
5000102	30	2.3	0	0.3	0	4	3	3	SLCSLC801	0-Dissatisfied
5000118	30	0.7	0	0	0	0	1	1	SANMCA210	0-Dissatisfied
5000122	17	0	0	0	0	0	2	1	KCYKCK913	1-Highest
5000126	30	5.3	0	2	1.7	0	1	1	SANMCA210	4- Medium
5000130	35	3.3	0.25	0	0.7	0	1	1	OKCOKC405	1-Highest
5000134	17	7.3	0	1.3	3	0	1	1	KCYNEW316	1-Highest
5000138	30	1.3	0	0.3	0	0	2	1	SLCSLC801	1-Highest
5000142	75	53.3	0.5	11	5	2.7	1	1	KCYKCM816	1-Highest
5000146	30	3	0	2	2	0	2	2	KCYKCM816	1-Highest
5000158	30	6.3	0	6.7	0.3	0	2	1	DENDEN303	1-Highest

Table 3 displays a dataset of customer care call data, such as their satisfactory level, dissatisfactory level, and level of opinion from customer care support, from which it can analyses what problem is made and whether or not the solution is satisfied. We must monitor the person's future response to call data if they provide an unsatisfactory level. If the response is low, it indicates the possibility of churn, and we can easily predict customer churn.

1.9.2 EVALUATION CRITERIA

To test and evaluate the features, we used 10-fold cross validation. In this process, the initial data is randomly partitioned into ten mutually exclusive subsets or "folds," each of approximately equal size. Training and testing are carried out ten times. In iteration I partition Di is set aside as the test set, and the remaining partitions are used to collectively train the model. The classification accuracy estimate is calculated by dividing the total number of correct classifications from the 10 iterations by the total number of tuples in the initial data. This indicates how well the classifier will perform on untested data.

TABLE 4. DECISION TREE CLASSIFICATION

Name of Method	**Decision Stump**	**Hoeffding Tree**	**J48**	**Random Forest**	**Random Tree**	**REPTree**	**IBK**	**LWL**	**Extra Trees Classifier**	**LMT**
No feature selection accuracy (%)	88.67	89.58	92.03	89.31	88.41	85.55	81.10	83.55	93.18	93.55
Accuracy with feature selection (a) (%)	88.67	88.21	88.43	87.55	87.58	85.55	85.61	85.45	88.51	86.77
Accuracy with feature selection (b) (%)	88.67	88.67	90.61	92.36	88.51	91.41	90.30	87.11	91.87	91.18

TABLE 5. NAIVE BAYES CLASSIFICATION

Name of Method	**Bayes Net**	**Naïve Bayes**	**Naïve Bayes Updateable**
Accuracy without feature selection (%)	83.55	85.62	85.62
Accuracy with feature selection (a) (%)	85.95	84.38	84.38
Accuracy with feature selection (a) (%)	85.47	84.60	84.60

TABLE 6. DECISION TABLE CLASSIFICATION

Name of Method	Accuracy without feature selection (%)	Accuracy with feature selection (a) (%)	Accuracy with feature selection (b) (%)
Decision Table	92.18	86.65	92.35
JRip	96.55	86.45	93.25
OneR	83.53	83.96	84.51
PART	92.48	86.53	93.13

TABLE 7. ACCURACY OF THE SELECTED MODELS

Type of classification	Name of Method	Accuracy (%)
Neural Network	Multilayer Perceptron	94.65
Neural Network	Voted Perceptron	84.78
Decision Tree	J48	95.44
Decision Tree	LMT	96.47
Decision Rule	PART	95.19
Decision Rule	JRip	96.22
Naïve Bayes	Naïve Bayes	90.35
Naïve Bayes	Naïve Bayes Updateable	90.35

Table 7 summarizes the best classification technique from among the available options. As a result, this step can be referred to as feature selection. WEKA employs no feature selection method. The highest accuracy was achieved by Logistic Model Trees (LMT), which achieved 96.47 percent. In conclusion, feature selection is required, but selecting the right feature selection is critical. As a result, additional research is required.

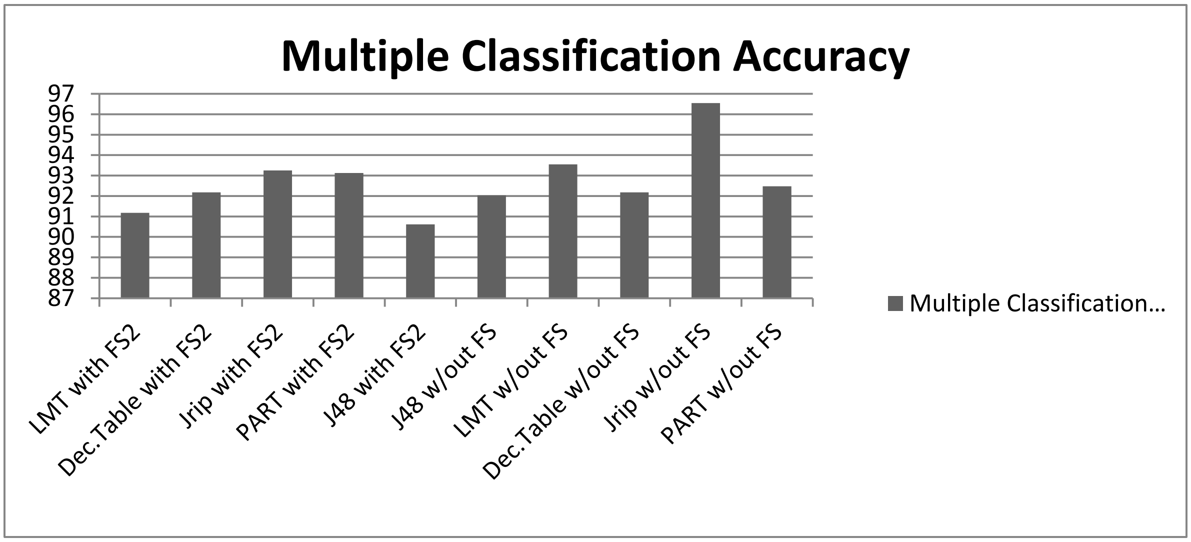

Figure 1. Multiple Classification Accuracy using Different Feature Selections

Figures 1 and 2 summarise the best classification methods among the four classifiers. Figure 1 depicts accuracy with and without a feature selection (b) (b). Figure 2 depicts the best classification method when attributes such as Customer ID and Service Area are removed. The LMT classifier outperformed the other five classifiers in terms of accuracy.

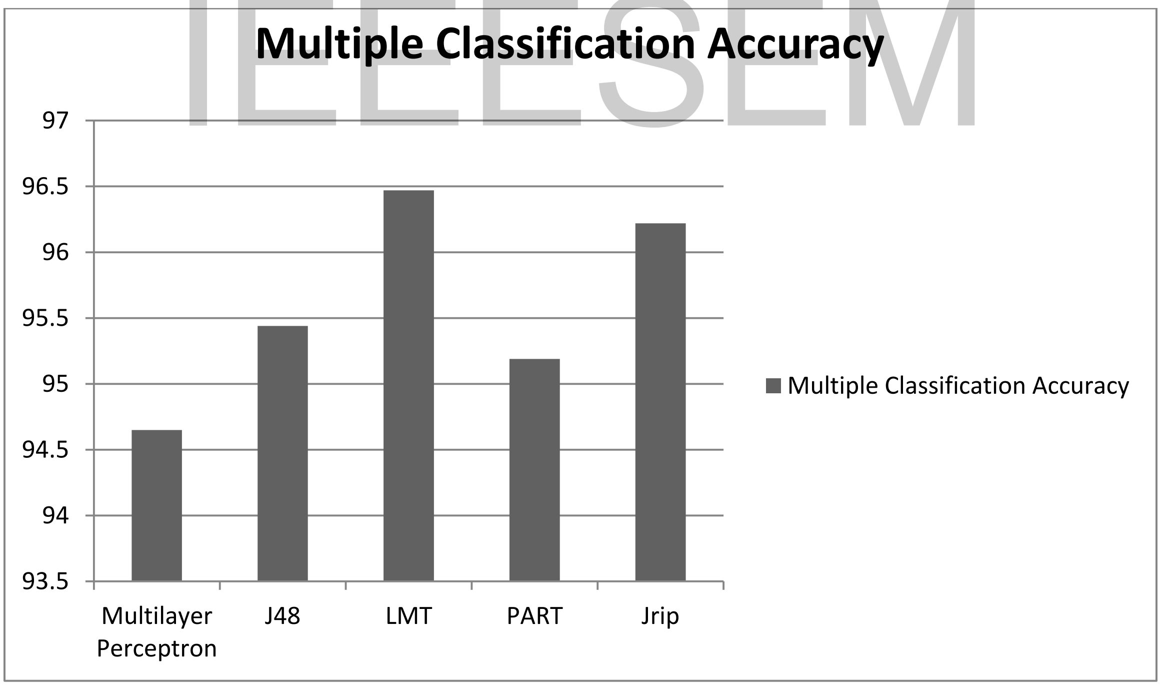

Figure 2. Multiple Classification Accuracy with ‘State ‘and ‘Phone ‘attribute removed

Table 8. Confusion Matrix for JRip Classifier

JRip Classifier			
True Label	**False**	**True**	**Total**
False	2683	167	2850
True	239	244	483
Total	2922	411	3333

Table 9. Confusion Matrix for LMT Classifier

LMT Classifier			
True Label	**False**	**True**	**Total**
False	2811	39	2850
True	117	366	483
Total	2928	405	3333

Tables 8 and 9 show two distinct confusion matrices for LMT and JRip. The LMT classifier correctly classified about 91 percent of churners, while JRip correctly predicted 90 percent of churners. In short, the LMT is superior at predicting customer churn. As a result, it is the best classification model for this dataset, but the LMT is also good at classifying non-churners with 97 percent accuracy. However, it is critical to predict churners as opposed to non-churners because the company's goal is to maximise profit by focusing on churners. For non-churners, a misclassification error would have no effect on the CRM or the overall company profit.

CONCLUSION

Churn prediction is a critical issue for CRM in today's competitive telecom market in order to retain valuable customers by identifying similar groups of customers and offering competitive offers/services to the respective groups. As a result, researchers in this domain have been looking at the key churn factors in order to retain customers and solve CRM and decision maker problems.

FUTURE WORK

Because large open source CRM datasets are currently unavailable, the following improvements to the proposed work can be made if large open source CRM datasets become available in the future:

1. The selection of the algorithm's feature set is critical. With the availability of larger CRM datasets, this step of the process can be automated by creating algorithms that automatically select the best set of features and then form subsequent rules based on the feature set.
2. Partial matches generated during the process are left unprocessed due to a lack of abundant data. These are the most difficult entries to separate, and finding a suitable solution requires a large amount of data.

3. Human intervention is required to select the required entry in the case of a potential match. This intervention can be greatly reduced with the availability of a large dataset by training an algorithm to create the most up-to-date entry.

4. Multithreading would solve the problem because the algorithm is time consuming. The entire algorithm can be redesigned to run faster by dividing files into chunks and processing them in parallel.

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