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OPTIMIZED PERFORMANCE FOR CONSUMER CHURN PREDICTION USING DATA-MINING FRAMEWORK

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Abstract

Predicting whether a company will churn or not, is one of the most important tasks to be done in a business competitive environment, regarding keeping the consumers. We present an optimized data-mining framework to predict and proactively address customer churn in the consumer industry. We deploy a combination of machine learning techniques to predict churn pattern. Additionally, we present a novel feature selection measure that helps us to predict churn and enables better computational efficiency and reduced prediction time. In addition, to combine the predictions of various models, we employ ensemble learning. Experimental results reveal that our framework significantly outperforms traditional methods with 89.03% accuracy, 85.78% Precision, 91.14% Recall, and 95.07% f1-score on a real-world consumer churn dataset. We are proposing a framework where businesses can proactively catch customers at risk and go for prevent retention measures which can enhance customer retention and revenue as well.

Keywords: Churn, Prediction, Business, Data-Mining, Machine Learning, Accuracy, Precision, Recall, F1-Score

1. Introduction

Consumer churn prediction is the prediction of whether or not a consumer will end their relationship with a company, followed by switching to a competitor. It is a most important part of business analytics [1] which involves recognizing and holding profitable customers. Using machine learning, data mining, and statistical analysis, customer behaviour is analysed to identify patterns that could predict churn [2].

Customer behaviour and interactions data related to the company is the starting point for consumer churn prediction. The data is pre-processed and cleaned once collected. to remove invalid or duplicate information. Using different algorithms, the churn prediction model is trained on the mentioned data in order to observe the patterns and identify the main factors that contribute to churn [3].

Then the model generates a churn score for each customer indicating the likelihood of churn [4]. Machine Learning is used for a churn prediction which is one of the major approaches. These algorithms are trained on data of past churn and identify similar markers based on the current user base to detect cases of churn in future users [5].

High Accuracy In churn prediction, machine learning algorithms provided the highest accuracy. Another important factor in churn prediction is customer segmentation [6]. This is when customers are segmented, or identified to groups of those with similar characteristics. Customer segmentation enables companies to get a better idea of the unique needs of each group so retention strategies can be tailored to target those consumers who are most in need of retention [7]

Having identified at-risk customers using the churn prediction model, the identified customers can have retention strategies created towards them. Such strategies may include specific advertising campaigns. Tools also avail analyses such as customer churn, detection, and churn prediction trends which provides a significant advantage to companies in managing customer churn. Firms may retain customers proactively, rather than losing them reactively [8].

This not only helps reduce customer churning but also aids in maximizing customer satiety and fostering customer loyalty. Similar data can also help firms better target their marketing and other resources. It can use that information to find out which customers are most likely to churn and target those customers with retention efforts. If a consumer churn prediction was accurate, it has significant impacts on the bottom line of a company.

Churn prediction models provide a financial forecast of possible revenue loss in terms of customer churn that assist any company in budget plan and forecasting. This enables the company to offset revenue loss from customer churning, and in some cases actually boost revenue through execution of successful churn strategies [9].

Consumer churn prediction is a business analytics process to help companies to better understand and manage customer churn [10]. This allows them to reduce churn rates, increase customer satisfaction, and drive revenue growth. As big data and complex analytical methods continues to be infused into more and more companies, churn prediction is becoming a necessity for companies that want to remain competitive in a rapidly-changing, highly-competitive landscape. The key contribution of proposed research has the following,

- Most datasets used for predicting consumer churn are highly imbalanced as the number of customers who churn is far lower than the number of retained customers. Churn prediction model can be improved by using data-mining approaches to balance the dataset.
- Predicting consumer churn typically uses several different pieces of information, such as customer demographics, usage case, and sales information. Such data-mining techniques can be used, including ensemble learning, using different data sources to improve the quality of predictions.
- CLV is a metric of the value that a customer provides to a company throughout their lifetime. However, data-mining techniques can improve the accuracy of churn predictions by including the financial impact of losing a customer over its lifetime.
- Customer attrition predictive value prediction is in real time allowing companies the means to proactively intervene before customers at risk to leave.

2. Related Works

Prasad, U. D., et al. [10] that data cleaning and preprocessing are methods used by data mining to predict consumer churn. It includes removing NaN values, handling noisy data and managing datasets from multiple sources. Precision is critical in order to make accurate predictions of their experiments. The companies have lots and lots of data from fields like customer service, sales, marketing, and operations discussed by Gopal, P., et al. [11]. These datasets are often rich, varied, and complex, posing challenges to integration and analysis and making it difficult to convey actionable insights. Lee, E. B., et al. [12] explained consumer churn prediction requires identifying the most techniques in customer churn prediction. It can be a tedious and complex process, particularly in high dimensional datasets with lots of features. Note that the number of churners is usually far smaller than that of non-churners discussed by Keramati, A., et al. [13], which leads to imbalanced dataset. This may result in biased predictions and pose difficulties in training reliable models. Dolatabadi, S. H., et al. [14] has reviewed several data mining techniques which can be used for churn prediction. Selecting the appropriate technique for a particular dataset can be difficult since these algorithms have nuances that need to be understood more deeply. Kirui, C., et al. [15] discussed customer behaviour is very nonlinear, making traditional Linear models to be not appropriate. In order to predict churn accurately, data mining algorithms need to detect and capture these non-linear relationships.

Naz, N. A., et al. [16] have explored the Consumer churn prediction not only identify churners but also the insights behind them. But some data mining algorithms, making it difficult to understand the factors behind churn. Data mining have the ability to give precise predictions, however it can be complicated to implement these insights into successful business decisions explained by Tianyuan, Z., et al. [17]. It is necessary for the companies to know how to read and account the results for forming a successful churn prevention strategy. Handling sensitive customer data for churn prediction raises concerns about data privacy and security as discussed by Lukita, C., et al. [18]. To maintain customer trust, companies need to make sure that customer data is collected, stored, and used according to ethical standards and regulations. Consumer behaviour and churn factors can exhibit temporal dynamics, thus maintaining the accuracy of churn prediction models requires them to be updated and retrained over time explained by Chayjan, M. R., et al. [19]. This needs an effective and fast process to collect new data and integrate it into existing models. Umayaparvathi, V., et al. [20] has argued that one important approach to the consumer churn prediction using data-mining is that it ensures that the data is of high quality and sufficiently consistent. The above also includes a lot of data from various sources. Inadequate data affects the prediction models of churn adversely.

Yiğit, İ. O., et al. [21] have mentioned that consumer data is usually stored in various formats and several databases that make it hard to integrate and analyze them. Data integration is the process of integrating information from different sources to gain a single view of the customer. Au, W. H., et al. [22] have addressed customer churn prediction focuses on the best model achieving the highest accuracy when most of the customers do not churn, leading to bias towards the majority class. This could cause the predictions to be slightly skewed and therefore affect the overall performance of the model. The success of churn prediction models given by Hung, S. Y., et al. [23] is highly dependent on algorithms and appropriate selection of parameters. But, picking the best model is a tough job and involves a deep analysis of data, business objectives and application needs. However, to ensure the reliability and generalizability of models, they must be validated and tested on unseen data. Dahiya, K., et al. [24] have discussed Feature selection involves selecting the top features that are relevant from a vast set of available data and converting them into more predictive variables. This requires domain expertise and can be time-consuming, particularly with large and complex datasets.

Lejeune, M. A. et al. [25] discussed the missing data can introduce bias in model predictions, adversely affecting the accuracy and performance of churn prediction models. Hence, handling missing data are of utmost importance strategies to have. Verbeke, W., et al. [26] address enormous data, the scalability and performance of churn prediction models becomes a key issue. It is hard to deploy them to real-time applications as with an increase in the size of data, both the processing time and memory requirement of the models also increases. Thus, it is important to select and implement effective algorithms and methods to manage these extensive datasets for accurate and scalable churn predictions. Hudaib, A., et al. [27] discussed the integration of churn prediction models into existing business processes and systems can be a daunting challenge. This is where it needs teamed up of data scientists, business analysts, and IT professionals to integrate and deploy models without any problem. This transformation can include data as well as system and application programming, and can involve technical complexity. Mahajan, V., et al. [28] use consumer data to predict churn, which raises ethical concerns. When collecting, using, and storing customer data, organizations must adhere to ethical and legal regulations. Such a scenario would make it difficult to have access to required data points for building a churn prediction model, which would compromise the performance and the usefulness of the build models. Lima, E., et al. [29] have also highlighted that customers need to know the reason behind their churn predictions and actions for prevention. Model interpretation and explainability are also critical as we would need to explain and identify the reasons behind churn. Although some of the data-mining techniques are black-box type, hence less interpretable and a challenge to explain the predictions to the customers/stakeholders

2.1.Research Gaps

- As of now, there is no established or generic methodology for the prediction of customer churn using data mining techniques. This can result in poor performance and variation in outcomes, which hinder comparison and replication.
- To accurately predict consumer churn, data about customer behaviours, preferences, and interactions with the company is needed. Data collection and maintenance can be arduous, and there may be discrepancies in the quality of the data that can affect the accuracy of the predictions.
- Consumer churn predictions are most helpful when used in conjunction with other business systems. However, many data mining techniques for churn prediction do not easily fit into these systems, which can result in siloed data and inaccurate predictions.
- Imbalanced dataset, churn data typically are imbalanced data, that is there are a lot more non-churners than churners in the data. This causes the model to produce skewed predictions because it fails to predict churn if there is no prior data about churners available. This imbalance in the data is a significant technical hurdle in the research of consumer churn prediction.

2.2.Research Novelty

- Researchers has extended consumer churn prediction modelling with more unstructured data from sources. Which in turn, helps to better understand the consumer behaviour and sentiment, as a result more accurate prediction.
- Most of the statistical approaches used currently for predicting churn have a time lag due to their batch-wise processing of data. New studies are already dedicated to creating real-

time prediction models that are constantly refined and adapted, based upon new information.

- Beyond traditional customer data is tying in contextual data. This sets the stage for deeper comprehension of the outside forces that may have an impact on a consumer's churn decision

3. Proposed Model

This paper presents a data-mining based framework that performs various sequential operations in predicting the time before a customer churn from an organization. By using data from sources.

3.1.Construction

Data collection is the first step of sequential working. This means collecting big data from various sources concerning the target consumers group. The construction of proposed model has shown in the following fig.1

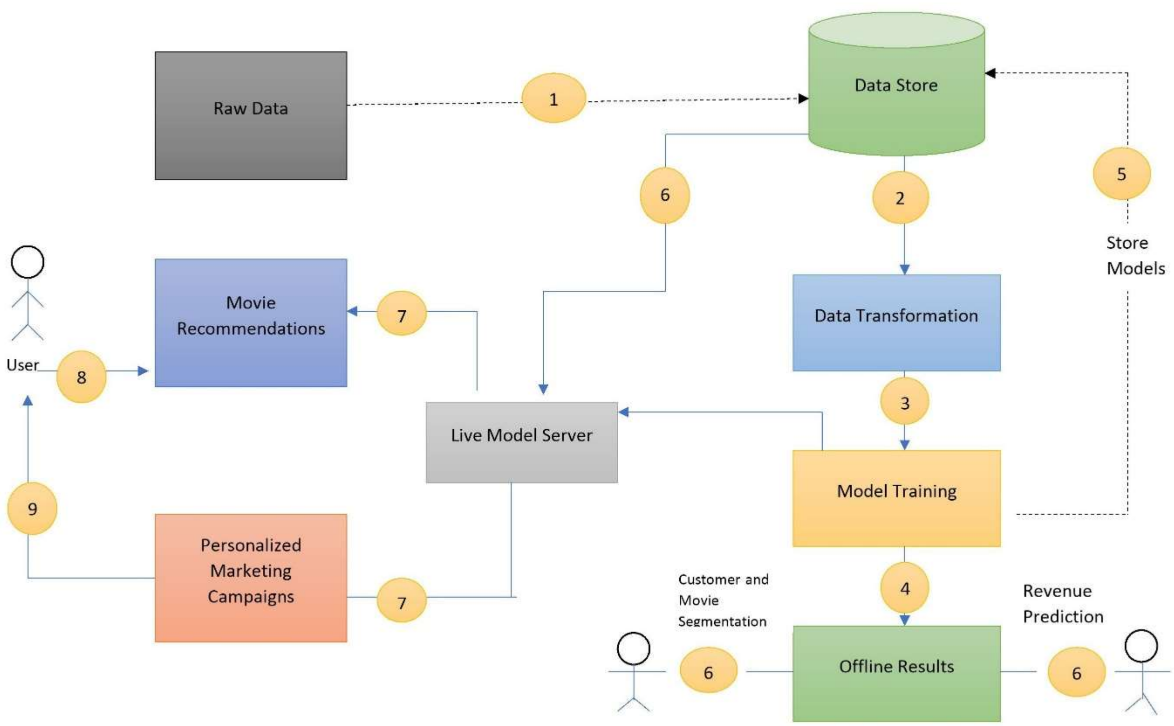

Fig.1: Construction of proposed model

With more collected data, the predictions become more accurate. Once all the data is collected, the next step is Data preprocessing. This includes preparing and cleaning the data to ensure that it is in a format that can be analyzed. Once the data is pre-processed, it is given to a data mining algorithm. This algorithm identifies patterns and connections in data using multiple techniques. The patterns are then used to build a model which can determine whether or not a customer will churn. Next comes model evaluation, where the model developed is evaluated based on how accurate and effective it is at modelling. To do this, the model is evaluated on an independent dataset and predicted results are compared to actual results. Assuming the model is performing adequately it can then be put into production model. Deployment is the last step, which involves introducing the developed model in the business process to assist decision-making. For instance, it can build a dashboard that showcases real-time customer churn predictions or automated actions based on the model predictions. The consumer churn prediction system proposed sequentially processes the collected data and analyzes it to predict possible future churn instances. By doing so, businesses can apply the insights gained to find ways around the scenario with customers that are likely to churn.

3.2.Functional Working

Churn dataset is a data sets contains information about customers who no longer are using a product or service. Churning prediction models are trained on this dataset, where the learning target is to predict if a customer is likely to churn or not. This involves visual exploratory data analysis to gain insights into the dataset with respect to the variables and their relationships.

It aids in recognizing any trends or outliers in the data that may affect model performance. This means cleaning the data, managing lost values, converting categorical variables to numerical variables that can be fed to the model, etc. The churn dataset is then split into a testing set and used to assess the performance of the trained model. Fig.2 shows the functional working of the proposed model.

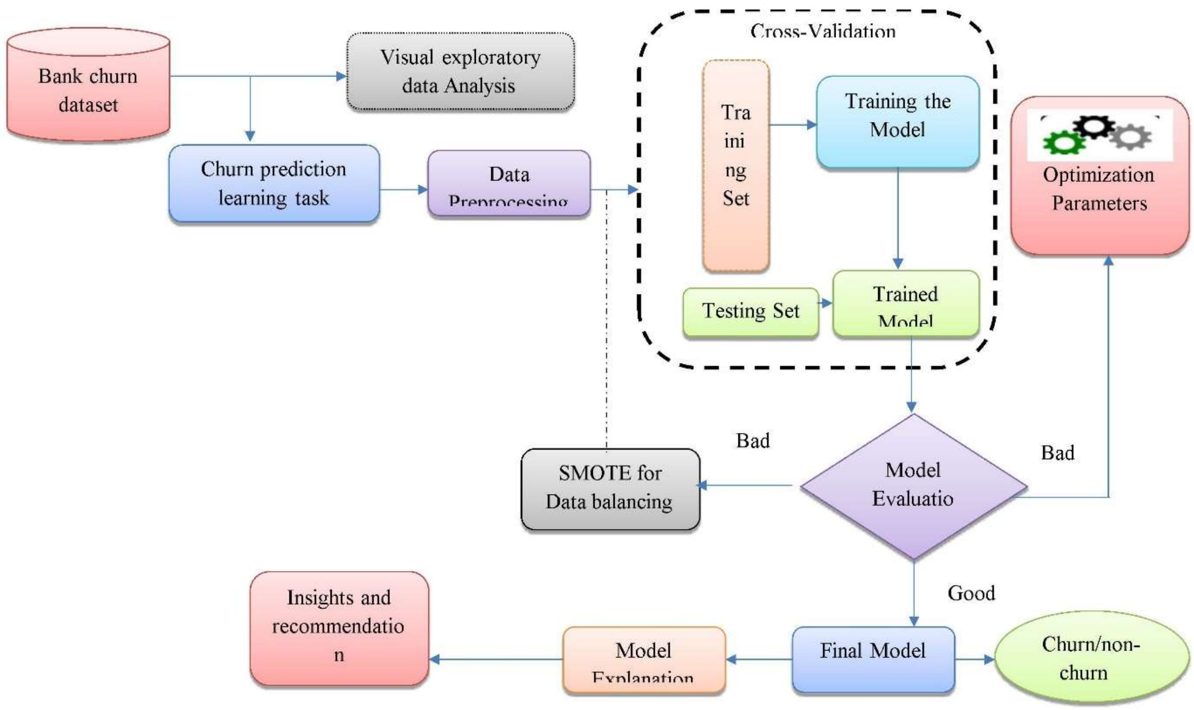

Fig.2: Functional Working of the proposed model

The trained model is then applied to the testing set to make predictions, which are compared against the actual churn status to evaluate the accuracy of the model. Cross-validation is used to prevent overfitting and make sure a model performs well on unseen data. In this technique, the data is split into several subsets and then the model is trained on a subset while the remaining subsets are used for testing. It helps in testing the model and obtaining the parameters that best suit the model. The churn dataset is trained with a set called training set to train the model. It need to use machine learning algorithms which will train the model such that it can accurately predict the churn. The next step is for the model to be evaluated on various metrics after being trained. This is so that one can assess the effectiveness of the model as well as identify areas for improvement. Hence, the approach includes out of the box techniques like SMOTE to balance the dataset to fine-tune the model parameters and build a highly efficient model. Basically, you need synthetic data of the minority class (churn) so it matches the majority class (non-churn). Selects the best model as the final model. Then this is used to predict the new data whether a customer is a churn or not. Additionally, the model can help identify the features that lead to churn, enabling us to recommend action for customer retention.

4. Results and discussion

he performance of proposed model have compared with the existing churn prediction model (CPM), data mining approach (DMAP), data mining algorithm (DMAL) and profit driven data mining (PDDM)

4.1.Computation of Accuracy

Accuracy is a widely used metric for assessing the performance of a model predicting consumer churn. And it calculates the proportion of the accurately predicted churn events to the instances in the data. Specifically, this involves comparing the predictions that the model makes, whether an instance will churn or not, against their actual labels for the same instances and generating a count of correct predictions to use in calculating accuracy. Then you convert this count of correct prediction to percentage by dividing it to total number of instances in the dataset. Table.1 shows the computation of accuracy.

Table.1: Comparison of Accuracy (in %)

No. of Inputs	CPM	DMAP	DMAL	PDDM	Proposed
100	53.634	64.159	67.610	73.769	84.533
200	53.882	65.685	67.922	74.110	86.544
300	54.553	65.932	68.768	75.033	86.869
400	55.480	67.431	69.936	76.308	88.844
500	56.399	67.572	71.095	77.572	89.030

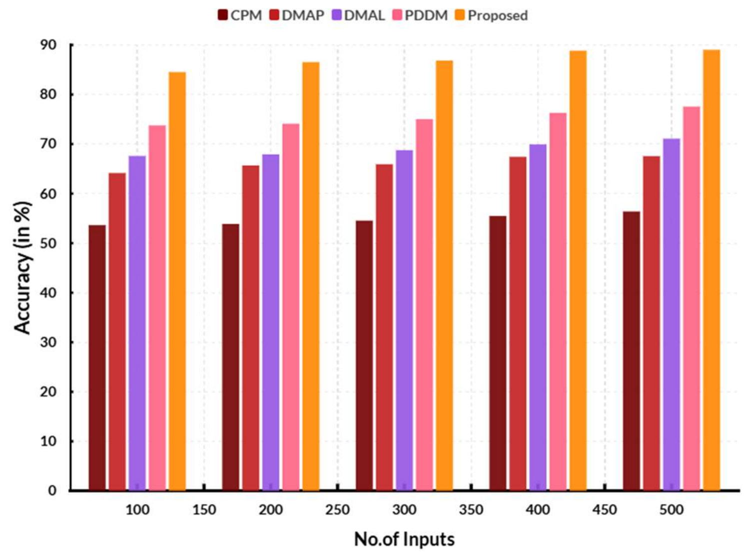

Fig.3: Comparison of Accuracy

Fig. 3 compares their accuracy. In a computational tip, the proposed model reached 89.03% accuracy. The existing CPA reached 56.39%, DMAP obtained 62.57%, DMAL reached 71.09% and PDDM obtained 77.57% accuracy. A better model will have higher accuracy. On its own, accuracy might not be enough, and other metrics will need to be examined to gain a clearer picture of the model's performance in predicting consumer churn.

4.2.Computation of Precision

Precision is the metric that is commonly used to quantify the performance of a consumer churn prediction model using a data-mining framework. In other words, it gauges how good the model is at accurately estimating the number of positive cases, i.e. customers that are about to churn. For precision we will have to divide number of correct churn cases predicted at the numerator by predicted churn case number in denominator. In other words, precision indicates how many times out of the predicted churners the model correctly predicts a churner. Table.2 shows the computation of Precision.

Table.2: Comparison of Precision (in %)

No. of Inputs	CPM	DMAP	DMAL	PDDM	Proposed
100	56.939	64.038	60.194	67.117	81.215
200	57.467	64.743	61.421	68.672	82.565
300	57.759	65.635	61.682	69.073	83.732
400	58.985	66.446	62.980	70.668	84.306
500	59.199	67.038	63.558	71.019	85.789

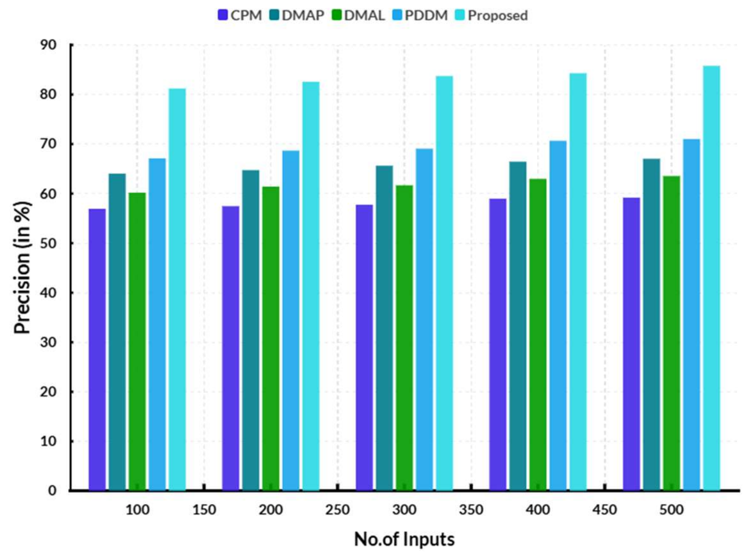

Fig.4: Comparison of Precision

Fig.4 shows the Precision comparisons. In a computational tip, the proposed model reached 85.78% Precision. The existing CPA reached 59.19%, DMAP obtained 67.03%, DMAL reached 63.55% and PDDM obtained 71.01% Precision. Higher precision means that the model is accurately identifying the customers who are more likely to churn, and so it is an important metric for evaluating a consumer churn prediction model.

4.3.Computation of Recall

Recall is a metric used to gauge how well a consumer churn prediction model performs. It shows the proportion of churned customers who were correctly identified by the model. Table.3 shows the computation of Recall.

Table.3: Comparison of Recall (in %)

No. of Inputs	CPM	DMAP	DMAL	PDDM	Proposed
100	59.883	67.889	64.452	72.253	86.785
200	60.482	68.659	65.283	73.226	87.876
300	61.088	69.430	66.114	74.209	88.967
400	61.694	70.200	66.938	75.193	90.057
500	62.300	70.970	67.769	76.176	91.148

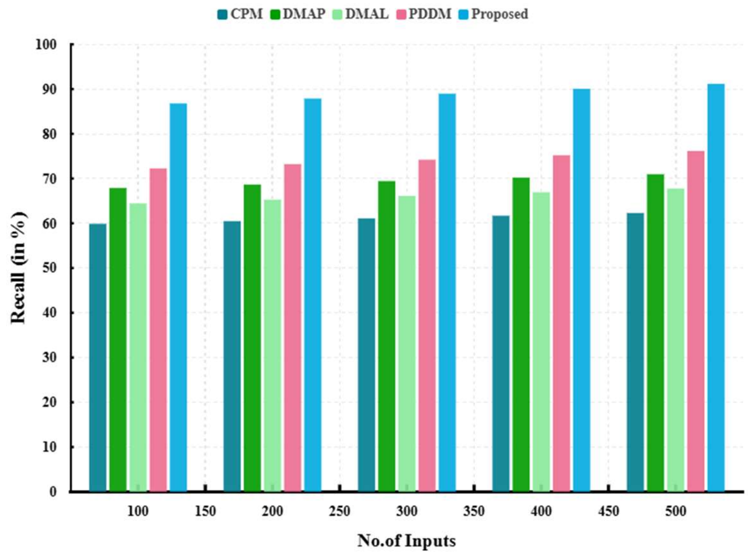

Fig.5: Comparison of recall

Fig. 5 shows the Recall comparison. In a computational tip, the proposed model reached 91.14% Recall. The existing CPA reached 62.30%, DMAP obtained 70.97%, DMAL reached 67.76% and PDDM obtained 76.17% Recall. High recall value signifies that our model is right in predicting the churned customers. This can also generate insights in terms of the model's ability to identify potential churners and identify customers on the verge of leaving the company and take preventive actions. It is an important metric to assess the accuracy of a model at predicting customer departures, and can help businesses make better decisions.

4.4.Computation of F1-Score

The f1-score used to calculate the consumer churn prediction model is based on its precision and recall. Precision, on the other hand, assesses how many of those predicted churners actually did leave. Recall tells us how many of the actual churners are correctly identified by the model. The precision and recall are then used to compute the f1-score, which is the harmonic mean and treats both measures equally. Table.4 shows the computation of f1-score.

Table.4: Comparison of f1-score (in %)

No. of Inputs	CPM	DMAP	DMAL	PDDM	Proposed
100	56.932	68.728	71.767	78.305	90.552
200	57.639	69.592	72.659	79.278	91.691
300	58.355	70.447	73.560	80.262	92.818
400	59.070	71.303	74.462	81.245	93.945
500	59.777	72.158	75.354	82.218	95.073

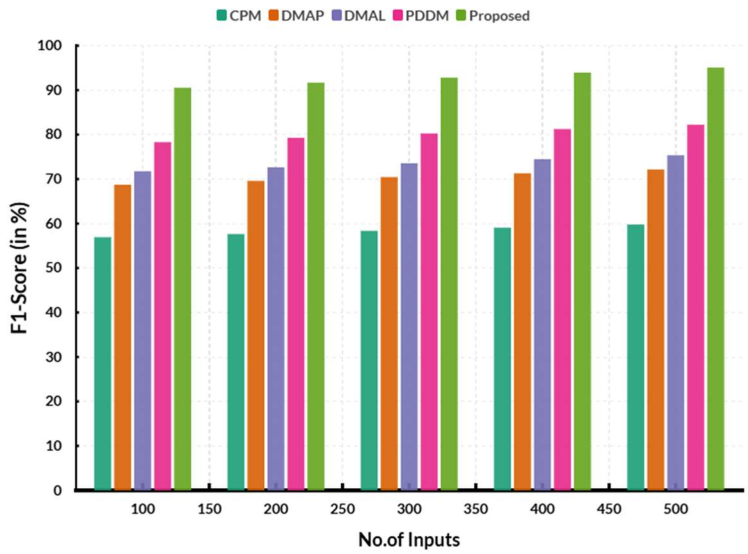

Fig.6: Comparison of f1-score

Fig.6 shows the f1-score comparison. In a computational tip, the proposed model reached 95.07% f1-score. The existing CPA reached 59.77%, DMAP obtained 72.15%, DMAL reached 75.35% and PDDM obtained 82.21% f1-score. It is a value between 0 and 1, higher values mean that model performed better in predicting whether customers would cancel or not. The computation of f1-score helps evaluate the overall accuracy of the model and is an important metric in assessing the success of a data-mining framework for consumer churn prediction.

5. Conclusion

The data-mining framework constructs consumer churn prediction model that has become a useful tool of prediction and reduction of customer churn. The model can analyze huge volumes of information of customers, identify the features and data points that cause customers to churn, and to help businesses with insights for targeted retention strategies. The proposed model obtained 89.03% accuracy, 85.78% Precision, 91.14% Recall, and 95.07% f1-score. it shows that data-mining framework with the combination of advanced analytics and the machine-learning techniques can really enhance an accuracy and efficiency of the model. This model can be particularly useful in a business environment where competition and customer expectations are high, allowing businesses to proactively identify customers that may at risk of churning and enabling them to take that action needed to retain those customers, ultimately increasing customer retention and profitability. Method on how this data-mining framework on the predicting consumer churn model can help the enterprise in the competitive market.

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