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Performance analysis of OKMSVM Learning Model with Existing Churn Prediction Models

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Abstract:
Due to a large clientele, the telecom industry generates enormous amounts of data every day. The telecom market is growing rapidly and is profitable from protocols, new computers, and communication skills in several countries. In this situation, data mining is essential to meet business needs, describe communication models, use sources efficiently, and improve facility excellence. Business analysts and decision-makers stressed that acquiring new clients is more expensive than keeping the ones you already have. They need to be aware of the causes of customer churn as well as any patterns in past churn customers' behaviour. In this article, we compared our proposed OKMSVM model with popular churn analysis models such as CNN, PBCCP and Ensemble learning model to have a better insight into the popular approaches for effective churn prediction.
Keywords: Customer Churn Analysis, Telecommunication, Optimized Kernel Multiclass Support Vector Machine, Feature extraction using KPCA, Hybrid Two Level SVM model.
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1. Introduction

For some firms, the concepts of determining the primary reason for customer loss, assessing customer loyalty, and regaining customers has become crucial.Companies are doing a lot of research and effort to attract new customers and avoid losing them. With more green technology, more users, and solution ratings. Due to technical difficulties and uncontrolled rapid development, there has been an increase in failure in this sector. New methodological techniques must be developed as a result. Companies must identify consumers who are willing to switch providers in order to establish activities to increase customer happiness and create plans to increase customer retention. This study tries to shed light on how carriers lose clients. In the same way that the cause is looked at, it also looks into what kind of consumer abandons [1]. A churn can be characterised in a number of ways. Contractual and non-contractual cancellations are the two most crucial avenues. Contract churn occurs when a party does not renew the agreement after the notification period has passed. These cancellations start when a consumer sabotages the product's appeal and it becomes impossible to convince him to renew his engagement[2]. This is most common with churn issues that occur when a user cancels a savings account or switches carriers from carrier. Non-contract cancellation is the second condition. Users can typically opt out of service in out-of-contract scenarios without a specific time limit. The customer operations team first establishes a churn status, and then customers who meet this criterion are identified as churn customers. To achieve this, the user's behavior modification time is used. If the period of inactivity or behavioral change exceeds the limit, the individual is considered a surrender customer. The time frame designated as the upper limit for the inactive period throughout this procedure is the period [3]. Churn prediction usually has two phases: (i) selection of criteria for judging subsectionsof features that determine whether users preferentially churn, and (ii) churn prediction. A useful technique to keep track of the amount of lost clients is through customer churn. Telecommunications companies often lose valuable consumers and therefore lose revenue to their competitors. The telecom business has undergone major changes over the last few decades, including product growth, scientific innovation and increased competitiveness. Therefore, customer attrition forecasts across the telecommunications sector are important to industry players who need to protect current client commitment, enhance consumer interactions while gaining a reasonable edge [5].One of the most difficult circumstances in the telecommunications sector is assisting clientswho are likely to be unemployed. Consumers typically opt for churn options because of the increasing number of service providers and cutthroat pressure. As a result, telcos recognize the value of retaining customers rather than acquiring new ones [16]. Various reasons affect customer attrition. Prepaid customers, unlike postpaidones, aren't actually bound by agreements in writing. Therefore, they are often modified for minimal purposes. Therefore, it is difficult to predict customer churn rates [13]. In addition to this, there is customer loyalty that is affected by performance of the product and service of the service provider. Broadband coverage and transmission security issues allow customers to switch to competitors with longer distances and higher transmission quality [17] [18]. Poor responsiveness to complaints and billing problemsis another variable that increases the likelihood that customers will move to opposition. Customers may switch to competitors due to shipping costs, poor functionality, and older equipment. Customers often value their vendors and change to those they think provide noticeably better costs. Even if you don't get potential customers, your telco can work well and provide better service to your existing customers. The global average for the turnover rate in the telecom industry is roughly 2 percent, translating into annual losses of about $1 trillion.The above issue was the inspiration for the researchthat the company needs to accurately predict the behavior of the customer. The possibility of churn is predictable as part of a prophylactic approach, and customers will appropriately offer alternatives. This is a supervised learning model [15] that distinguishes between those who are willing to leave and those who are not. Machine learning, including regression analysis, vector support networks, RF, NB, LR, etc., proved to be a very effective way to predict performance data on previously collected information to address this challenge. The accuracy of machine learning approaches for classification is improved through pre-processing and feature selection. Numerous feature selection techniques have been created by researchers to reduce overfitting, computing time, and dimension. The provided input sequence identifies characteristics relevant to churn prediction [4]. This study tries to categorise various consumer types and pinpoint the elements that influence sales in each area. There are several existing models of telecommunications industry churn analysis.

In this work, we compared our proposed OKMSVM model with popular churn analysis models such as CNN, PBCCP and Ensemble learning model on the basis of AUC, RMSE score and accuracy as classifiers.

2. Literature Review

For better analysis, the methodologies for churn prediction are analysed and compared in this section. A solution for multi-attribute strategic planning that uses machine learningwas suggested by Jain et al. in 2021 [6]. The proposed tactic was known as the worker churn prediction and retention approach. We classified employees using a two-step technique and developed an incredible paradigm about the value of employment and benefits. The first proposal of the suggested methodology was to improve the use of an entropy-based system for giving weighting factors to staff performance.In addition, an advanced methodology (CatBoost) was implemented to evaluate staff performance and the value of its class-based classification. TheCatBoost approach was then applied to categorise and forecast employee absenteeism. The authors then proposed a retention strategy based on the outcomes of the forecasts and attribute scores.To predict whether a client will unsubscribe and to estimate how customers will pay for services, [7] created a two-tier unsubscribe technique. This classifier utilised the SVM classification method, and SVR based on machine learning was employed to forecast the monthly recurring cost. The best-fit features, including both ratings, were chosen using a method for choosing attributes called the MCFS approach. The same attribute selection method was employed in both evaluations to maintain consistency and evaluate the efficacy of the method. Then, mostly using IBM, the proposed schema technique was evaluated. To ensure its applicability and generalizability, the dataset for Telco Customer Churn, which contains more than 7000 customers, was used.

Using an advanced learning technique, Bayrak, A. T., et al devised a model for estimating churn rate in 2020 [10]. The LSTM (Long Short Term Memory) approach was used to create the model. In the customer information architecture, customer information is set up in a particular order. Information sequencing is used to construct a long shortterm memory design that compares existing classification techniques while identifying user conversion stages. Even with the assumptions, the proposed model was successful and distinguished itself from the related study. [11] offered paper highlighting the characteristics of churn, that are importantconsiderations when determining its primary source. CRMs can increase productivity, provide talented customers with targeted incentives tied to particular behaviour patterns, and significantly enhance an organization's advertising campaigns by recognising dynamics. user insights are a driving factor. The proposed consumptive estimating method's receiver performance characteristic, recovery, accuracy, precision, and f-measurement are all studied. The findings show that the proposed churn approach significantly classified customers' time and preferences using R.F. and k-means cluster formation. A model based on anticipating frequent interruptions rather than quarterly interruptions, depending on the characteristics of active users was proposed by Alboukaey et al. in 2020 [19]. The authors provide four description-based predictions to forecast daily client income and portray daily consumer behaviour as multidimensional data.Seymen, et al. (2020) [20] have suggested a deep learning approach to ascertain whether commercial buyers come back later. Regression analysis and cumulative neural network techniques, which are frequently used in churn estimates assessments, were used to validate the framework. Remember that a reliability classifier was used by Precision andA.U.C. to evaluate algorithm outputs. The research demonstrates that in terms of predictionandclassification, the trained model performs better than alternative approaches.A framework for machine learning that uses an integrated approachwas created by Hu, X., et al. in 2020 [21]. In the integration approach, neural networks based on machine learning and decision trees were used. In this study, an effective statistical churn prediction model is created, and its effectiveness is evaluated using statistical findings.

An approach to forecasting telecoms discontinuity that incorporates composite overlay and elevation approaches has been put out by Ahmed et al. (2019) [22]. The assessments have made use of conventional cost and performance (cost) heuristics, with expenditure heuristics getting the greatest attention. The suggested methodology and activities are suitable for most procedures with a high cost of operationdue to the high degree of correlation between performance metrics and business goals.

For phones that estimate consumer time spent, [23] developed a method attributed to machine learning approaches and particle classifier performance tuned back-propagation network (B.P.). It is advised to periodically execute PFC (Particle Physical Computation) and PCO (Particle Classification Optimization).

In order to anticipate churn using the approach of machine learning, [24] and[25] have created estimating methods.

Machine learning approaches were utilised by Butgereit et al. (2020) [26] to forecast when a customer is about to unsubscribe and while unsubscribes are being thought about. Following that, these estimations are used to look for user input log files that are semi-structured orunstructured in order to provide reasons why a user might unsubscribe.

3. Methods

Existing Churn Prediction Models

This section discusses the existing and popular churn prediction models for telecom churn prediction and analysis.

3.1.1. Hybrid Two-Level SVM model

The hybrid two-level SVM (Support Vector Machine) model used SVR (Support Vector Regression) and MCFS (Multi-Cluster Feature Selection) model. For this categorization component, a classification approach known as support vector machine was used, and a machine learning-based support vector regression methodology was used to anticipate a recurring monthly cost [7]. The most pertinent characteristics, taking into account both evaluations, were selected using an autonomous feature selection technique called the multi-cluster feature selection approach. The same attribute selection technique for uniformity was used in both evaluations to assess its efficacy. IBM Telecom dataset having 7036 samples (users) with 21 features was used and simulation was done with the help of e-commerce tools. It evaluated and performed at the similar time with a maximum accuracy rate. It provided an accuracy of 81.5%, AUC of 85.6% and RMSE score of 1.27.

3.1.2. Integrated Churn Prediction and Customer Segmentation Framework

Customer segmentation, factor analysis, churn prediction, data pre-processing, exploratory data analysis (EDA), and customer behaviour analyticsare the six components of the Integrated Churn Prediction and Customer Segmentation Framework (ICPCSF) for Telco Business [9]. This approach combines customer segmentation and churn prediction to give telco operators a comprehensive study of customer churn. The tests using six machine learning classifiers use three datasets.First, several machine learning classifiers are used to estimate the consumers' churn state. To address the issues with unbalanced datasets, the training set is subjected to the Synthetic Minority Oversampling Technique (SMOTE). The models are evaluated using 10-fold cross-validation. The F1-score and accuracy are used to evaluate the model. Since the basis of churn management is the ability to detect customers who will leave, F1-score is regarded as a crucial indicator to evaluate models for unbalanced datasets.AdaBoost demonstrated the best performance in Dataset 1 according to experimental study, with a F1-score of 63.11 percentand anaccuracy rate of 77.19 percent. With anF1-score of 77.20 percent and an accuracy rate of 93.6 percent, Random Forest performed the best in Dataset 2. Random Forest outperformed Multi-layer Perceptron in Dataset 3 in terms of F1-score, scoring 63.09 percent, and42.84 percentaccuracy. Following the implementation of churn prediction, factor analysis is done using Bayesian Logistic Regression to identify some key features for turnover customer segmentation. Then, K-means clustering is utilised to divide up customerswho churn. Customers are divided into various groups, allowing marketing professionals and promoterstomore precisely implement retention measures.

3.1.3. Machine learning Approach

Lalwani et al. employed a machine learning approach in 2021 [12]. Six steps make up the suggested strategy. During the first two phases, feature analysis and data pre-processing are done. The gravitational search technique is utilisedto consider feature selection in the third phase. Next, the data was divided into two groups:the test set, which comprised 20% of the data, and the train set, which comprised 80% of the data. The most common predictive models have been used in the prediction processincluding naive bayes, logistic regression,random forests , support vector machines, decision treesetc. on train sets as well as ensembleandboosting techniques to examine the impact on model accuracy. Additionally, on the train set, K-fold cross validation has been used in order to tune the hyperparameters and avoid overfitting the models.Finally, the test set's outcomes were analysed using the AUC curve and confusion matrix.XGboostandAdaboostClassifier were discovered to provide the highest accuracy, with respective values of 80.8 and 81.71 percent. Both the XGBoostandAdaboost classifiers beat others and get the greatest AUC score of 84 percent.

3.1.4. Deep Neural Network

Hyperparameter tuning random search testing is used in DNN modelling to ascertain the learning rate, dropout, and number of nodes in each hidden layer [8]. Testing was then done with three different hidden layer counts, two different activation functions (Sigmoid and ReLu), and five different optimizer modifications (Adam,SGD,Adagrad,RMSpropand Adadelta). 30 batch sizes and 50 epochs were used to train this model. Findings indicate that the DNN algorithm, which uses hyperparameter tuning random search, outperforms modelling using thedecision tree (DT), random forest (RF), and k-nearest neighbour (K-NN) as comparison algorithms, utilising three hidden layers and the RMSprop optimizer, [20, 35, 15] being nodes per hidden layer,a learning rate of 0.01, and 0.1 dropout, with a performance value of 83.09 percent accuracy.

Proposed Optimized Kernel MSVM (OK-MSVM) MODEL

This section explains the proposed optimized kernel MSVM model [27]. For the optimization purpose, the ALO technique is used, and KPCA is employed to decreasethe dimensions of the features. The feature patterns combine M*N matrix numbers that make up an exclusive combination against a certain case. The KPCA modelling the suggested architecture handles the feature extraction procedure. The features of a matrix are extracted using the KPCA technique. Without considerable data loss, it decreases the dimensionality of the data. It is used on the dataset that can be linearly separated. Unlike previous techniques, the database is projected into a high-dimensional, linearly separable feature space via KPCA using a kernel function. The Ant Lion optimizer processes the extracted characteristics. The suggested architecture's ALO optimization module aids in lowering the likelihood of an error in the feature set. The reduced error probability training set delivers more accuracy in the trained model.Determining the most economical input feature patternsis an iterative process. The initial module of the estimation method analyzes the data element once all cases have been processed. The optimized data elements are processed by this module, which also creates various subsets of the original datasets. The prediction model is trained, validated, and tested using these subsets. During this phase, the patterns' labels and training subsetare processed with the training module. To load and carry out test phases, it introducesand stores the OKMSVM model in the secondary storage.Testing the Churn analysis method makes predictions based on the available input dataset. The test set loads the training module and test subset before starting the MSVM prediction algorithm. Because MSVMs employ a risk-minimization algorithm that contains the error, this model holds promise for forecasting online datasets. Following the prediction module, the performance of the suggested architecture is calculated using a variety of performance metrics. To create the comparison sets and verify the contribution of this improvement, the computed performance metrics are employed. The flowchart of the optimized kernel MSVM model is presented in fig.1.

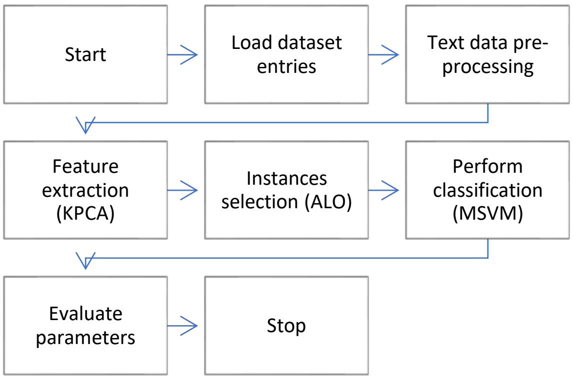

Figure 1 Process flow of Optimized Kernel MSVM Model

4. Results and Discussion

In this section, we compared our proposed model with the existing models on three classification metrics i.e. Accuracy, AUC and RMSE Score.

Tools and Dataset

All the existing models and proposed model have been implemented on a common dataset i.e. "WA_Fn-UseC-Telco-Customer-Churn" dataset. [19]. This dataset contains 21 columns (referred to as “properties”) and 7043 rows (referred to as "users") of raw data. 21 characteristics are used as the target position for the regression and categorization activities. The training phase is created using Python, a language with a scripting foundation. In order to help the user to click and see the outcomes, it creates the man-to-machine interfaces. The new web-based interactive development framework for code, data, and notebooks is done with the help ofJupyter. Users may validate and manage workflows in the DS(data science) with the help of this trustworthy interface.

Evaluation Parameters

Three parameters are used for the evaluation of performance of these models. These are Accuracy, AUC and RMSE Score.

AUC: The entire amount of classification assessment necessary to implement all projected categorization options can be calculated from the area under the curve. The accuracy percentage can be described as ;

$$Accuracy = 100 * \frac{no.of\ correctly\ classified\ samples}{no.of\ all\ samples\ in\ the\ database} \text{..(i)}$$

RMSE: The error of a model in predicting quantitative data is typically measured using the Root Mean Square Error (RMSE). It is officially defined as follows:

$$RMSE = \sqrt{\frac{\sum_i^n (y1_i - y1'_i)^2}{n1}} \quad \text{...................... (ii)}$$

Here, n1 stands for the total sample count in the tele-comm dataset, and y1i and y'1i for the intended and expected values.

Accuracy: Calculating the proportion of true positive and true negative results in all analysed cases is necessary to estimate a test's accuracy. The following can be expressed mathematically as:

$$accuracy = \frac{tp+tn}{tp+fp+fn+tn} \text{..........................(iii)}$$

Here,tpstandsfor True Positive, tn for True Negative, fp for False Positive, fn for False Negative respectively.

Results comparison

The values of the three parameters in the proposed and existing models are determined in Table 1.

Table 1 Comparison based on different evaluation parameters

MODEL	Accuracy	AUC	RMSE Score
OKMSVM	91.05%	85.76%	2.838
HTL SVM	81.50%	85.60%	3.01
DNN	83.09%		
ICPCSF		84.52%	
ML Approach	81.26%	84%	

The results indicate that the OK-MSVM based model performs better than other models due to its ability to select unique and relevant features. Using ALO, it achieved a high classification accuracy rate of 91.05% and AUC of 85.76%, outperforming the results of other models. As we can see from the above table, the OK-MSVM model outperforms the most popular churn prediction modelslike HTLSVM, DNN,ICPCSF and ML approach in terms of accuracy and AUC.

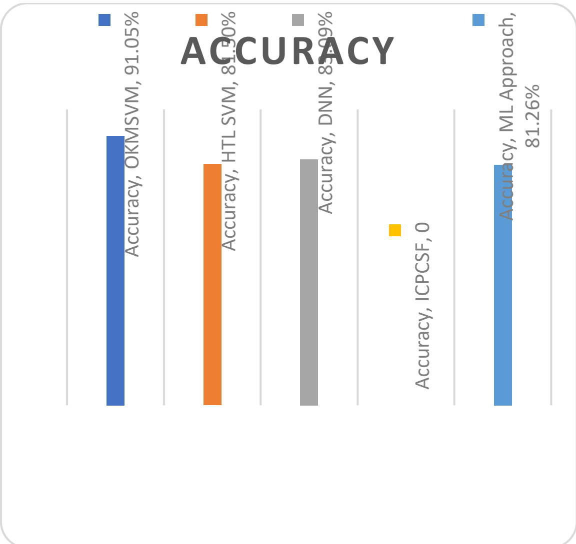

Figure 2 Accuracy comparison of OK-MSVM with popular churn prediction models

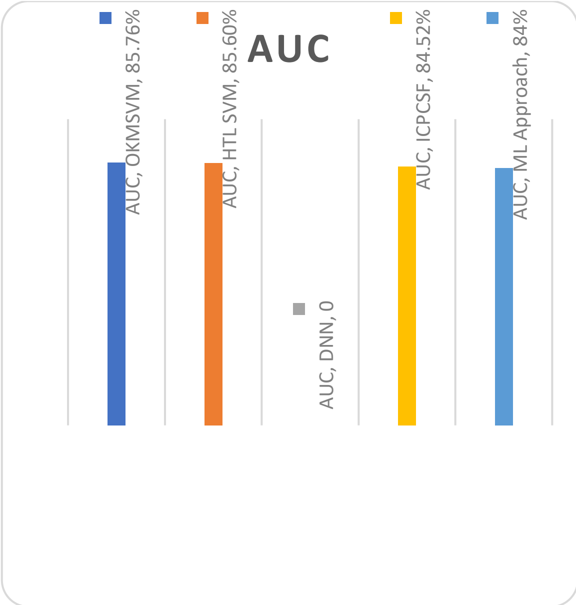

Figure 3AUC comparison of OK-MSVM with popular churn prediction models

As demonstrated in Figs. 2 and 3, the suggested OK-MSVM model outperforms rival models regarding accuracy and AUC.

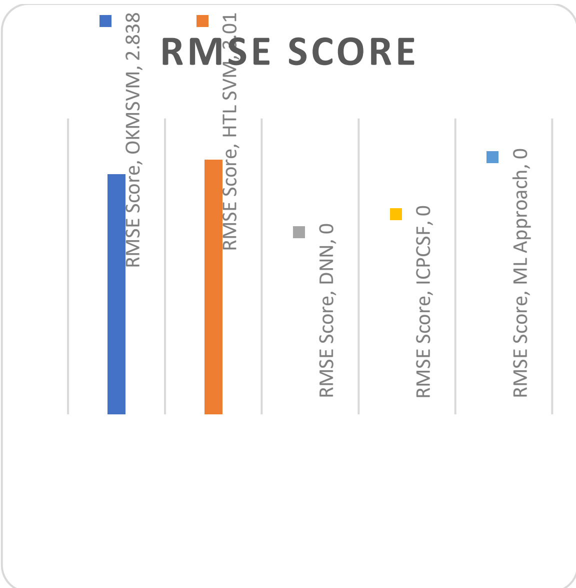

Figure 4RMSE comparison of OK-SVM with popular churn prediction models

Because OK-MSVM optimized the classification model and feature selection was implemented, it contains improved performance measures as compared to existing models such as HTLSVM, DNN,ICPCSF and ML approach.Additionally, ALO reduces the RMSE score to 2.838, reducing the possibility that feature sets may contain errors. Model proposed with all feature sets have better root mean square error rates than existing popular models.

5. Conclusion And Future Work

The CCA (customer churn analysis) system used by the telecommunications sector serves as the foundation for the proposed approach. The KPCA algorithm in the suggested architecture takes care of finding high-throughput mathematical information in the features and carrying out the feature extraction process. The Ant Lion optimizer is used to process the extracted pieces. ALO is a suggested architectural optimization module that lowers the likelihood that feature sets may contain errors. More accuracy in the trained model is provided by the decreased error probability training set. The optimal cost solutions for the input feature models are discovered through an iterative approach. The data is processed with the predictive model initialization module after all the cases have been handled. This module prepares various subsets of the original data set by processing optimal data pieces. The predictive model is trained, validated, and tested using these subsets. The training and label subset of these models is processed in the stage's training module. For running and loading test phases, itintroduces and stores the OKMSVM model in the secondary storage. The test suite loads the training module and test subset before switching to the predictive method used by MSVM. The classification yields the mean squared ratio optimum for the existing models, AUC, and the maximum accuracy rate. Future research will allow for the development of new ML-based and SC (soft computing) techniques that are more dependable for boosting performance measures.Additionally,a prediction framework will be developed to determine those who are most willing to quit.To create forecasting models, many algorithms will be created utilising methods including neural networks, decision trees, andregression analysis. Additionally, the ability to generalize can be determined utilizing various classification and feature selection (FS) techniques, as well as their application to other databases.

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