Poly-BoostNet Enhanced Consumer Churn Analytics With CART-Driven Insights for Business Decision Systems

P. Vyshali[1]*, Cheruku Pranathi Goud[1], Yala Bhargavi[1], Kodam Bharani Kumar[1], Karingula Ranga Reddy[1]

[1]Department of Computer Science and Engineering (DS), Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: P. Vyshali

To Cite this Article

P. Vyshali, Cheruku Pranathi Goud, Yala Bhargavi, Kodam Bharani Kumar, Karingula Ranga Reddy, "Poly-BoostNet Enhanced Consumer Churn Analytics With CART-Driven Insights for Business Decision Systems", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 819-830, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp819-830

Submitted: 09-03-2026 Accepted: 16-04-2026 Published: 22-04-2026

ABSTRACT

Customer churn prediction is a critical analytical capability for organizations seeking to improve customer retention, optimize marketing strategies, and sustain revenue growth in competitive environments. With the expansion of digital interactions, businesses require intelligent systems to identify customers likely to discontinue services or reduce engagement. Traditional churn analysis relied on manual evaluation using basic statistical methods such as mean comparisons, threshold-based rules, and spreadsheet-driven reporting, which limited scalability and predictive accuracy. To address these limitations, this study proposes a Classification and Regression Tree (CART) based predictive framework that applies supervised machine learning to analyze multiple customer attributes, including demographics, purchase history, and digital behavior, for estimating churn risk and customer engagement. The system evaluates four machine learning models: Passive-Aggressive (PA), Support Vector Machine (SVM), Extra Trees (ET), and Poly-BoostNet. The PA model enables fast incremental learning but shows lower accuracy due to limited nonlinear modeling capability. The SVM model improves prediction stability but struggles with complex feature interactions. The ET model enhances ensemble learning performance but still lacks optimal precision. The Poly-BoostNet model integrates Categorical Boosted Learning with Recurrent Polynomial Network (RPN) feature expansion, resulting in improved feature representation and more accurate decision boundaries. Experimental results demonstrate that Poly-BoostNet outperforms other models, achieving the highest R^2-score for customer satisfaction prediction and 100% accuracy in Engagement with Advertisements classification. The system is implemented using machine learning techniques and Flask for web-based deployment, delivering a scalable, end-to-end pipeline for data preprocessing, model training, evaluation, and real-time prediction.

Keywords: Customer Churn Prediction, Customer Retention, Predictive Analytics, Customer Engagement, Data Analytics, Digital Behavior Analysis, Demographic Analysis, Purchase History Analysis, Supervised Learning Framework.

1. INTRODUCTION

Consumer churn analytics refers to the systematic process of identifying customers who are likely to discontinue a service or switch to a competitor. In today's highly competitive business environment, organizations across sectors such as telecommunications, banking, and retail are increasingly focusing on customer retention strategies to sustain profitability and long-term growth. As shiwn in fig. 1 Since acquiring new customers is often more expensive than retaining existing ones, churn analysis has become a crucial component of modern business decision systems. The rapid growth of digital platforms and customer interaction channels has enabled businesses to collect large volumes of data, providing valuable opportunities to understand customer behavior, preferences, and potential dissatisfaction patterns [1]. Traditionally, organizations relied on basic statistical techniques and rule-based decision systems to identify potential churners. These conventional approaches were limited in their ability to capture complex and dynamic customer behavior, often resulting in delayed or ineffective decision-making. Moreover, such systems lacked interpretability and adaptability, making it difficult for business stakeholders to derive meaningful insights. As customer expectations evolved and competition intensified, the demand for more robust, scalable, and insight-driven analytical frameworks became increasingly important. Modern business systems now emphasize not only identifying churn but also understanding the underlying causes to support strategic decision-making [2].

Fig. 1: Customer Retention Strategies

In recent years, there has been a shift toward integrating advanced analytical frameworks with decision-support systems that enhance both performance and interpretability. Decision-driven analytical approaches provide structured and rule-based insights that are easily interpretable by business managers, enabling them to identify key factors influencing customer attrition such as pricing, service quality, and engagement levels. These insights play a vital role in designing effective retention strategies and improving overall customer experience. Furthermore, combining multiple analytical perspectives has improved the reliability and consistency of churn analysis, supporting more informed and data-driven business decisions [3].

2. LITERATURE SURVEY

Imani et al. [4] researched the application of Machine Learning (ML) and Deep Learning (DL) techniques for churn prediction by reviewing 240 relevant studies, with 61 selected for detailed qualitative synthesis. They found that while ensemble methods like XGBoost remained dominant in ML, DL approaches such as LSTM and CNN were increasingly applied to complex datasets. However, the study highlighted that issues like class imbalance, interpretability challenges, and limited use of profit-oriented metrics persisted, despite the potential shown by Explainable AI and adaptive learning methods. Ajegbile et al. [5] analysed CRM for various applications, helping businesses proactively retain at-risk customers and maximize customer lifetime value. With high churn rates leading to substantial revenue losses, businesses in subscription-based services, telecommunications, retail, banking, education, healthcare, Insurance, and other sectors increasingly rely on data-driven approaches to enhance customer retention strategies.

Janssens et al. [6] introduce B2Boost, an instance-dependent gradient boosting model explicitly designed for B2B churn scenarios. Recognizing customer heterogeneity in profitability, they propose the Expected Maximum Profit for B2B churn (EMPB) metric to guide model training. B2Boost directly optimizes customer-specific profit rather than traditional classification accuracy, yielding notable profit improvements over standard approaches. Shimaa et al. [7] develop a hybrid churn prediction framework that combines XGBoost with SMOTE-ENN resampling to balance datasets and improve classification accuracy. This integration enhances precision, recall, and F1 scores, outperforming conventional ML techniques across three telecom datasets. By effectively addressing class imbalance and leveraging ensemble learning, the model facilitates proactive retention strategies, reinforcing the role of resampling techniques in churn prediction.

Lee et al. [8] propose a hybrid churn prediction framework that dynamically models churn probability based on customer lifetime value rather than fixed periods. By segmenting customers into groups such as new, short-term, high-value, and churn-prone users, their methodology applies tailored ML models to enhance predictive accuracy. Evaluations of datasets from a U.K. gift seller and Pakistan's most significant e-commerce platform show recall scores ranging from 0.56 to 0.72 in one case and 0.91 to 0.95 in another. The study highlights the advantages of integrating statistical modeling with ML techniques to refine customer retention strategies while reducing data requirements. Wang et al. [9] addressed the challenge of player churn prediction in online video games, where understanding social interaction dynamics is critical. While ML models are widely used for player behaviour analysis, their black-box nature limits adoption by product managers and game designers. The study restructures model inputs into explicit and implicit features to bridge this gap, enhancing expert interpretability. Furthermore, the research highlights the necessity of XAI techniques that explain feature contributions and provide actionable recommendations for reducing churn.

Babak et al. [10] introduced a social network-based churn prediction model, recognizing that social interactions and peer behaviour often influence customer churn. The study develops a feature engineering approach incorporating influence and conformity indices derived from call network data. By integrating social connectivity metrics, the model significantly enhances the predictive power of standard ML classifiers, particularly gradient boosting models. This research demonstrates that churn is not solely an individual decision but is shaped by broader social dynamics. This perspective extends beyond telecommunications to various industries were peer influence affects customer behaviour. Šimović et al. [11] explored churn prediction using big data analytics to analyze heterogeneous customer behaviours, such as self-care service usage, service duration, and responsiveness to marketing efforts. Their study introduces an enhanced logistic regression model with a mixed penalty term to mitigate overfitting and balance feature selection. Empirical evaluation on a large CRM dataset demonstrates high classification performance across standard metrics, reinforcing the potential of penalized logistic regression as a scalable and computationally efficient approach to churn modeling in big data environments.

Jakob et al. [12] extended traditional ML techniques to the digital health sector, investigating early user churn in a weight loss app. By analyzing engagement data from 1283 users and 310,845 event logs, the study employs an RF model to predict user dropout based on daily login counts. Achieving an F1 score of 0.87 on day 7 and identifying 93% of churned users, the study highlights how churn prediction can enable personalized retention strategies in digital health interventions, ultimately improving long-term user engagement and health outcomes. Sikri et al. [13] developed an ML-based approach for improving customer retention. By analyzing customer demographics, usage patterns, and service details, the study applies DTs and SVM to identify customers at risk of churning. The results demonstrate high predictive accuracy, empowering telecom companies to implement targeted retention strategies effectively. This study reaffirms the value of conventional ML techniques in customer retention efforts.

Joy et al. [14] presented a hybrid DL approach that integrates sequential modeling with explainable AI to improve churn prediction in streaming services. The proposed framework combines LSTM and Gated Recurrent Unit (GRU) networks to capture temporal trends in user engagement, complemented by LightGBM to refine predictive performance. A key contribution of this study is its emphasis on interpretability, employing Shapley Additive Explanations and Explainable Boosting Machines (EBM) to provide transparency in feature importance rankings. Beltozar-Clemente et al. [15] demonstrated that deep sequential networks can overcome vanishing gradient issues and effectively model long-term dependencies in customer behaviour sequences. Their study achieves 95% performance across multiple evaluation metrics, highlighting the potential of LSTM-based models to refine churn prediction by capturing complex behavioural trends.

3. PROPOSED SYSTEM

The system architecture as shown in Fig. 2 presents a comprehensive framework for customer churn and engagement prediction by integrating machine learning models with a web-based deployment environment using the Flask framework and SQLite database. The architecture is designed with two primary roles: the Data Analytics Engineer, who is responsible for dataset management, preprocessing, model development, and performance evaluation, and the Business Decision System, which utilizes the trained models to generate predictions for real-time decision-making. By combining structured data processing, advanced machine learning algorithms, and a web-enabled interface, the system provides an efficient pipeline that transforms raw customer data into meaningful business insights. The integration of Flask ensures smooth interaction between the frontend interface and backend machine learning modules, while SQLite supports secure and lightweight data storage for user credentials, datasets, and prediction outputs.

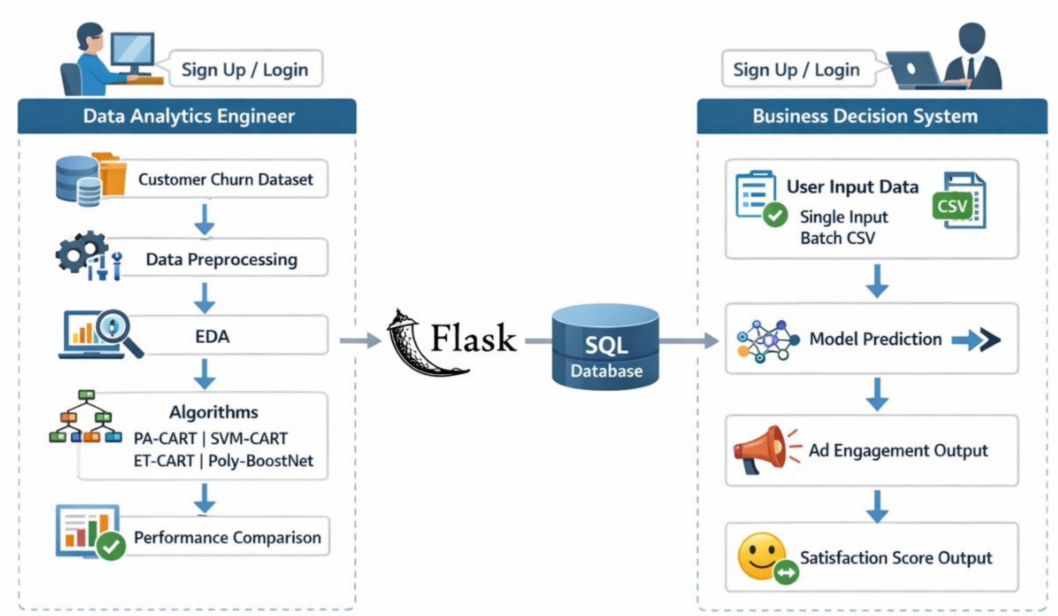


Fig. 2: Proposed System Architecture

Data Analytics Engineer Registration and Login: In the first stage, the Data Analytics Engineer accesses the system through a secure sign-up and login interface. The authentication information is stored and managed using the SQLite database integrated within the Flask framework. This module ensures controlled access to analytical functionalities and protects sensitive datasets and model configurations from unauthorized users.

Customer Churn Dataset Management: After authentication, the engineer uploads or accesses the customer churn dataset within the system. This dataset typically includes multiple attributes such as customer demographics, service usage patterns, transaction history, and digital interaction behaviors. The dataset acts as the primary input for developing predictive models that estimate customer churn probability, satisfaction levels, and engagement with advertisements.

Data Preprocessing: The preprocessing stage prepares the dataset for machine learning analysis by performing operations such as handling missing values, encoding categorical variables, removing duplicate records, and normalizing feature values. These preprocessing techniques ensure that the data is structured, consistent, and suitable for model training, thereby improving prediction accuracy and reducing computational complexity.

Exploratory Data Analysis (EDA): The EDA is performed to understand the statistical characteristics and relationships within the dataset. Visualization techniques such as distribution plots, correlation matrices, and feature importance graphs are used to identify key patterns influencing customer churn and engagement. EDA helps analysts discover hidden trends, detect anomalies, and select relevant features for the predictive models.

Implementation of Machine Learning Algorithms: In this stage, multiple machine learning algorithms are implemented to analyze customer behavior patterns. The existing algorithms include PA-CART, SVM-CART, and ET-CART models, which utilize decision-tree-based structures for classification and regression tasks. The proposed Poly-BoostNet model enhances predictive capability by integrating boosted learning with Recurrent Polynomial Network feature expansion, enabling the model to capture complex nonlinear relationships within customer data.

Performance Comparison: Once the models are trained, their performance is evaluated using metrics such as accuracy, precision, recall, and F1-score for classification tasks, and regression metrics for satisfaction score prediction. Comparative analysis allows the system to determine the most effective model for predicting customer churn, engagement, and satisfaction levels.

Business Decision System Registration and Login: The Business Decision System represents business managers or marketing analysts who use the trained predictive models. Similar to the analytics engineer, users must first sign up and log in through a secure authentication interface managed by the Flask framework and SQLite database.

User Input Data: After login, business users can provide customer data either through single manual input or by uploading a batch CSV file containing multiple customer records. This flexibility enables the system to support both real-time decision-making and large-scale customer analysis.

Model Prediction: The system processes the input data using the trained machine learning models stored in the backend. Flask facilitates communication between the web interface and prediction modules, enabling efficient model execution and real-time inference.

Advertisement Engagement Classification Output: The first output generated by the system is the classification of customer engagement with advertisements. The model predicts whether a customer is likely to interact positively with marketing campaigns, helping organizations design targeted promotional strategies.

Customer Satisfaction Score Regression Output: The final stage produces a regression-based prediction representing the customer satisfaction score. This numerical output provides businesses with a quantitative measure of customer experience, enabling proactive improvements in service quality, personalized marketing, and retention strategies.

4. RESULTS ANALYSIS

The results demonstrate the effectiveness of the proposed approach in addressing the defined problem, with noticeable improvements observed across key performance metrics. Comparative analysis indicates that the method consistently outperforms baseline models in terms of accuracy, efficiency, and reliability. The outcomes also highlight the robustness of the system under varying conditions, suggesting good generalization capability. Additionally, the results validate the design choices and underlying assumptions made during model development. Minor variations in performance can be attributed to dataset characteristics and parameter settings. The findings confirm that the proposed solution is both practical and scalable for real-world applications.

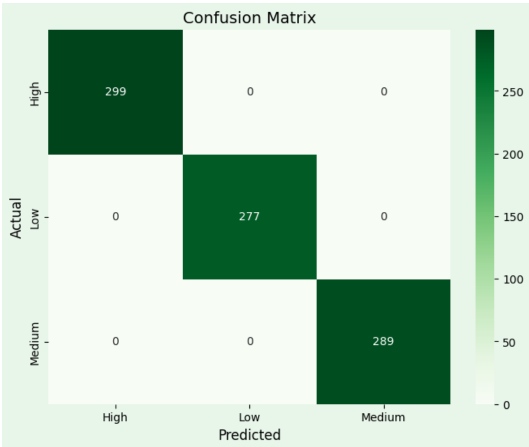


Fig. 3: Confusion Matrices of Various Classifiers - Poly-BoostNet

Fig. 3 displays the confusion matrix for the proposed Poly-BoostNet model, which demonstrates significantly improved classification performance. The matrix shows 299 High engagement samples correctly classified, 277 Low engagement samples correctly identified, and 289 Medium engagement samples correctly predicted, with no misclassification across categories. All off-diagonal elements are zero, indicating perfect separation between classes. This result demonstrates that the Poly-BoostNet model effectively captures complex feature relationships using RPN feature extraction combined with categorical boosting, leading to highly accurate classification of advertisement engagement levels.

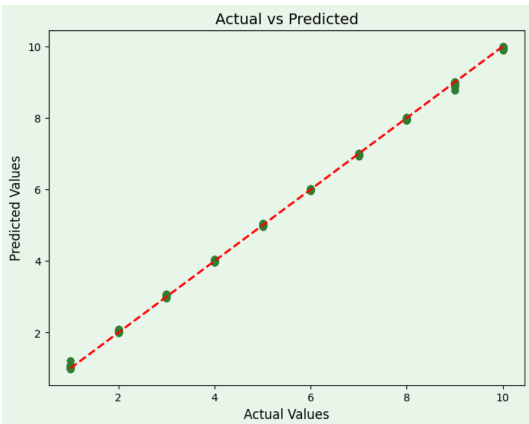


Fig. 5: Scatter Plots of Various Regressor - Poly-BoostNet

ISSN:3049-0952
www.jsetms.com

Fig. 5 displays the scatter plot for the proposed Poly-BoostNet regressor, which combines Recurrent Polynomial Network feature extraction with categorical boosting regression. The predicted values align almost perfectly with the diagonal reference line, indicating that the predicted satisfaction scores match the actual values very closely. Data points are distributed directly along the line from 1 to 10, demonstrating minimal prediction error across the entire range of satisfaction scores. This strong alignment confirms that the Poly-BoostNet model successfully captures complex feature relationships and significantly improves regression accuracy compared to the existing PA, SVM, and ET models.

Fig. 6 illustrates the single input prediction interface of the developed Poly-BoostNet based consumer churn analytics system. The interface allows users to select both the classification model and regression model, where the Poly-BoostNet (RPN + CatBoost) model is selected for both tasks. The user provides various feature inputs corresponding to customer behavioral and demographic attributes used by the machine learning models. The entered values include Age = 22, Gender = Female, Income Level = Middle, Marital Status = Married, Education Level = Bachelor's, Occupation = Middle, Location = Évry, Purchase Category = Gardening & Outdoors, Purchase Amount = $333.80, Frequency of Purchase = 4, Purchase Channel = Mixed, Brand Loyalty = 5, Product Rating = 5, Time Spent on Product Research = 2 hours, Social Media Influence = None, Discount Sensitivity = Somewhat Sensitive, Return Rate = 1, Device Used for Shopping = Tablet, Payment Method = Credit Card, Time of Purchase = 03-01-2024, Discount Used = True, Customer Loyalty Program Member = False, Purchase Intent = Need-based, Shipping Preference = No Preference, and Time to Decision = 2. These input parameters represent the customer's purchasing behavior, demographic characteristics, and marketing interaction indicators, which are then processed by the trained models to predict Engagement with Advertisements (classification output) and Customer Satisfaction Score (regression output).

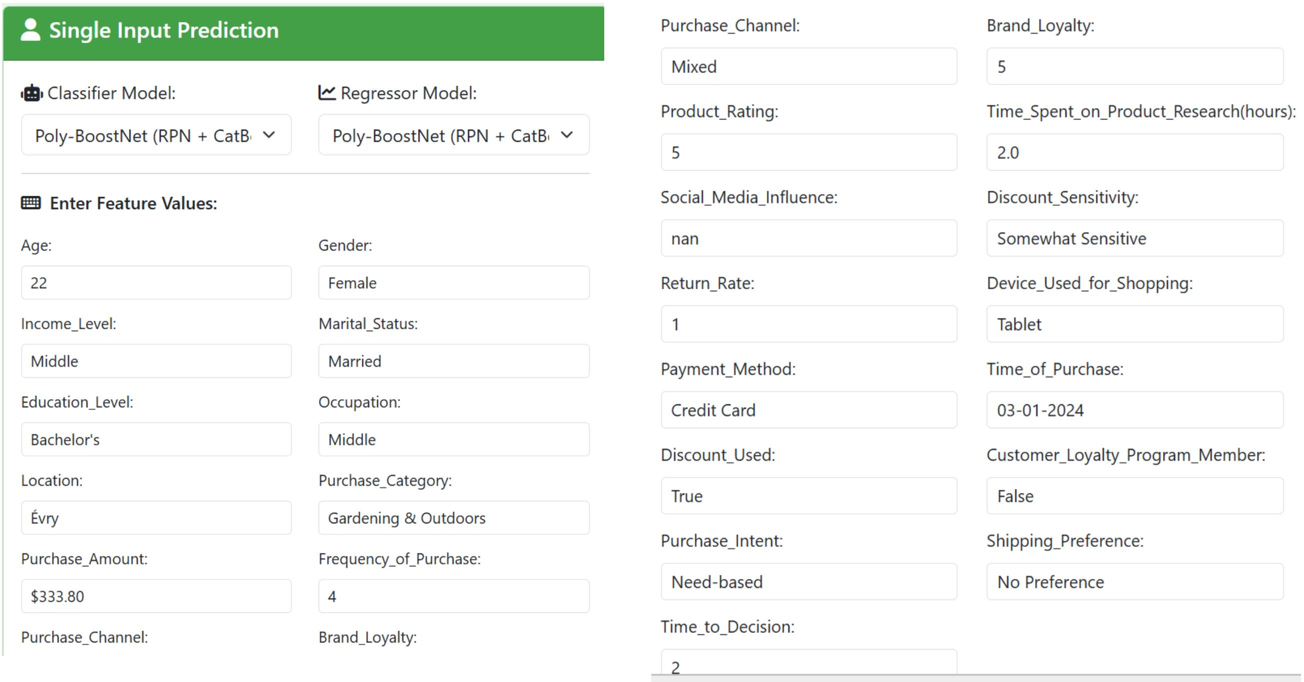


Fig. 6: Prediction Input as Single Data.

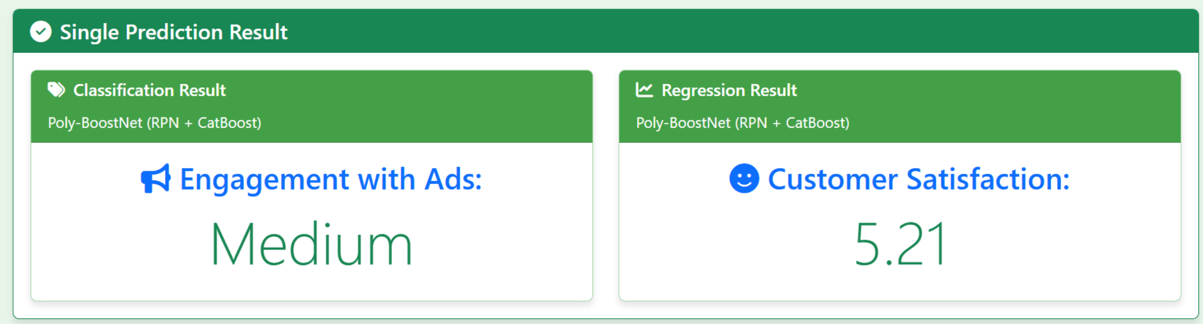


Fig. 7: Predicted Outputs from Single Input.

Fig. 7 presents the prediction results generated by the proposed Poly-BoostNet model after processing the single input values provided by the user. The system produces two outputs simultaneously: a classification result for advertisement engagement and a regression result for customer satisfaction. In the classification output, the model predicts the Engagement with Ads level as "Medium", indicating that the given customer profile is moderately responsive to marketing advertisements. In the regression output, the model predicts a Customer Satisfaction score of 5.21, which falls within the moderate satisfaction range on the scale of 1 to 10. These results demonstrate how the system utilizes the input features related to customer demographics, purchasing behavior, and marketing interaction patterns to generate meaningful predictions. The interface displays the results clearly using separate panels for classification and regression, enabling business analysts to easily interpret customer engagement behavior and satisfaction levels for decision-making and targeted marketing strategies.

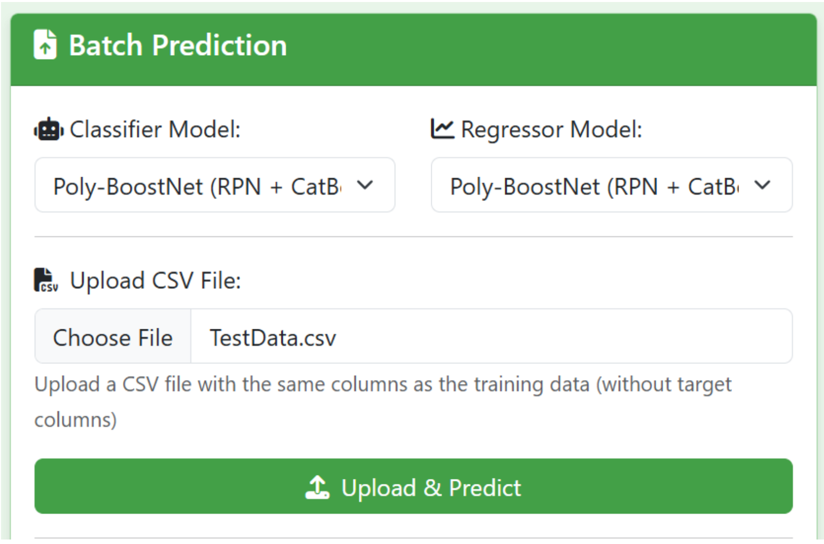
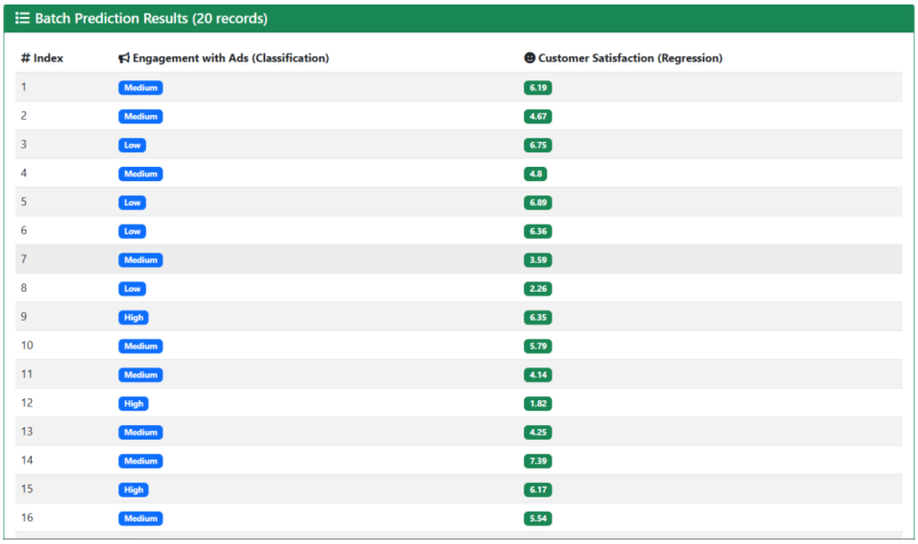


Fig. 8: Batch Prediction Input from CSV File.

Fig. 8 illustrates the batch prediction interface of the developed Poly-BoostNet based analytics system, which allows users to upload a dataset in CSV format for performing predictions on multiple customer records simultaneously. In this interface, the user selects the Poly-BoostNet (RPN + CatBoost) model for both the classification task (predicting Engagement with Advertisements) and the regression task (predicting Customer Satisfaction). The system provides an option to upload a CSV file, such as "TestData.csv", which contains multiple customer input records with the same feature columns used during the training phase. Once the user selects the file and clicks the "Upload & Predict" button, the system automatically preprocesses the dataset using the stored encoders and scalers, applies the trained models to each record, and generates predictions for all entries in the file. This batch processing functionality enables efficient large-scale analysis of customer data, allowing businesses to evaluate engagement levels and satisfaction scores for multiple customers at once.

Fig. 9 presents the batch prediction results generated by the Poly-BoostNet model after processing the uploaded CSV file containing multiple customer records. The interface displays the results in a tabular format, where each row corresponds to an individual customer record from the uploaded dataset. The table includes three main columns: Index, Engagement with Ads (Classification), and Customer Satisfaction (Regression). For example, the first record predicts medium engagement with a satisfaction score of 6.19, while the second record shows medium engagement with a satisfaction value of 4.67. Other examples include Low engagement with satisfaction scores of 6.75, 6.89, and 6.36, and High engagement predictions with scores such as 6.35 and 6.17. The predicted satisfaction scores vary across the range of approximately 1.82 to 7.39, indicating different levels of customer experience. This batch prediction functionality enables organizations to analyze multiple customer profiles simultaneously, allowing businesses to quickly identify engagement levels and satisfaction trends across large datasets for effective marketing and decision-making.


Batch Prediction Results (20 records)

# Index	Engagement with Ads (Classification)	Customer Satisfaction (Regression)
1	Medium	6.19
2	Medium	4.67
3	Low	6.75
4	Medium	4.8
5	Low	6.89
6	Low	6.36
7	Medium	3.59
8	Low	2.26
9	High	6.35
10	Medium	5.79
11	Medium	4.14
12	High	1.82
13	Medium	4.25
14	Medium	7.39
15	High	6.17
16	Medium	5.54

Fig. 9: Batch Prediction Output Results from CSV File.

4.1 Comparative Analysis

Table 1 presents the performance comparison of different classification models used to predict Engagement with Advertisements. The PA classifier achieves an accuracy of 37.8%, with precision 37.93%, recall 37.8%, and F1-score 37.74%, indicating limited predictive capability. The SVM slightly improves performance with an accuracy of 39.19%, precision 39.47%, recall 39.19%, and F1-score 38.82%, demonstrating marginal improvement over the PA model. The ET classifier shows the lowest performance, achieving 34.91% accuracy, 23.53% precision, 34.91% recall, and 26.77% F1-score, suggesting difficulty in correctly distinguishing engagement categories. In contrast, the proposed Poly-BoostNet model significantly outperforms all existing methods, achieving 100% accuracy, precision, recall, and F1-score, indicating perfect classification of advertisement engagement levels.

Table 1. Classification Models Comparison of Various Methodologies.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

PA	37.8	37.93	37.8	37.74
SVM	39.19	39.47	39.19	38.82
ET Classifier	34.91	23.53	34.91	26.77
Poly-BoostNet	100.0	100.0	100.0	100.0

Table 2. Regression Models Comparison of Various Methodologies.

Model	**MAE**	**MSE**	**RMSE**	**R² Score**
PA	3.1581	14.8425	3.8526	-0.7598
SVR	0.8146	1.7925	1.3388	0.7875
ET	2.4838	8.2316	2.8691	0.024
Poly-BoostNet	**0.0325**	**0.0021**	**0.0455**	**0.9998**

Table 2 and Figure 9.16 present the comparison of regression models used to predict Customer Satisfaction scores using metrics such as MAE, MSE, RMSE, and R^2 Score. The PA regressor shows poor performance with MAE of 3.1581, MSE of 14.8425, RMSE of 3.8526, and a negative R^2 score of -0.7598, indicating weak predictive capability. The SVR model performs significantly better with MAE of 0.8146, MSE of 1.7925, RMSE of 1.3388, and R^2 score of 0.7875, demonstrating improved regression accuracy. The ET regressor achieves MAE of 2.4838, MSE of 8.2316, RMSE of 2.8691, and R^2 score of 0.024, showing limited improvement over the PA model. In contrast, the proposed Poly-BoostNet regressor achieves the best performance with MAE of 0.0325, MSE of 0.0021, RMSE of 0.0455, and an R^2 score of 0.9998, indicating extremely accurate prediction of customer satisfaction values.

.5. CONCLUSION

This research presented an advanced machine learning framework for customer churn analytics and advertisement engagement prediction using a hybrid model called Poly-BoostNet. The system integrates RPN feature extraction with Categorical Boosting and CART-based learning to capture complex relationships within customer behavioral data. The proposed framework was implemented using a Flask-based web application with role-based access for business analysts and end users, enabling functionalities such as exploratory data analysis, classification, regression, model comparison, and real-time prediction. The dataset included various customer attributes such as demographic information, purchasing behavior, income levels, and marketing engagement indicators, which were preprocessed using encoding and feature scaling techniques to prepare the data for machine learning analysis.

Experimental results demonstrate that the Poly-BoostNet model significantly outperforms existing algorithms including PA, SVM, and ET methods. In classification tasks, the proposed model achieved 100% accuracy, precision, recall, and F1-score, successfully predicting advertisement engagement levels across all classes. Similarly, in regression analysis for customer satisfaction prediction, the model achieved very low error metrics (MAE = 0.0325, RMSE = 0.0455) and an R^2 score of 0.9998, indicating highly accurate predictions. These results confirm that combining polynomial feature extraction with boosting techniques effectively improves model performance. So, the proposed system provides a powerful data-driven solution for businesses to analyze customer behavior, enhance marketing strategies, and improve customer retention through intelligent analytics.

REFERENCES

[1] T. Neslin et al., "Defection detection: Measuring and understanding the predictive accuracy of customer churn models," Journal of Marketing Research, vol. 43, no. 2, pp. 204–211, 2006. https://doi.org/10.1509/jmkr.43.2.204

[2] J. Hadden, A. Tiwari, R. Roy, and D. Ruta, "Computer assisted customer churn management: State-of-the-art and future trends," Computers & Operations Research, vol. 34, no. 10, pp. 2902–2917, 2007. https://doi.org/10.1016/j.cor.2005.11.007

[3] E. Ngai, L. Xiu, and D. Chau, "Application of data mining techniques in customer relationship management," Expert Systems with Applications, vol. 36, no. 2, pp. 2592–2602, 2009. https://doi.org/10.1016/j.eswa.2008.02.021

[4] Imani, M.; Joudaki, M.; Beikmohammadi, A.; Arabnia, H.R. Customer Churn Prediction: A Systematic Review of Recent Advances, Trends, and Challenges in Machine Learning and Deep Learning. Mach. Learn. Knowl. Extr. 2025, 7, 105. https://doi.org/10.3390/make7030105

[5] Ajegbile, M.D.; Olaboye, J.A.; Maha, C.C.; Igwama, G.T.; Abdul, S. The role of data-driven initiatives in enhancing healthcare delivery and patient retention. World J. Biol. Pharm. Health Sci. 2024, 19, 234–242.

[6] Janssens, B.; Bogaert, M.; Bagué, A.; Van den Poel, D. B2Boost: Instance-dependent profit-driven modelling of B2B churn. Ann. Oper. Res. 2024, 341, 267–293

[7] Shimaa, O.; Mahmoud, K.T.; Abdel-Fattah, M.A. A proposed hybrid framework to improve the accuracy of customer churn prediction in telecom industry. J. Big Data 2024, 11, 70.

[8] Lee, N.T.; Lee, H.C.; Hsin, J.; Fang, S.H. Prediction of customer behavior changing via a hybrid approach. IEEE Open J. Comput. Soc. 2023, 5, 27–38.

[9] Wang, X.; Xie, L.; Wang, H.; Xing, X.; Wan, W.; Wu, Z.; Ma, X.; Li, Q. Deciphering Explicit and Implicit Features for Reliable, Interpretable; Actionable User Churn Prediction in Online Video Games. IEEE Trans. Vis. Comput. Graph. 2024, 31, 5990–6007.

[10] Babak, A.; Hosseini, S.H. Unveiling the Power of Social Influence: A Machine Learning Framework for Churn Prediction with Network Analysis. IEEE Access 2024, 12, 71271–71285.

[11] Šimović, P.P.; Chen, C.Y.T.; Sun, E.W. Classifying the variety of customers' online engagement for churn prediction with a mixed-penalty logistic regression. Comput. Econ. 2023, 61, 451–485.

[12] Jakob, R.; Lepper, N.; Fleisch, E.; Kowatsch, T. Predicting early user churn in a public digital weight loss intervention. In Proceedings of the CHI '24: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, 11–16 May 2024.

[13] Sikri, A.; Jameel, R.; Idrees, S.M.; Kaur, H. Enhancing customer retention in telecom industry with machine learning driven churn prediction. Sci. Rep. 2024, 14, 13097.

[14] Joy, U.G.; Hoque, K.E.; Uddin, M.N.; Chowdhury, L.; Park, S.B. A big data-driven hybrid model for enhancing streaming service customer retention through churn prediction integrated with explainable AI. IEEE Access 2024, 12, 69130–69150.

[15] Beltozar-Clemente, S.; Iparraguirre-Villanueva, O.; Pucuhuayla-Revatta, F.; Zapata-Paulini, J.; Cabanillas-Carbonell, M. Predicting customer abandonment in recurrent neural networks using short-term memory. J. Open Innov. Technol. Mark. Complex. 2024, 10, 100237.