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Predicting Customer Intent for Enhanced Support in the Telecommunications Industry Using Machine Learning

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Abstract: In the competitive telecommunications sector, accurately predicting customer intent is pivotal for improving service delivery, reducing operational costs, and enhancing customer satisfaction. This research introduces a machine learning-based framework that combines natural language processing (NLP) with behavioral analytics to identify customer intents such as billing inquiries, technical support, service upgrades, and potential churn. The framework processes structured and unstructured data from customer interactions, including call center transcripts, chatbot conversations, CRM data, and network usage logs. By leveraging state-of-the-art models like BERT and BiLSTM, the system achieves high precision in multi-label classification tasks. The proposed approach demonstrates that accurate intent prediction allows telecom operators to proactively resolve issues, personalize customer engagement, and implement timely retention strategies, thus providing a significant competitive advantage.

Keywords: *retention, engagement, BERT, significant*

1. Introduction

In today's data-driven environment, customer experience (CX) is a critical differentiator for telecommunications companies. The ability to identify and understand a customer's intent what the customer aims to achieve in their interaction with the service provider is essential for delivering proactive support and ensuring long-term loyalty. Traditional customer service systems react only after a customer presents a problem, often resulting in delayed responses and suboptimal satisfaction. This paper aims to develop a predictive framework that infers customer intent in real-time to preemptively address queries, reduce customer frustration, and optimize support operations.

2. Literature Review

Prior studies on customer intent prediction have primarily focused on domains such as e-commerce and conversational AI. Research by Devriendt et al. emphasized the role of uplift models over traditional churn prediction, while Ullah et al. demonstrated that ensemble methods like Random Forest improve predictive performance in telecom churn scenarios. Other works have explored customer segmentation, sentiment analysis, and real-time analytics for customer interaction data. However, few studies have integrated cross-domain features textual, behavioral, and transactional data for telecom-specific intent classification. This gap motivates the present work, which proposes a hybrid model tailored to telecom datasets and operational workflows.

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3. Methodology

3.1 Data Acquisition: Data sources include call center speech-to-text logs, chatbot interactions, billing history and CRM metadata, web/app clickstream behavior, and service usage records (calls, SMS, data).

3.2 Preprocessing: All text data undergo cleaning (lowercasing, punctuation removal), lemmatization, and tokenization. Numeric features are normalized and missing values imputed. Categorical data is encoded.

3.3 Intent Taxonomy & Labeling: Intents include "Billing Query," "Technical Issue," "Upgrade Request," "Churn Intent," etc., labeled via manual and semi-automated methods.

3.4 Feature Engineering: Includes tenure, ARPU, complaint frequency, payment behavior, and demographics.

3.5 Model Training & Evaluation: Models tested include Logistic Regression, Random Forest, BiLSTM, and BERT. Evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. SMOTE and grid search applied.

4. Results

BERT outperformed other models with a macro-F1 score of 93%. BiLSTM followed closely. Confusion matrix analysis indicated strong performance across major intent classes, and SMOTE improved results on minority classes. Important predictors included service tenure, monthly charges, and textual sentiment.

5. Applications and Use Cases

- Smart Routing: Intent-based routing reduces response time.

- Personalized Responses: Bots suggest next actions based on inferred intent.

- Retention Management: Early churn detection enables targeted offers.

- Knowledge Base Enhancement: Frequent intents guide content updates.

6. Discussion

Integrating NLP with structured metadata improves prediction accuracy. However, challenges include multilingual and code-mixed inputs, and audio-to-text accuracy. Future work includes ensemble transformers, emotion detection, and continuous retraining.

7. Conclusion

This research confirms the viability of using machine learning—particularly BERT—for accurate customer intent prediction in telecom. The system enables proactive, personalized service strategies that enhance customer experience and reduce churn, laying the groundwork for intelligent, AI-driven support ecosystems.

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