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A Context-Aware ELECTRA-Based Dual-Output Framework for Intelligent Mobile Review Title and Rating Prediction

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Abstract

The increasing popularity of mobile applications has resulted in a substantial growth in user-generated reviews and ratings, making them valuable resources for evaluating customer satisfaction and application quality. These reviews contain important information regarding user experiences, feature requests, software performance, and overall product perception. However, manually analysing large volumes of textual feedback is labour-intensive, inconsistent, and incapable of efficiently processing continuously growing datasets. Furthermore, conventional review analysis methods often struggle to capture contextual semantics and handle imbalanced rating distributions, leading to reduced prediction accuracy. To overcome these challenges, this research proposes an intelligent dual-target classification framework for mobile user reviews and ratings. The proposed system initially performs comprehensive Natural Language Processing (NLP) preprocessing and Exploratory Data Analysis (EDA) to improve data quality and examine the characteristics of the review dataset. Subsequently, Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) is employed to generate contextual feature representations that preserve semantic relationships within user reviews. To alleviate class imbalance, the K-Means Synthetic Minority Over-Sampling Technique (K-Means SMOTE) is utilized to generate representative samples for minority classes, thereby improving model generalization. The extracted features are then processed using an Extra Trees Classifier (ETC) to simultaneously predict review titles and corresponding user ratings. Comparative analysis with Adaptive Boosting Classifier (ABC) and Tao Tree Classifier (TTC) demonstrates that the proposed framework achieves superior predictive performance. The developed system provides an efficient and scalable solution for automated mobile review analysis, enabling organizations to understand customer opinions, monitor application quality, and support data-driven product improvement strategies.

Keywords: Adaptive Boosting Classifier (ABC), Exploratory Data Analysis (EDA), Extra Trees Classifier (ETC), K-Means Synthetic Minority Over-Sampling Technique (K-Means SMOTE), Natural Language Processing (NLP).

1. Introduction

The rapid advancement of smartphone technology has significantly transformed consumer purchasing behavior, making online reviews and ratings one of the most influential sources of product information. Before purchasing a mobile device, customers increasingly rely on the experiences shared by existing users to evaluate product quality, performance, reliability, and overall satisfaction. Consequently, user-generated reviews have become valuable assets for manufacturers, retailers, and service providers seeking to understand customer expectations and improve product quality. As the number of reviews

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continues to increase across various digital platforms, extracting meaningful information from this unstructured textual data has become an important research challenge.

India has emerged as one of the world's largest smartphone markets, with hundreds of millions of active users contributing reviews through e-commerce platforms and dedicated mobile marketplaces. The widespread adoption of online shopping has further accelerated the generation of customer feedback, where users express their experiences through detailed textual reviews accompanied by numerical ratings. These reviews contain valuable information regarding device performance, software quality, hardware reliability, customer satisfaction, and overall user perception. Efficient analysis of this information enables organizations to identify customer preferences, detect product limitations, and develop effective business strategies for improving customer experience.

The relationship between textual reviews and numerical ratings provides an opportunity to understand customer opinions more comprehensively. While ratings provide a quantitative measure of customer satisfaction, textual reviews explain the underlying reasons behind those ratings by expressing user emotions, expectations, and experiences. NLP enables intelligent processing of these large collections of customer reviews by transforming unstructured textual information into meaningful representations suitable for automated analysis. Such analysis assists organizations in understanding customer sentiment, evaluating product performance, and identifying factors that influence customer satisfaction.

Despite considerable progress in review analytics, accurately predicting customer opinions and ratings remains challenging because mobile reviews often contain informal language, contextual expressions, ambiguous statements, and uneven class distributions. Traditional review analysis techniques frequently struggle to capture semantic relationships within customer feedback while maintaining consistent classification performance across multiple output categories. Therefore, there is a growing need for intelligent dual-target prediction frameworks capable of simultaneously analyzing review content and rating information. Such systems provide valuable decision-support tools for product improvement, customer engagement, marketing optimization, and informed purchasing decisions while enhancing the overall quality of mobile commerce services.

2. Literature Survey

Li, et al. [1] proposed a two-stage nonlinear User Satisfaction Decision Model (USDM) for predicting customer satisfaction using online product reviews. The framework initially employed Word2Vec together with lexicon-based sentiment analysis to determine the sentiment polarity associated with individual product attributes. Subsequently, KANO mapping rules and utility functions were incorporated to categorize customer preferences according to attribute importance. A genetic algorithm was developed to optimize the proposed model using review data collected from JD.com. Pu, et al. [2] introduced a multi-task learning framework for stance detection by integrating sentiment analysis into the learning process. Alabdan, et al. [3] presented a comprehensive review of phishing attack techniques by examining traditional, modern, and emerging attack strategies. The study analysed the characteristics of different phishing methods while discussing existing prevention mechanisms and security awareness approaches.

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Pota, et al. [4] proposed a two-stage sentiment analysis approach for Twitter data. Initially, tweet-specific expressions, including emojis and emoticons, were transformed into plain textual content using language-independent preprocessing techniques. The normalized tweets were subsequently classified using a BERT language model that had been pretrained on standard text corpora rather than Twitter-specific data.

Borna, et al. [5] investigated the role of artificial intelligence in supporting informal caregivers through a systematic review conducted according to the PRISMA 2020 guidelines. The analysis covered studies published between 2012 and 2023 that employed various AI techniques, with machine learning being the most widely adopted approach. Performance evaluations reported classification accuracies ranging from 71.60% to 99.33%, highlighting the capability of AI systems to provide adaptive assistance, improve caregiver effectiveness, and enhance overall well-being despite differences in implementation methodologies. Allouch, et al. [6] presented a comprehensive review of Conversational Agents (CAs) by examining the core technologies responsible for enabling intelligent human-computer interaction. The study discussed the integration of NLP, deep learning, and emotion-aware computing techniques that support continuous and natural conversations. Chen, et al. [7] investigated the application of artificial intelligence for understanding emotional responses in interactive installation art. The study explored the relationship between affective computing, sensory stimulation, multi-dimensional interaction, and user engagement to establish a conceptual framework for emotion recognition.

Leo, et al. [8] presented a detailed survey of computer vision techniques for facial cue analysis in healthcare applications. Instead of focusing solely on complete facial recognition, the review systematically analyzed individual facial components, including the eyes, mouth, muscles, skin, and facial shape. García-Madurga, et al. [9] conducted a systematic literature review to examine the role of artificial intelligence in promoting workplace well-being. Following the PRISMA guidelines, the authors analyzed studies retrieved from the Scopus and Web of Science databases, ultimately selecting 31 relevant publications. Silva, et al. [10] reviewed the utilization of ontologies and knowledge graphs in cancer research by analyzing 141 published studies. The selected works were organized into fourteen hierarchical categories according to their application of semantic technologies.

3. Proposed Methodology

The proposed dual-target mobile review analysis framework is designed to simultaneously predict review titles and user ratings by integrating advanced text processing, contextual feature extraction, class balancing, and ensemble learning techniques. The overall architecture of the proposed framework is illustrated in Figure 1. The methodology consists of five major phases: review preprocessing and exploratory analysis, contextual feature extraction, data balancing, dual-target classification, and performance evaluation. Each stage contributes to improving the accuracy and robustness of the proposed prediction framework.

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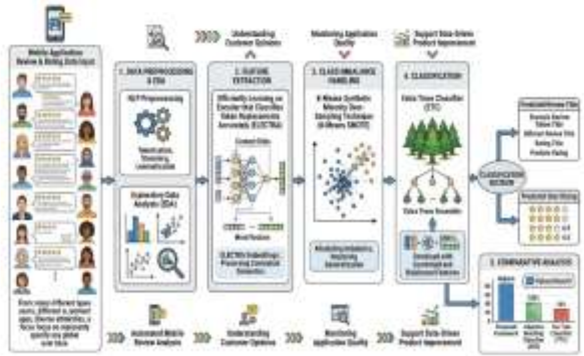

Figure. 1: Proposed system architecture for intelligent mobile review title and rating prediction

Dataset Collection: The first step of the proposed system involves collecting raw customer reviews for the Review Preprocessing and Exploratory Analysis

Mobile application reviews generally contain informal writing styles, abbreviations, spelling variations, punctuation symbols, and redundant textual information that may reduce prediction performance. To improve data quality, the proposed framework first applies a comprehensive preprocessing pipeline. The review text is normalized by converting all characters into lowercase, followed by the removal of punctuation marks, special symbols, and unnecessary white spaces. Tokenization is then performed to divide each review into meaningful textual units, while label encoding transforms categorical review titles and rating labels into numerical representations suitable for machine learning models. After preprocessing, EDA is conducted to examine the characteristics of the dataset. Statistical summaries and graphical visualizations are generated to analyze review distributions, rating frequencies, review lengths, and class imbalance, providing a comprehensive understanding of the dataset before model training.

Contextual Feature Extraction Using ELECTRA

Following preprocessing, the cleaned review text is processed using ELECTRA to obtain contextual feature representations. Unlike conventional text representation methods that rely on frequency statistics, ELECTRA learns contextual relationships by distinguishing replaced tokens from original tokens during pretraining. This enables the model to capture semantic dependencies, linguistic structures, and contextual information embedded within customer reviews. The generated feature vectors provide rich representations of user opinions, enabling the classifier to distinguish subtle differences among various review patterns and rating categories.

Data Balancing Using K-Means SMOTE

Real-world review datasets often contain unequal distributions among different rating classes, causing classification models to become biased toward majority categories. To overcome this limitation, K-Means SMOTE is incorporated into the proposed framework. Initially, K-Means clustering partitions the feature space into homogeneous regions, after which synthetic minority samples are generated within each cluster. This strategy preserves the local data structure while improving the representation of underrepresented classes. As a result, the learning algorithm becomes more robust and achieves improved prediction performance across all review categories.

Dual-Target Classification Using ETC

The balanced contextual feature vectors are subsequently supplied to the ETC for simultaneous prediction of review titles and customer ratings. The classifier constructs multiple randomized decision trees and combines their outputs to improve prediction

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stability and reduce variance. By exploiting ensemble learning, the proposed framework effectively captures nonlinear relationships between review content and the corresponding output variables. Unlike single-target classification models, the proposed architecture performs dual-target learning by generating predictions for both review titles and numerical ratings within a unified framework. This enables comprehensive understanding of customer opinions while maintaining high predictive accuracy and computational efficiency.

Performance Evaluation

The effectiveness of the proposed framework is assessed through a comparative evaluation against conventional classifiers, including ABC and TTC. The dataset is divided into training and testing subsets to validate the generalization capability of the proposed model. Performance is measured using Accuracy, Precision, Recall, F1-Score, and Mean Absolute Error (MAE) for the respective prediction tasks. In addition, confusion matrices, receiver operating characteristic curves, and other graphical analyses are employed to examine classification performance across different review categories. Experimental results demonstrate that integrating ELECTRA, K-Means SMOTE, and ETC significantly improves the prediction of review titles and user ratings, making the proposed framework suitable for intelligent mobile review analytics and real-world deployment.

3.1 ELECTRA

The effectiveness of any review analysis system largely depends on its ability to understand the contextual meaning of customer feedback. To achieve this, the proposed framework employs ELECTRA as the primary feature extraction model because of its efficient pretraining strategy and strong capability to learn semantic relationships from textual data. Unlike conventional transformer models that reconstruct masked words during training, ELECTRA adopts a discriminative learning mechanism that identifies whether individual tokens within a sentence are original or artificially substituted. This learning strategy enables the model to utilize every input token during training, resulting in improved computational efficiency.

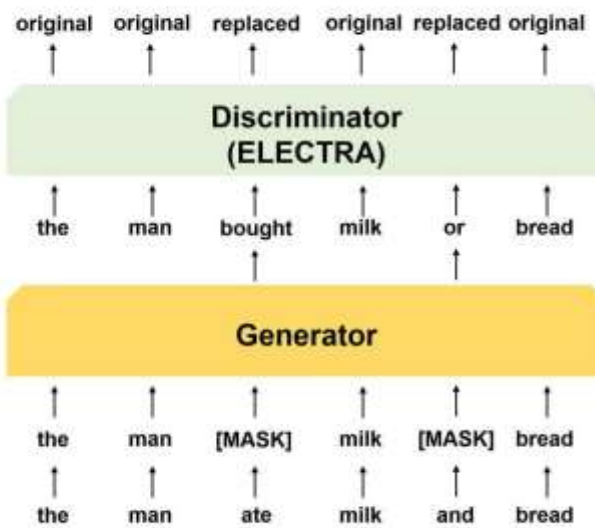

Figure 2: ELECTRA architecture generator discriminator based contextual feature extraction framework

The ELECTRA framework consists of two interconnected components: the Generator and the Discriminator, as illustrated in Figure 2. Initially, the input review sentence is tokenized, and a subset of tokens is randomly selected for replacement. The Generator predicts suitable alternatives for these selected positions, producing a modified sequence that closely resembles natural language. This newly generated sequence is subsequently supplied to the Discriminator, whose objective is to determine whether each token originates from the original sentence or has been replaced by the Generator. Instead of reconstructing missing

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words, the Discriminator performs binary classification for every token, allowing it to learn contextual dependencies across the entire sentence more effectively.

The interaction between these two components enables ELECTRA to capture both syntactic and semantic characteristics embedded within customer reviews. By learning from authentic and replaced tokens simultaneously, the model develops contextual feature representations capable of identifying opinion expressions, linguistic dependencies, contextual variations, and subtle sentiment patterns that may not be recognized by conventional feature extraction techniques. The Generator is utilized only to create meaningful replacement tokens during pretraining, whereas the Discriminator receives the majority of the optimization process, making the overall architecture computationally efficient without compromising representation quality.

In the proposed framework, the contextual representations generated by ELECTRA are used as the input features for the subsequent classification stage. These feature vectors preserve the semantic meaning of customer reviews while effectively representing contextual relationships among words and phrases. The extracted embeddings are then supplied to the ETC, which performs simultaneous prediction of review titles and user ratings. The integration of contextual transformer-based representations with ensemble learning enables the proposed framework to achieve reliable dual-target prediction while maintaining high classification accuracy, scalability, and robustness for large-scale mobile review analysis.

4. Results Description

Result analysis is an essential phase of the proposed framework, as it evaluates the effectiveness of the developed model in achieving the intended research objectives. It involves examining the experimental outcomes to measure the predictive capability, reliability, and overall performance of the system. Through systematic analysis, meaningful patterns, classification behaviour, and performance trends are identified from the generated results. The obtained outcomes are compared with those of existing methods to determine the improvements achieved by the proposed approach. Performance metrics and graphical visualizations further assist in assessing the model's consistency, robustness, and generalization capability across different test scenarios. The findings obtained from the result analysis validate the effectiveness of the proposed framework and provide valuable insights for future enhancements and real-world deployment.

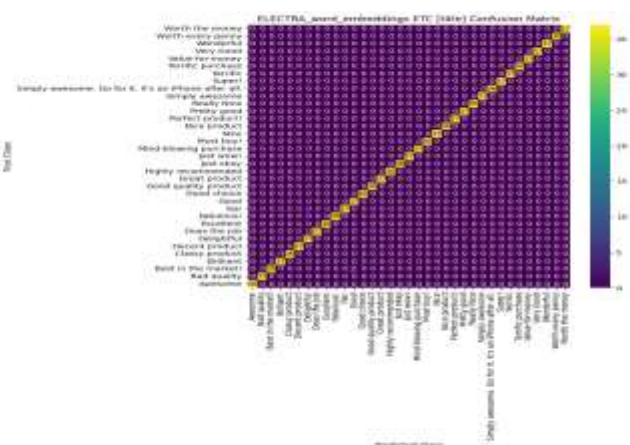

Figure. 3: Confusion matrix obtained using ELECTRA _WE_ ETC Classifier for title.

Figure 3 presents a comparative analysis of confusion matrices for review title classification using ELECTRA word embeddings across showcases the confusion matrix for the proposed ETC Classifier, demonstrating superior performance with near-perfect diagonal alignment across all title classes, minimal off-diagonal noise, and exceptionally high

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prediction counts on correct labels (e.g., "Worth the money," "Simply awesome"), confirming its robustness and accuracy in multi-class sentiment title prediction.

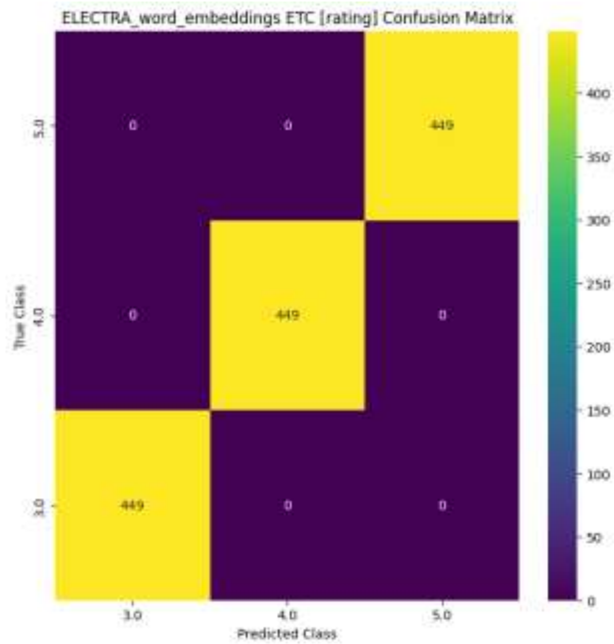

Figure. 4: Confusion matrix obtained using ELECTRA _WE_ETC for rating.

Figure 4 compares confusion matrices for rating prediction (classes 3.0, 4.0, 5.0) using ELECTRA word embeddings across displays the proposed ETC Classifier's confusion matrix, achieving near-perfect diagonal dominance with 449 correct predictions each for classes 3.0, 4.0, and 5.0, and zero misclassifications across all off-diagonal cells, confirming its exceptional ability to accurately predict star ratings despite severe class imbalance.

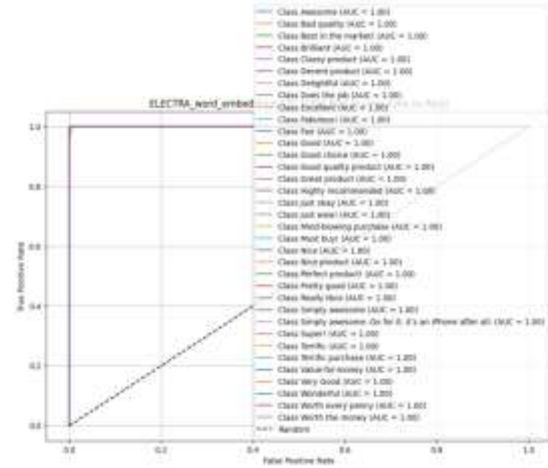

Figure. 5: ROC Curve obtained using ELECTRA _WE_ETC for title

Figure 5 presents the Receiver Operating Characteristic (ROC) curves with corresponding Area Under the Curve (AUC) scores for multi-class review title classification using ELECTRA word embeddings ETC Classifier, achieving perfect AUC = 1.00 across all title classes, with every curve tightly aligned to the top-left corner, indicating flawless true positive detection at zero false positives and confirming the model's outstanding capability to accurately distinguish even subtle variations in customer sentiment titles.

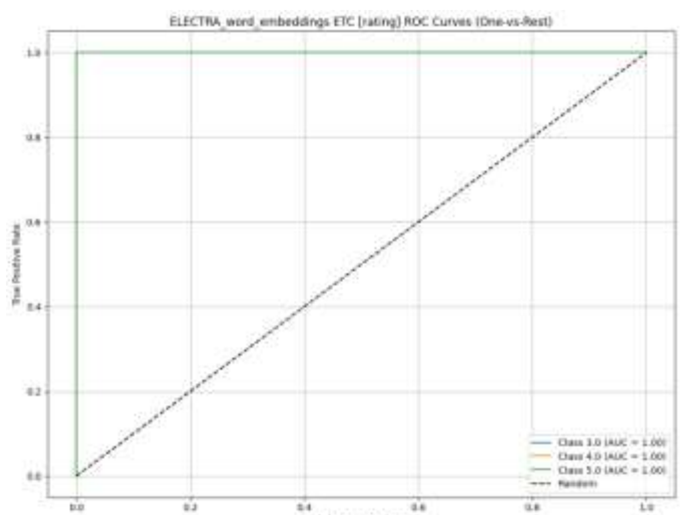

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Figure. 6: ROC Curve obtained using ELECTRA _WE _ETC for rating.

Figure 6 presents the One-vs-Rest ROC curves for rating classification (3.0, 4.0, 5.0) using ELECTRA word embeddings across displays the ROC curves for the proposed ETC Classifier, achieving perfect AUC = 1.00 for all three classes (3.0, 4.0, and 5.0), with each curve tightly hugging the top-left corner, confirming flawless class separation and exceptional model performance across the entire rating spectrum.

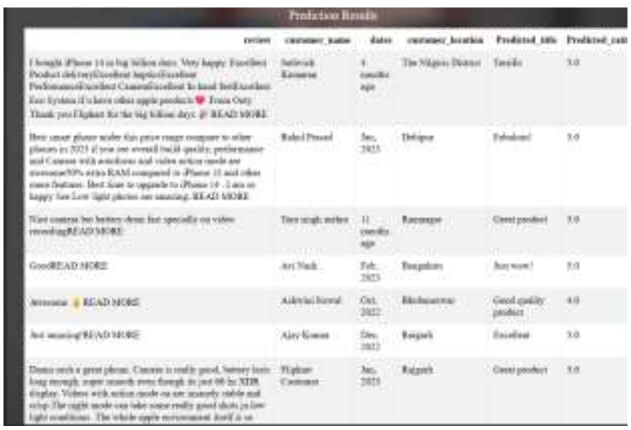

Figure. 7: Predictions page screen

Figure 7 represents the Predictions Page, displaying the results generated after processing the uploaded test dataset. The output table contains multiple columns such as review, customer_name, dates, customer_location, Predicted_title, and Predicted_rating, presenting both original data and model-generated outputs. Each row corresponds to an individual entry from the test dataset and its respective predictions. This page allows users to view how the system interprets and evaluates the review content.

Table 1 presents a performance comparison of three classifiers ABC, TTC, and the proposed ETC using ELECTRA word embeddings for review title classification. The table reports four key metrics: Accuracy, Precision, Recall, and F1-Score (all in percentage). The results reveal a stark contrast in model effectiveness: while ABC and TTC achieve low performance (Accuracy: ~23.8% and ~24.4%, respectively), with particularly weak precision and recall, the proposed ETC Classifier delivers near-perfect results (Accuracy: 99.844%, Precision: 99.853%, Recall: 99.846%, F1-Score: 99.845%), demonstrating exceptional capability in accurately predicting diverse sentiment-laden review titles despite high class complexity and potential imbalance.

Table 1: Performance comparison of ELECTRA_WE classifier models for title column.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ABC	23.810	33.509	23.775	23.013
TTC	24.356	26.064	24.331	22.617
ETC	99.844	99.853	99.846	99.845

Table 2 presents a performance comparison of three classifiers such as ABC, TTC, and the proposed ETC using ELECTRA word embeddings for rating prediction (3.0, 4.0, 5.0). The table evaluates Accuracy, Precision, Recall, and F1-Score (all in percentage). Results show that while ABC and TTC deliver moderate performance (Accuracy: 79.510% and 78.471%, respectively), with balanced but limited discriminative power, the proposed ETC

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Classifier achieves perfect scores across all metrics (100.000%), confirming its superior ability to accurately predict star ratings with zero misclassification, even in the presence of class imbalance and semantic complexity.

Table 2: Performance comparison of ELECTRA_WE classifier models for Rating column.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ABC	79.510	79.390	79.510	79.442
TTC	78.471	78.346	78.471	78.327
ETC	100.000	100.000	100.000	100.000

5. Conclusion

This research successfully automates the extraction of customer sentiment and the prediction of review ratings, delivering a high-precision, scalable alternative to traditional manual or rule-based methods. By utilizing the ELECTRA model for contextual feature extraction, the system captures nuanced linguistic variations, while the K-Means SMOTE algorithm ensures robustness by effectively balancing the dataset. The ETC further enhances the pipeline, providing interpretable and accurate predictions for both titles and ratings. Demonstrating superior performance and lower computational costs compared to existing ABC and TTC methods, the framework is complemented by an intuitive for seamless data visualization and processing. Ultimately, this holistic approach offers organizations a reliable, real-time solution for monitoring brand perception and driving product improvements across diverse e-commerce platforms.

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