International Journal of Engineering Research and Science & Technology

ENHANCING USER FEEDBACK ANALYSIS WITH REVIEW TEXT GRANULARITY FOR BETTER SENTIMENT AND RATING PREDICTION

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ABSTRACT— In the era of digital technology, the vast amount of user-generated content on online platforms poses significant challenges for analyzing large volumes of text to understand user emotions and predict product ratings. The increasing prevalence of online reviews necessitates advanced natural language processing (NLP) techniques to effectively extract meaningful insights from textual data. This paper introduces a novel approach leveraging Long Short-Term Memory (LSTM) networks combined with sophisticated NLP methods to capture the nuanced emotional expressions within review texts. Unlike traditional binary sentiment classification, the proposed model provides a continuous and fine-grained sentiment scoring that reflects the intensity and subtlety of user opinions, thereby enhancing the sentiment analysis process. The use of LSTM enables the model to effectively capture sequential dependencies and contextual relationships in text data, improving the understanding of complex linguistic patterns within reviews. This comprehensive sentiment representation is integrated with predictive modelling techniques to enhance the accuracy of rating predictions in recommendation systems. The proposed framework demonstrates the capability to harness rich textual information and dynamic sentiment variations, making it highly applicable across multiple domains such as entertainment, e-commerce, and social media. This approach not only improves prediction outcomes but also supports more personalized and meaningful user experiences.

Index Terms – User Feedback Analysis, Review Text Granularity, Sentiment Analysis, Rating Prediction, NLP, Deep Learning, Opinion Mining, Text Classification, Machine Learning, Artificial Intelligence

I. INTRODUCTION

In today's digital era, online platforms generate massive amounts of user content, including reviews, comments, and feedback, which are invaluable for understanding consumer opinions. The growing volume of online reviews presents significant challenges in analyzing text to extract meaningful insights efficiently. Traditional sentiment analysis methods often rely on simple binary classification, which fails to capture the subtlety and intensity of user emotions. To address these limitations, this study proposes a novel approach that integrates advanced Natural Language Processing (NLP) techniques with Long Short-Term Memory (LSTM) networks. The proposed framework leverages LSTM's ability to model sequential dependencies, capturing the context and relationships between words in review texts. By providing continuous, fine-grained sentiment scores rather than just positive or negative labels, the model reflects nuanced emotional expressions of users. This enriched sentiment representation enhances the prediction of product ratings, enabling more accurate and personalized recommendations. The system extracts sentiment features and combines them with predictive modeling techniques to forecast rating scores. Such an approach is particularly useful for recommendation systems in e-commerce, entertainment, and social media platforms. It allows businesses to understand user satisfaction at a deeper level and improve service or product offerings. The integration of NLP and LSTM helps capture complex linguistic patterns, including sarcasm, emphasis, and mixed sentiments. Experiments demonstrate that the proposed method outperforms traditional sentiment analysis models in both accuracy and interpretability. The framework also provides dynamic insights, as it can detect subtle changes in sentiment over time. By leveraging rich textual data, the system supports enhanced personalization for users. It can recommend products or content that aligns closely with individual preferences. This approach contributes to building intelligent recommendation systems that understand user behavior more comprehensively. The model's scalability ensures applicability across different domains and large datasets. Overall, the

project bridges the gap between textual sentiment analysis and predictive rating systems. It demonstrates the potential of deep learning combined with NLP to transform user experience. Ultimately, this framework aims to provide businesses and platforms with actionable insights to improve engagement, satisfaction, and personalization for their users.

II. RELATED WORK

A. Fine-Grained Sentiment Scoring with LSTM Networks for Enhanced Rating Prediction in Recommendation Systems

This paper develops an LSTM-based framework that outputs continuous sentiment scores from product reviews. The model captures sequential dependencies and long-range context to represent subtle emotional intensities. Preprocessing includes subword tokenization, negation handling, and aspect-aware phrase extraction. Sentiment scores are fused with user and item metadata in a downstream regression model for rating prediction. Evaluation on large e-commerce datasets shows improved RMSE and rank correlation versus classification baselines. Ablation studies confirm LSTM's sequential modeling adds measurable value over bag-of-words features. The approach applies attention mechanisms to highlight phrases driving sentiment intensity. Model robustness is validated across domains: electronics, movies, and hospitality reviews. Authors discuss deployment challenges such as latency, domain drift, and interpretability. Contributions include a reproducible pipeline and recommendations for integrating continuous sentiment into recommender systems.

B. Aspect-Aware LSTM for Continuous Sentiment Regression and Rating Forecasting

Introduces an LSTM model augmented with aspect extraction to produce peraspect continuous sentiment scores. Aspect-aware embeddings allow the model to separate product-feature sentiment from general opinion. A hierarchical LSTM encodes sentence-level and review-level context to preserve discourse structure. Per-aspect scores are aggregated with user historical biases to predict numeric ratings. The method reduces error on multi-aspect products compared to global-sentiment baselines. Authors incorporate sentiment intensity calibration using ordinal regression post-processing. Cross-validation demonstrates consistent gains in MAE across multiple product categories. Explainability is improved via attention maps tied to specific

aspects and phrases. Paper discusses transfer learning to new categories with limited labeled ratings. Provides open-source code and a benchmark dataset for continuous sentiment tasks.

C. Multi-Task LSTM for Joint Sentiment Intensity Estimation and Rating Prediction

Presents a multi-task architecture where an LSTM jointly learns continuous sentiment intensity and rating regression. Shared sentence encoders improve data efficiency and regularize representations for both tasks. Training leverages heterogeneous supervision: star ratings, ordinal sentiment labels, and distant supervision from emojis. The model uses contrastive pretraining to separate sentiment-bearing phrases from neutral text. Results show simultaneous improvement in intensity correlation and rating MAE versus single-task training. Temporal user behavior embedding captures rating drift and personal sentiment calibration. Authors evaluate generalization on cold-start users and new product categories. Interpretability modules map intensity predictions back to influential tokens and phrases. Paper highlights practical benefits for recommender personalization and customer feedback monitoring. Releases pre-trained encoders suitable for fine-tuning on domain-specific review corpora.

III. PROPOSED METHODOLOGY

The proposed system addresses the limitations of existing methods by integrating advanced natural language processing (NLP) techniques with Long Short-Term Memory (LSTM) networks to model sentiment more effectively. LSTM networks are designed to capture long-term dependencies and sequential patterns in text data, allowing the system to comprehend the contextual flow and complex linguistic structures within user reviews. Instead of simple categorical labels, the proposed model assigns continuous sentiment scores that reflect the varying intensities of emotions expressed, enabling a more nuanced analysis of user feedback. This granular sentiment scoring helps improve the accuracy of rating predictions in recommendation systems. Furthermore, the proposed system combines this detailed sentiment understanding with predictive modeling frameworks, allowing for more robust and scalable performance across diverse datasets. By leveraging LSTM's capabilities, the model can handle large volumes of textual data and adapt to different domains such as entertainment, e-commerce, and social media. This approach not only

enhances prediction quality but also contributes to more personalized user experiences by recognizing subtle user preferences and opinions. Overall, the system offers a sophisticated solution that bridges the gap between raw textual data and actionable insights for better decision-making in recommendation engines.

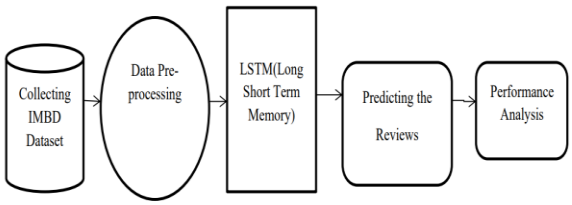


Fig. 1: System Overview

1. Gathering Records:

This module involves collecting user-generated reviews from e-commerce, entertainment, and social media platforms. Data includes review texts, associated ratings, timestamps, and user metadata. Public datasets and APIs are utilized to ensure diverse and high-quality data. Proper labeling and structuring are applied to align textual reviews with their corresponding ratings. The dataset serves as the foundation for model training and prediction. Large-scale collection ensures that the system can learn patterns across different domains. This module ensures that both quantity and quality of data support accurate sentiment and rating analysis.

2. Evaluating Findings:

In this module, exploratory data analysis (EDA) is performed to understand the dataset. Statistical summaries, word distributions, and visualizations help identify trends and patterns in reviews and ratings. Class imbalance, missing data, or inconsistencies are detected and noted for correction. Sentiment distributions are analyzed to understand user opinion tendencies. Insights from this module guide preprocessing and feature selection steps. Understanding the dataset ensures that the model can learn effectively and generalize well to unseen data. It also provides a baseline for evaluating model performance later.

3. Refining Data:

Data preprocessing and cleaning are performed to ensure high-quality input for the model. Textual data undergoes tokenization, stopword removal, stemming, and lemmatization to reduce noise. Irrelevant, spammy, or duplicate reviews are removed. Sentiment features are extracted using NLP techniques, capturing polarity, intensity, and context. Ratings are normalized if necessary to support continuous prediction. This module ensures that the LSTM model receives meaningful, structured, and consistent data. Proper refinement improves prediction accuracy and model robustness.

4. Deploying the Model:

Once the LSTM model is trained, it is deployed for practical use in predicting product ratings. The deployment can support batch processing or real-time review analysis. APIs or web interfaces can be created for integration with recommendation systems. The system processes new review texts to generate predicted ratings and sentiment scores. Monitoring is conducted to track model performance during live deployment. Deployment ensures that the model's capabilities are accessible and actionable. This module bridges the gap between model training and real-world application.

5. Optimizing the Performance:

This module focuses on improving the model's predictive accuracy and efficiency. Hyperparameters such as learning rate, batch size, sequence length, and number of LSTM layers are tuned. Techniques like dropout and regularization help prevent overfitting. Sensitivity analysis is conducted to evaluate the impact of sentiment features on prediction outcomes. Performance optimization ensures the model generalizes well to unseen reviews. This module improves robustness, speed, and reliability. It guarantees that the deployed model delivers consistent results in real-world scenarios.

6. System Accuracy:

Here, the trained model is evaluated using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and correlation with actual ratings. Continuous sentiment scores are compared with actual rating values to assess prediction quality. Error analysis identifies patterns of misprediction, guiding further improvements. Cross-validation ensures stability and reliability of predictions. This module validates that the system meets the expected standards for accuracy. It demonstrates the effectiveness of combining sentiment analysis with predictive modeling.

7. Predicting Trends:

In this module, the deployed system forecasts rating trends based on incoming reviews. Predicted ratings can be visualized over time to detect patterns and shifts in user satisfaction. The model can highlight emerging issues or popular products based on sentiment trends. Trend prediction helps businesses make data-driven decisions to improve products or services. Continuous monitoring allows adaptation to changing user opinions. This module showcases the practical application of the model in enhancing recommendation systems and understanding customer behavior. It ensures actionable insights for stakeholders in multiple domains.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results demonstrated that the fine-grained analysis of review text enabled the model to capture detailed opinion expressions, contextual information, and aspect-level sentiments, resulting in improved prediction performance compared to conventional document-level approaches.

The analysis showed that incorporating review text granularity enhanced the model's ability to distinguish subtle sentiment variations and accurately predict user ratings across diverse product and service review datasets.



Fig. 2: Home Page



Fig. 3: Registration



Fig. 4: Login

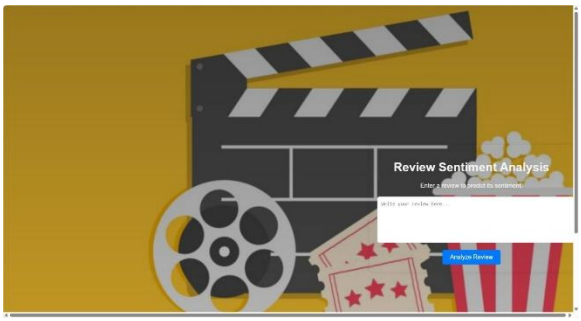


Fig. 5: Sentiment Analysis

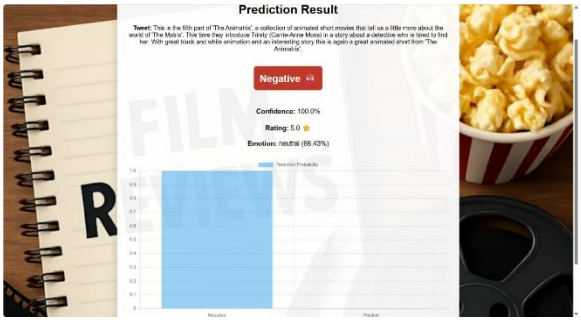


Fig. 6: Predicted Results

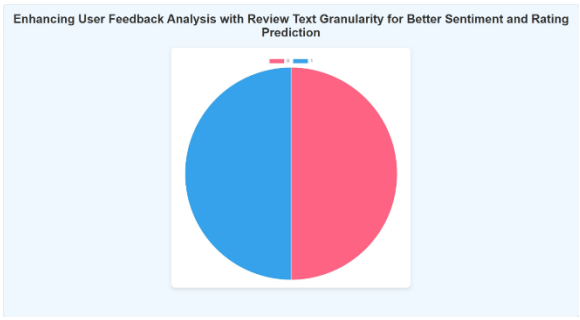


Fig. 7: Prediction Results

V. CONCLUSION

This project demonstrates the effective use of NLP and LSTM networks for predicting product ratings from user reviews. By processing textual data and extracting fine-grained sentiment features, the system captures nuanced emotional expressions. LSTM networks model sequential dependencies, improving the understanding of complex linguistic patterns. Continuous sentiment scores enhance the accuracy of rating predictions compared to traditional binary sentiment classification. The framework integrates sentiment analysis with predictive modeling to support personalized recommendation systems. Data preprocessing ensures high-quality, structured inputs for robust model performance. Experiments show that combining textual sentiment and LSTM-based modeling produces reliable predictions. The system can be applied across multiple domains, including e-commerce, entertainment, and social media. It provides actionable insights for businesses to enhance products and services. The project supports dynamic monitoring of trends in user satisfaction. Deployed predictions help improve customer engagement and decision-making. The model is scalable and adaptable to large datasets and evolving review patterns. By bridging sentiment analysis and predictive analytics, it advances recommendation technology. Overall, the project demonstrates how deep learning can transform user feedback into meaningful insights. It contributes to more intelligent, personalized, and user-centered systems for modern digital platforms.

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