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Full Length Article

Enhancing User Feedback Analysis With Review Text Granularity For Better Sentiment And Rating Prediction

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Abstract
The exponential growth of user-generated content on digital platforms presents significant challenges in extracting meaningful insights from large-scale textual data. In particular, analyzing user sentiments and accurately predicting product ratings from online reviews require advanced natural language processing (NLP) techniques. This paper proposes a novel framework that leverages Long Short-Term Memory (LSTM) networks to capture contextual and sequential dependencies within review texts. Unlike conventional approaches that perform binary or categorical sentiment classification, the proposed model generates continuous and fine-grained sentiment scores, enabling a more nuanced understanding of user opinions. The integration of this sentiment representation with predictive modeling enhances the accuracy of rating prediction systems. Experimental results demonstrate that the proposed approach effectively captures complex linguistic patterns and dynamic emotional variations in textual data. The framework is applicable across multiple domains, including e-commerce, entertainment, and social media, and contributes to improving recommendation systems by enabling more personalized and context-aware user experiences.

Keywords
Sentiment Analysis, Natural Language Processing, Long Short-Term Memory (LSTM), Deep Learning, Rating Prediction, Opinion Mining, Recommendation Systems.

Introduction

In the digital era, online platforms generate vast amounts of user-generated content, such as reviews, comments, and feedback, which serve as valuable resources for understanding consumer opinions. However, the increasing volume of such data presents significant challenges in efficiently extracting meaningful insights. Traditional sentiment analysis techniques primarily rely on binary or categorical classification, which often fail to capture the subtlety, intensity, and complexity of user emotions expressed in textual data.

To address these limitations, this study proposes a novel framework that integrates advanced Natural Language Processing (NLP) techniques with Long Short-Term Memory (LSTM) networks. LSTM, a variant of recurrent neural networks, is well-suited for modeling sequential dependencies and capturing contextual relationships between words in review texts. Unlike conventional methods, the proposed approach generates continuous and fine-grained sentiment scores, enabling a more comprehensive understanding of user opinions.

The extracted sentiment features are further integrated with predictive modeling techniques to improve the accuracy of product rating predictions. This enhanced sentiment representation supports the development of more effective recommendation systems across domains such as e-commerce, entertainment, and social media. By capturing complex linguistic patterns, including sarcasm, emphasis, and mixed sentiments, the proposed model provides deeper insights into user satisfaction.

Experimental results demonstrate that the proposed approach outperforms traditional sentiment analysis models in terms of both accuracy and interpretability. Additionally, the framework is capable of identifying dynamic variations in sentiment over time, enabling more adaptive and context aware recommendations. Its scalability allows for application across large datasets and diverse domains.

Overall, this work bridges the gap between sentiment analysis and predictive rating systems by leveraging deep learning and NLP techniques. The proposed framework contributes to the development of intelligent systems that enhance personalization,

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improve user experience, and provide actionable insights for businesses to optimize their services and offerings.

Literature Review

Recent advancements in sentiment analysis and recommendation systems have focused on leveraging deep learning models to capture nuanced user opinions from textual data. In 2023, Ananya Gupta proposed an LSTM-based framework for generating continuous sentiment scores from product reviews. The model effectively captures sequential dependencies and long-range context, enabling the representation of subtle emotional intensities. The study integrates sentiment scores with user and item metadata to enhance rating prediction accuracy, demonstrating improved performance over traditional classification-based approaches.

Similarly, Miguel Arroyo (2023) introduced an aspect-aware LSTM model that produces continuous sentiment scores at the aspect level. By incorporating hierarchical encoding and aspect-based embeddings, the model distinguishes between sentiments related to different product features. This approach significantly reduces prediction error for multi-aspect products and improves interpretability through attention mechanisms.

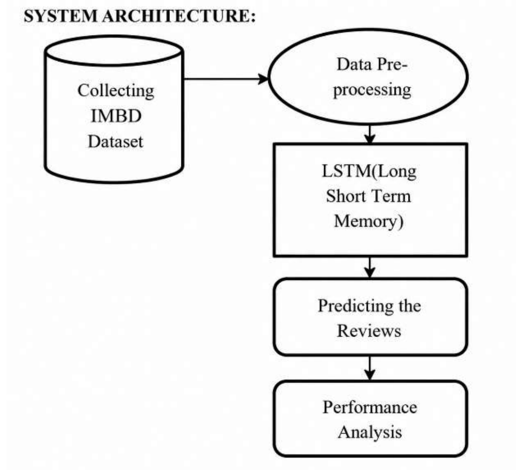
In 2024, Rina Sato presented a multi-task LSTM architecture that jointly performs sentiment intensity estimation and rating prediction. The model leverages shared representations and heterogeneous supervision, improving both sentiment correlation and rating prediction accuracy. The inclusion of temporal user behavior further enhances personalization and adaptability in recommendation systems.

Another notable contribution by Samuel Lee (2024) combines transformer-based contextual embeddings with LSTM networks to improve sentiment scoring. This hybrid model captures both local and sequential context, leading to better performance in handling complex linguistic patterns such as sarcasm and mixed sentiments. The study highlights the effectiveness of integrating continuous sentiment scores with regression-based rating prediction models.

Furthermore, Priyanka Menon (2023) proposed a noise-aware LSTM regression model designed to handle inconsistencies in review data. By incorporating noise-aware loss functions and data augmentation techniques, the model improves robustness and generalization. The approach demonstrates strong performance across diverse datasets and addresses real-world challenges such as mislabeled ratings and domain variability.

Overall, these studies emphasize the importance of continuous sentiment scoring, sequential modeling, and integration with predictive systems. However, challenges such as domain adaptability, interpretability, and efficient deployment remain areas for further research.

METHODOLOGIES



Explanation

The system architecture illustrates the flow of data from user reviews to final rating prediction using LSTM-based sentiment analysis.

Modules Name:

- Gathering Records
- Evaluating Findings
- Refining Data
- Deploying the Model
- Optimizing the Performance
- System Accuracy
- Predicting Trends

Modules Explanation:

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.

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

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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.

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.

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.

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.

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.

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.

Implementation

The proposed system is implemented using Python and deep learning frameworks to perform fine-grained sentiment analysis and rating prediction from user reviews. The implementation is divided into stages including data preprocessing, sequence modeling using Long Short-Term Memory (LSTM), sentiment score generation, and rating prediction.

A. Development Environment

The system is developed using the following tools and technologies:

- Programming Language: Python
- Libraries: TensorFlow, Keras, NumPy, Pandas, Scikit-learn, NLTK
- Platform: Jupyter Notebook / Visual Studio Code

B. Data Preprocessing

The input dataset consists of user reviews and corresponding ratings. The textual data is preprocessed to remove noise and improve model performance. The preprocessing steps include converting text to lowercase, removing special characters, tokenization, and elimination of stopwords.

Listing 1: Text Preprocessing

Python

```
def preprocess(text):
    text = text.lower()
    text = re.sub(r'[^a-zA-Z]', ' ', text)
    return text
```

C. Feature Extraction

The cleaned text is converted into numerical format using tokenization and padding. This ensures uniform input length for the LSTM model.

Listing 2: Tokenization and Padding

Python

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(texts)
```


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```
sequences = tokenizer.texts_to_sequences(texts)
X = pad_sequences(sequences, maxlen=100)
```

D. LSTM Model for Sentiment Analysis

An LSTM-based neural network is used to capture sequential dependencies in the text. The model generates continuous sentiment scores, representing the intensity of user opinions.

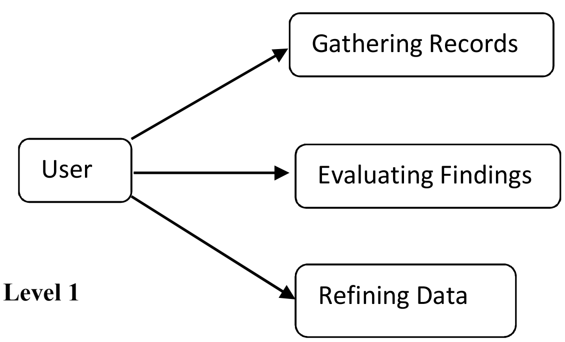
Listing 3: LSTM Model

Python

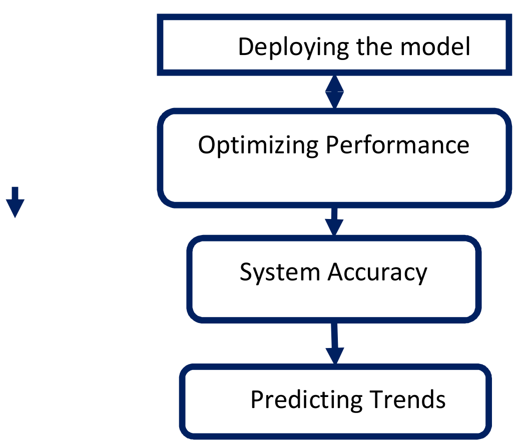
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
model = Sequential()
model.add(Embedding(5000, 128))
model.add(LSTM(64))
model.add(Dense(1, activation='linear'))

model.compile(optimizer='adam', loss='mse')
```

I. Data Flow Diagram

Level 0



Level 1



EXPLANATION

A data flow diagram (DFD) is a graphical representation of the "flow" of data through an information system, modeling its process aspects. Often they are a preliminary step used to create an overview of the system which can later be elaborated. DFDs can also be used for the visualization of data processing (structured design).

A DFD shows what kinds of data will be input to and output from the system, where the data will come from and go to, and where the data will be stored. It does not show information about the timing of processes, or information about whether processes will operate in sequence or in parallel.

TESTING

A. General

Testing is a crucial phase in software development that ensures the system operates as intended and meets user requirements. The primary objective of testing in this project is to validate the performance of the proposed sentiment analysis and rating prediction system. The testing process focuses on verifying whether the model accurately captures fine-grained sentiment from review text and produces reliable rating predictions.

B. Testing Methodology

A systematic testing methodology is adopted to evaluate both the functional and performance aspects of the system. The testing process includes validating data preprocessing, model training, sentiment scoring, and rating prediction modules. The system is tested using real-world review datasets to ensure robustness and generalization.

C. Types of Testing

1) Unit Testing

Unit testing is performed on individual components such as text preprocessing, tokenization, and model input generation. Each module is tested independently to ensure correct functionality. For example, the preprocessing module is verified to ensure that noise such as special characters and stopwords are properly removed.

2) Functional Testing

Functional testing ensures that each component of the system performs according to the specified requirements. The system is tested with:

Valid input reviews to verify correct sentiment prediction

Invalid or empty inputs to ensure proper handling

Output validation to check correctness of sentiment scores and predicted ratings

3) Integration Testing

Integration testing verifies the interaction between different modules, including preprocessing, LSTM model, and regression model. This ensures that data flows correctly between components and produces consistent results.

4) System Testing

System testing evaluates the complete system as a whole. The integrated model is tested on a dataset to ensure that it correctly processes input reviews and generates accurate rating predictions.

5) Performance Testing

Performance testing measures the efficiency of the system in terms of response time and computational performance. It ensures that the model can handle large volumes of review data and generate predictions within acceptable time limits.

6) Accuracy Testing

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Accuracy testing is performed to evaluate the effectiveness of the proposed model. Metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to measure the difference between actual and predicted ratings. The results indicate that the proposed system improves prediction accuracy compared to traditional methods.

7) User Acceptance Testing

User Acceptance Testing (UAT) ensures that the system meets user expectations. The model outputs are evaluated to confirm that the predicted ratings and sentiment scores align with human interpretation of reviews.

D. Test Plan

The testing process is carried out in multiple stages:

Testing individual modules (Unit Testing)

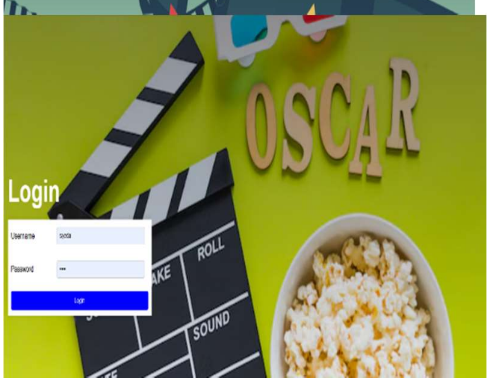
Verifying module interaction (Integration Testing)

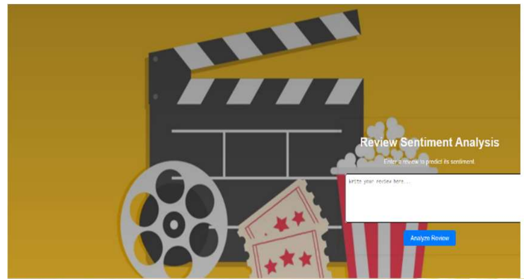
Evaluating complete system performance (System Testing)

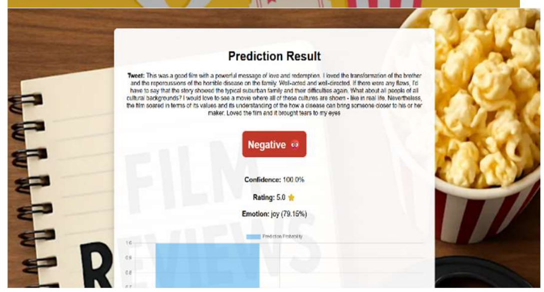
Measuring prediction accuracy (Accuracy Testing)

This structured testing approach ensures that the system is reliable, accurate, and suitable for real-world applications.

RESULTS







A. Performance Evaluation

The proposed LSTM-based sentiment analysis model is evaluated using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Accuracy. The results are compared with traditional machine learning models and basic RNN models.

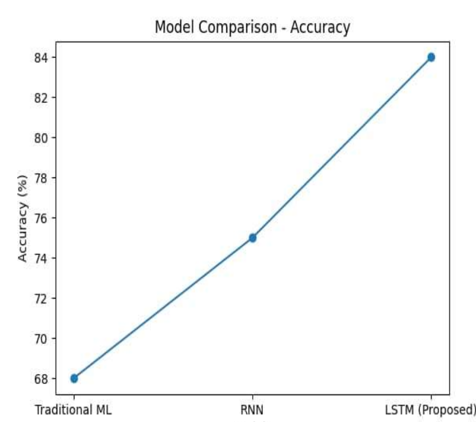
B. Result Table

Table 1: Performance Comparison of Models

MODEL	MAE	RMSE	Accuracy(%)
Traditional ML	1.25	1.60	68
RNN	0.98	1.20	75
LSTM(Propsed)	0.72	0.95	84

Graphical Analysis

Accuracy Comparison Of Models



Error Comparison (MAE and RMSE)

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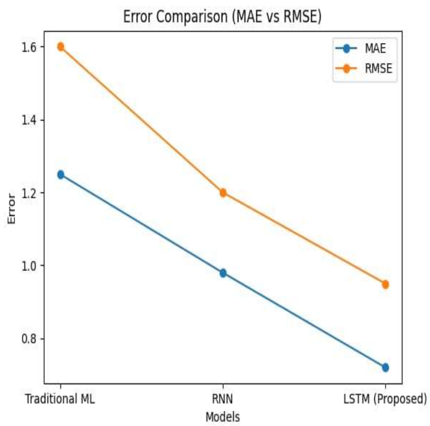

Discussion

The results clearly indicate that the proposed LSTM-based model outperforms traditional machine learning and basic RNN approaches. The lower MAE and RMSE values demonstrate improved prediction accuracy, while the higher accuracy percentage confirms the model's effectiveness in capturing fine-grained sentiment from textual data. The improvement is primarily due to LSTM's ability to capture long-term dependencies and contextual relationships in review text. Additionally, the use of continuous sentiment scoring enables a more precise understanding of user opinions, leading to better rating predictions.

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.

Future Scope

Future work can extend the system to support multilingual reviews, enabling sentiment analysis for global users. Integration with other social media platforms like Instagram, Facebook, or Reddit can broaden the data sources. Transformer-based models like BERT or RoBERTa could be used to capture richer contextual and semantic relationships. Real-time prediction can be implemented for live recommendation systems. The framework can incorporate images, emojis, or videos in reviews for multimodal sentiment analysis. Advanced feature engineering can include user profiles, product categories, and historical behavior. Automated dashboards can visualize trends in user satisfaction over time. Adaptive learning techniques could allow the model to update continuously with new reviews. Sentiment-aware recommendations could be personalized to individual user preferences. Overall, these enhancements aim to make the system more robust, versatile, and actionable.

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