ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 11| Issue: 11| November 2025|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2025: 8.691 || ISI Value: 1.188

NATURAL LANGUAGE PROCESSING: TRANSFORMING HUMAN-COMPUTER INTERACTION THROUGH ADVANCED ALGORITHMS

Rishabh Chaturvedi, Meenu
Dr.Akhilesh Das Gupta Institute of Professional Studies, Affiliated with Guru Gobind Singh Indraprasth University New Delhi

ABSTRACT

Natural Language Processing (NLP) has emerged as a pivotal technology in bridging the gap between human communication and computational systems. This research explores the development and application of NLP techniques to analyze, understand, and generate human language. Unlike rule-based systems, modern NLP leverages machine learning and deep learning to handle linguistic nuances, enabling applications such as sentiment analysis, machine translation, and chatbots.

To demonstrate the practicality of NLP, we utilized the IMDB movie review dataset for sentiment analysis, employing techniques like tokenization, word embeddings, and recurrent neural networks (RNNs). The system was evaluated using metrics such as accuracy, precision, and recall to ensure robustness. Additionally, we developed an interactive dashboard using Streamlit to visualize sentiment trends and allow users to input custom text for real-time analysis. This dashboard facilitates engagement with non-technical stakeholders, promoting data-driven insights.

Our results highlight the system's ability to classify sentiment with high accuracy and adapt to diverse linguistic patterns. By addressing challenges such as ambiguity and data scarcity, this research contributes to the broader goal of enhancing human-computer interaction through intelligent, scalable NLP system

KEYWORDS: *Natural Language Processing, Sentiment Analysis, Word Embeddings, RNNs, Accuracy, Precision, Streamlit, Human-Computer Interaction*

1. INTRODUCTION

The exponential growth of digital text data has made it imperative to develop systems capable of understanding and processing human language efficiently. NLP addresses this need by enabling machines to interpret, analyze, and respond to textual or spoken language. Applications span industries such as healthcare, customer service, and education, where NLP-driven tools like virtual assistants and automated translators significantly improve efficiency and user experience.

Traditional NLP methods relied on handcrafted rules, but they struggled with scalability and ambiguity. Modern approaches, powered by machine learning, excel in capturing context and semantics. This research focuses on implementing and evaluating an NLP-based sentiment analysis system, emphasizing performance and usability.

2. PROBLEM STATEMENT

Many platforms face challenges in extracting meaningful insights from unstructured text due to linguistic complexity and noise. Generic text processing methods often fail to capture sentiment or intent accurately. This project aims to address these challenges by developing an NLP system that:

- Accurately classifies text sentiment.
- Handles linguistic diversity and ambiguity.
- Provides actionable insights through an interactive dashboard.

3. OBJECTIVE

a. Implement sentiment analysis using word embeddings and RNNs.
b. Evaluate the system's performance using accuracy, precision, and recall.
c. Develop a user-friendly dashboard for real-time text analysis.
d. Address data scarcity and model interpretability through hybrid approaches.

4. LITERATURE REVIEW

NLP has evolved from rule-based systems to advanced neural networks, with word embeddings and transformer models revolutionizing the field. Past studies highlight the effectiveness of RNNs and LSTMs in sequence modeling, while recent advancements like BERT and GPT-4 demonstrate unparalleled performance in language understanding

5. METHODOLOGY

5.1 Data Collection

We used the IMDB movie review dataset, which contains labeled text for sentiment analysis. The dataset was preprocessed to remove noise and ensure consistency.

5.2 Preprocessing

- Removed stopwords and punctuation.
- Tokenized text and applied lemmatization.
- Split the data into training (80%) and testing (20%) sets.

5.3 Model Implementation

The sentiment analysis system was implemented using GloVe word embeddings and a bidirectional LSTM architecture. The model was trained using Adam optimization, with dropout layers to prevent overfitting. Hyperparameter tuning was performed via grid search, optimizing for embedding dimensions and learning rate. Evaluation metrics included accuracy, precision, and recall.

5.4 Visualization

- Created an interactive Streamlit dashboard to display sentiment trends.
- Included text input for users to test the model in real time.

6. RESULTS AND DISCUSSION

The system achieved an accuracy of 90%, precision of 0.88, and recall of 0.91, indicating strong performance. Key findings include:

- High accuracy in classifying positive and negative sentiment.
- Effective handling of linguistic diversity through embeddings.
- Improved usability via the interactive dashboard.

7. TOOLS AND TECHNOLOGIES

- Language: Python
- Libraries: TensorFlow, Keras, NLTK, Streamlit
- Environment: Jupyter Notebook, Streamlit Cloud

8. FUTURE SCOPE

- Incorporate transformer models like BERT for improved accuracy.
- Extend the system to multilingual text analysis.
- Deploy the dashboard online for broader accessibility.

9. CONCLUSION

This research demonstrates the effectiveness of modern NLP techniques in building scalable sentiment analysis systems. The interactive dashboard enhances usability, making NLP accessible to non-technical users. Future work will focus on hybrid models and broader applications to further improve language understanding.

REFERENCES

1. *Jurafsky, D., & Martin, J. H. (2020). Speech and Language Processing. Pearson.*
2. *Devlin, J., et al. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL.*
3. *IMDB Dataset: https://www.imdb.com/interfaces/*
4. *Streamlit Documentation: https://docs.streamlit.io/*
5. *Goldberg, Y. (2017). Neural Network Methods for Natural Language Processing. Morgan & Claypool.*
6. *Mikolov, T., et al. (2013). Efficient Estimation of Word Representations in Vector Space. arXiv.*
7. *Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation.*
8. *Pennington, J., et al. (2014). GloVe: Global Vectors for Word Representation. EMNLP.*