Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

NLP-Based Extended Lexicon Model For Sarcasm Detection With Tweets And Emojis

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- Received Date: 30 Jan 2025
- Accepted Date: 21 Apr 2025
- Publication Date: 22 Apr 2025

Keywords

Sarcasm Detection, NLP, Lexicon Model, Emojis, Twitter, Sentiment Analysis, Machine Learning, Text Classification.

Abstract

Sarcasm detection in social media, especially on platforms like Twitter, poses a significant challenge due to the informal and context-dependent nature of language. This research presents an NLP-based extended lexicon model for sarcasm detection, leveraging both textual features and emojis to enhance interpretability and accuracy. The proposed model integrates a sentiment lexicon with syntactic and semantic cues, enriched by emoji sentiment analysis, to capture subtle contradictions and ironic tones in tweets. A dataset of labeled tweets is preprocessed and analyzed using natural language processing techniques, including tokenization, POS tagging, and feature extraction. Machine learning classifiers are then employed to detect sarcasm. Experimental results demonstrate that the inclusion of emoji sentiment and lexicon-based features significantly improves detection performance, highlighting the importance of multimodal analysis in understanding sarcasm in social media texts.

Introduction

Social media has become a steadfast aspect of online life, with 97% of online adolescent users regularly accessing social media sites . Twitter, a social media site that serves as an online micro-blogging forum is ranked 10th for most internet traffic. Twitter is typically used to post about facts, opinions, events, ideas and humour, often accompanied by images, emotes, or videos. Additionally, Twitter has become a popular source of big data for analytics in marketing, politics , and stock predictions especially since Facebook, the most visited internet traffic site, eliminated access to their application programming interface's (API) in 2018. Companies mine user generated data on politics, products, media, and people. This mined data is explored for insights utilized in marketing and customer service, using sentiment analysis. Sentiment analysis is performed by using a variety of Natural Language Processing (NLP) techniques and algorithms to determine whether a given string of text has a positive or negative sentiment attached to it and thus allows one to derive a sentiment about the subject of the text.

For all these benefits of using Twitter data, there is still an ogre in the cupboard that must be addressed. Sarcasm is a form of irony or satire that inverts the sentiment of a post or remark, often in the form of a positive surface sentiment with a negative intended sentiment.

For example, in the context of a baseball game, " Way to go, Slugger" has a very different meaning if directed at a player that hit a home run versus a player that struck out. If the player had hit a home run, it would be a positive intended and surface sentiment. However, if the player had struck out, it would be a derisive or scornful intended sentiment conflicting with its positive surface sentiment.

Undetected sarcasm, by its nature, will create errors in sentiment analysis due to sarcastic statements being misinterpreted as literal statements. Sarcasm detection is considered a challenging problem as it may rely on a hybrid of both lexical and context detection methods While automated sarcasm detection is still a new area of research the rapid growth in research on this subject.

Literature Review

OSarcasm often involves the use of irony and humorous intent, which makes it tough for conventional rule-based or statistical approaches to accurately identify sarcastic expressions. In today's world, with the widespread use of social media platforms, especially Twitter, sarcasm has become prevalent in tweets, often accompanied by emojis that provide additional context. The traditional methods for sarcasm detection in NLP heavily relied on feature engineering and machine learning algorithms. These methods incorporated various features such as lexical cues (e.g., specific keywords or phrases associated with sarcasm), sentiment analysis, and part-of-speech patterns. While

Citation: Reddy SM, Bukkacherla A, Pujari C, Shaik BF, Narla N, Gosala DK. NLP-Based Extended Lexicon Model For Sarcasm Detection With Tweets And Emojis. GJEIIR. 2025;5(2):33.

these approaches achieved some level of success, they often struggled to grasp the subtleties of sarcasm, particularly when dealing with informal and concise texts like tweets. As a result, our project has been dedicated to developing the Extended Lexicon Model (ELM), aiming to accurately detect sarcasm, especially in the context of social media texts like tweets. These tweets are often characterized by their unconventional language, slang, and frequent use of emojis.

Sarcasm detection in textual data, especially in social media contexts such as tweets, has been an active research area in Natural Language Processing (NLP). Various methodologies have been employed to improve sarcasm detection, ranging from traditional machine learning models to deep learning-based approaches.

Lexicon-based approaches rely on predefined sentiment lexicons to identify sarcastic expressions. Studies such as Riloff et al. (2013) proposed a pattern-based approach using contrast between positive and negative sentiments within the same sentence to detect sarcasm. Similarly, Reyes et al. (2013) introduced a linguistic-based model leveraging humor and irony indicators to improve detection accuracy. However, these methods often struggle with contextual ambiguity and fail to incorporate non-textual cues such as emojis.

Supervised machine learning techniques have been widely used for sarcasm detection. Davidov et al. (2010) introduced a semi-supervised approach utilizing syntactic and pattern-based features to classify sarcastic tweets. González-Ibánez et al. (2011) extended this by incorporating features like pragmatic factors and user intent to refine sarcasm classification. Despite their effectiveness, these models heavily rely on feature engineering and labelled datasets, which can limit scalability and generalizability.

Recent advancements in deep learning have significantly improved sarcasm detection. Ghosh and Veale (2016) explored the use of deep neural networks, particularly LSTMs, to capture sequential dependencies in sarcastic texts. Tay et al. (2018) introduced a hybrid approach combining CNNs and attention mechanisms to extract both local and global contextual sarcasm patterns. However, deep learning models often require large amounts of labelled data and substantial computational resources.

Emojis play a crucial role in sentiment and sarcasm expression in social media. Felbo et al. (2017) proposed the DeepMoji model, which leverages emoji embeddings to predict sentiment and sarcasm. Similarly, Hazarika et al. (2018) demonstrated the significance of incorporating emojis as additional context in sarcasm detection models. These studies highlight the necessity of multimodal learning for improved sarcasm classification.

Recent work has attempted to extend lexicon-based models with contextual embeddings and emoji-aware features. Mishra et al. (2019) proposed a model that integrates lexical resources with contextual embeddings like Word2Vec and BERT to capture sarcasm more effectively. The use of external lexicons, such as SentiWordNet and VADER, combined with domain-specific sentiment dictionaries, has shown promising results in sarcasm detection tasks.

Proposed system

To overcome the limitations of traditional methods, the ELM leverages the power of advanced NLP techniques, including word embeddings, to better capture the complex linguistic and contextual cues indicative of sarcasm. One of the key features of the ELM is its incorporation of an extended lexicon of sarcastic words, phrases, and their associations with emojis. By doing so, the model seeks to enhance the detection of sarcasm in tweets, resulting in a more effective and reliable approach.

The inclusion of emojis is crucial, as they often play a significant role in conveying sentiments and intentions in tweets, providing vital contextual information. With the ELM's improved accuracy and ability to handle the nuances of social media language, it promises to be a valuable asset for researchers and practitioners in the field of NLP aiming to delve deeper into the world of sarcasm in modern communication.

Data Collection and Preprocessing:

The first step involves collecting a diverse dataset of tweets containing both sarcastic and non-sarcastic expressions. Preprocessing steps include:

- Removing special characters, URLs, and stopwords.
- Tokenizing text and normalizing emoji representations.
- Annotating the dataset with sarcasm labels, either manually or through weak supervision.

Extended Sentiment Lexicon Development

To enhance sarcasm detection, an extended sentiment lexicon will be developed by integrating:

- Pre-existing sentiment lexicons such as Senti WordNet and VADER.
- Emoji sentiment scores derived from studies like Deep Moji.
- Context-aware embeddings such as Word2Vec, GloVe, or BERT.

Feature Extraction

The model will extract relevant features, including:

- Lexical features: Sentiment scores, contrast-based expressions.
- Syntactic features: POS tagging, dependency parsing.
- Contextual features: Word embeddings and emoji embeddings.
- Pragmatic features: User metadata, tweet structure.

Model Architecture

A hybrid deep learning approach will be employed, combining:

- BiLSTM or Transformer models to capture sequential dependencies.
- Attention mechanisms to emphasize key sarcastic words and emojis. Lexicon-based augmentation to improve interpretability and robustness.

Model Training and Evaluation

The model will be trained using annotated sarcastic datasets.

- Performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score.

Ablation studies will be conducted to assess the contribution of each component.

Feature Extraction

The final model will be deployed as an API or integrated into social media analysis tools.

Real-world performance will be monitored, and feedback will be used to refine the model.

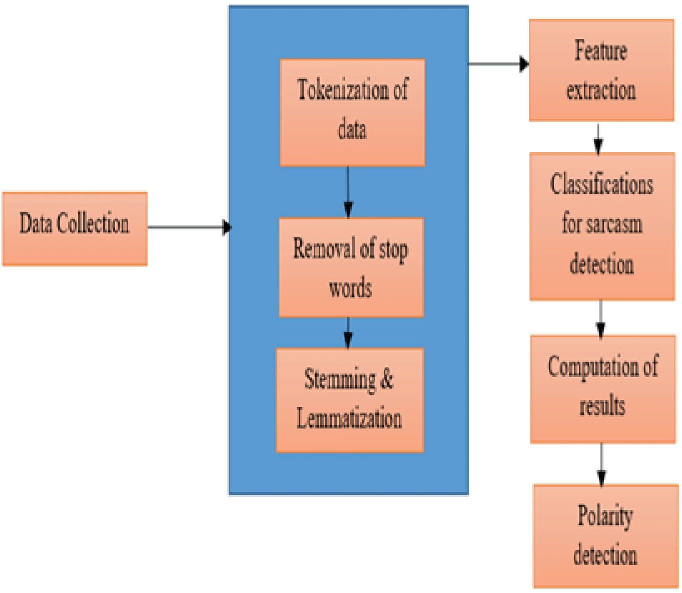


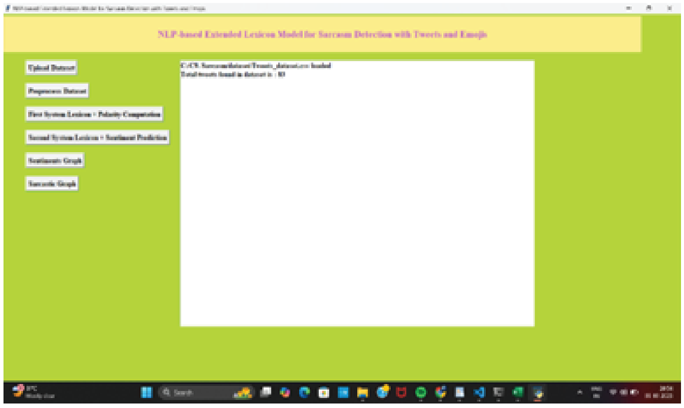
Fig: Workflow of sarcasm detection in sentiment analysis

Screen-1: User interface application

Output screens:

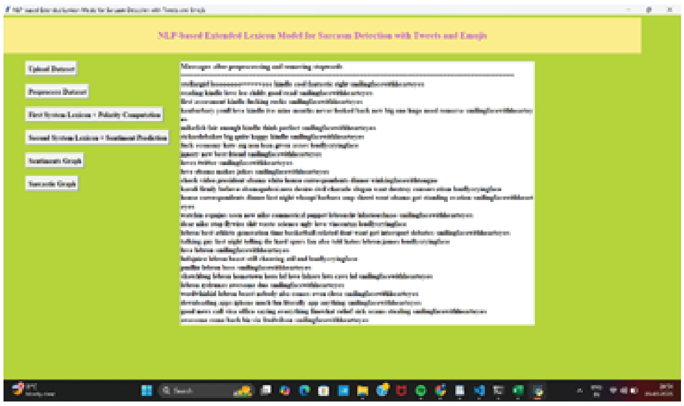
Screen 1. Screen illustrates the graphical user interface (GUI) of the sarcasm detection application. It shows the buttons, text fields, and other elements that users interact with. Users can perform tasks such as uploading datasets, initiating preprocessing, running algorithms, and visualizing results through this interface. The user interface is shown after the user has uploaded a dataset. The uploaded dataset contains tweets and associated data. The interface displays a confirmation message to inform the user that the dataset has been successfully uploaded along with the count of tweets in given dataset.

The user interface displaying preprocessed data after applying the Natural Language Toolkit (NLTK) library for text processing. The interface shows cleaned and tokenized text, and potentially processed emojis. This step aims to prepare the data for further analysis.The results obtained after applying lexicon-based sentiment analysis with polarity computation on the preprocessed data. The interface also indicates whether the tweet is categorized as positive, negative, or neutral.



Screen-2: Illustration of user interface application after uploading the dataset

Screen 2: The screenshot shows the user interface of the "NLP-Based Extended Lexicon Model for Sarcasm Detection with Tweets and Emojis" after uploading the dataset. The left panel contains functional buttons for uploading, preprocessing, sentiment analysis, and visualization. The right panel displays the dataset path and confirms that 83 tweets have been loaded. The UI has a green-yellow theme with a structured layout for easy navigation. The system processes tweets using lexicon-based and sentiment analysis models to detect sarcasm effectively.



Screen-3: Proposed UI application with preprocessed data using NLTK.

Screen 4. The screenshot displays the user interface after preprocessing the dataset using NLTK. The right panel now contains processed text, where stopwords and punctuation have been removed. The text is normalized, and emojis are converted into meaningful words. The left panel retains functional buttons for dataset processing and analysis. This preprocessing step enhances the accuracy of sarcasm detection by focusing on key lexical and sentiment based features.

The screenshot shows the UI after performing lexicon-based polarity computation. The right panel displays analyzed tweets with sentiment scores, including positive, negative, and neutral polarity values. Based on these scores, the system determines whether a tweet is sarcastic or not. The left panel retains functional buttons for dataset processing and analysis. This step enhances sarcasm detection by evaluating sentiment intensity in tweets.

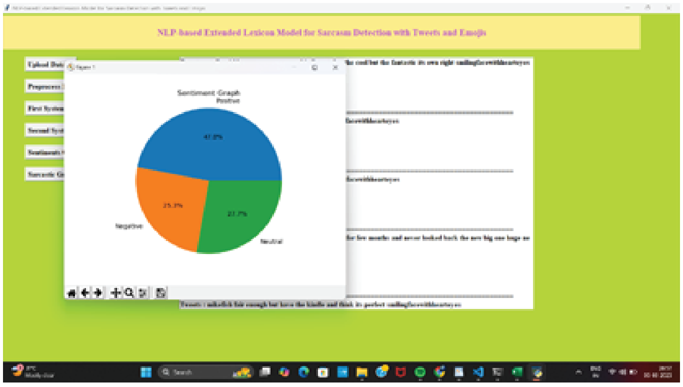
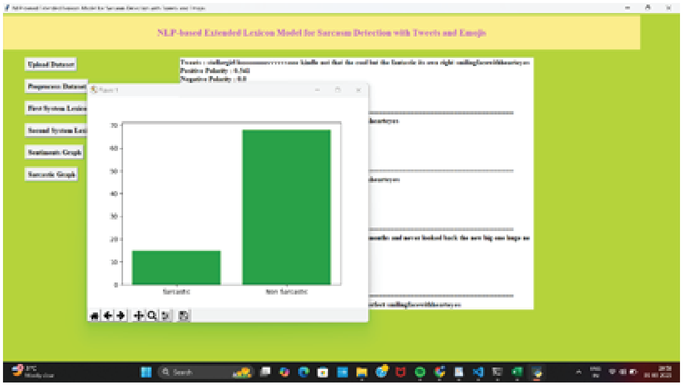


Figure 2. Pie chart of sentiment prediction on tweets dataset with different classes (positive, negative, and neutral)



Graph : Sarcasm prediction graph using proposed NLP-based extended lexicon model.

The pie chart represents the sentiment distribution of the tweets dataset based on sentiment prediction. It categorizes tweets into three classes: Positive (47.0%), Neutral (27.7%), and Negative (25.3%). The chart visually highlights the dominance of positive sentiments in the dataset, followed by neutral and negative sentiments. This sentiment analysis plays a crucial role in sarcasm detection by identifying inconsistencies between sentiment polarity and contextual meaning, thereby improving the accuracy of sarcasm classification. The graphical representation provides an intuitive understanding of overall sentiment trends in the analyzed dataset.

Conclusion

The aim of this work was to propose ways to extend the lexicon algorithm in order to build systems that would be more efficient for sarcasm detection. This aim has been successfully met as two systems have been developed to address this situation. However, in the first system, it had been noticed that the training set of the sarcasm analysis algorithm must be relevant to the actual data that need to be analyzed in order to obtain meaningful results and to improve the accuracy of the system. The second system constitutes a vast area of study. Some work needs to be done in order to develop a system that would allow the collection of environmental details under which the textual contents would be made on social media platforms. A consolidated way of computing the sentiment polarity of the environments based on their details should also be developed..

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