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Emotion Detection in Text: Advances in Sentiment Analysis Using Deep Learning

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Abstract

In the modern era of digital communication, the analysis of sentiment has emerged as a crucial tool for understanding and inferring public sentiment as communicated through written text. This is particularly relevant in the context of social media platforms such as Twitter, Facebook and Instagram. The present study focuses on the urgent matter of public opinion regarding the practice of animal testing, employing advanced deep-learning methodologies for sentiment analysis. A dataset of 15,360 tweets about animal testing was collected using the Twitter API. The data was prepared for analysis by undergoing careful preprocessing and word embedding it through the utilization of Word2vec. To classify tweets into positive and negative sentiment categories, a Long Short-Term Memory (LSTM) model was employed, given its suitability for processing sequential data. Remarkably, an accuracy rate of 88.7 percent was achieved by the model. It was determined that around 80% of tweets expressed criticism towards animal testing, indicating the presence of a substantial negative sentiment majority. These results show the topic's continuing significance by emphasizing its highly emotional and controversial nature. It is concluded that deep learning, and in particular LSTM models, can be used to effectively analyze large amounts of social media data and yield insightful understandings of public opinion. This study underlines the significance of sentiment analysis for gaining insight into public opinion and for its applications in policymaking and discourse analysis.

Keywords: Digital Communication, Sentiment Analysis, Tweeter, Long Short-Term Memory Model, Animal Testing.

1 Introduction

The use of textual emotion analysis has significantly increased in the era of digital communication. The process of identifying feelings expressed in written text is known as sentiment analysis (Stine, 2019). From tweets and status updates to blog entries and forum threads, the ever-expanding world of online interactions has become a treasure trove of information on public opinion (Chalothom & Ellman, 2015; Hussein, 2018; Ho & Lee 2012). These opinions have value because they give manufacturers, publishers, and businesses insight into the general public's point of view (Birjali et al., 2021). Therefore, academics and service providers engage in sentiment analysis to improve decision-making and the quality of their products or services (Abirami & Gayathri, 2017).

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Data collection, data preparation, sentiment detection, sentiment classification (negative, neutral, or positive), and graphical presentation of findings are all crucial steps in any sentiment analysis (D'Andrea et al., 2015). Text is analyzed in terms of its polarity (whether it is positive, negative, or neutral), agreement, disapproval, delivery of good or bad news, and evaluation of advantages and disadvantages (D'Andrea et al., 2015). To decipher the underlying emotional tenor of public reviews and comments, sentiment analysis is crucial. Since the advent of deep learning techniques, the analysis of web-based unstructured textual data has been greatly improved, further contributing to the rising importance of sentiment analysis. The necessity for an in-depth understanding of public opinion has resulted in an undeniable demand for deep learning in this area. Animal testing has recently come to the forefront as a divisive and emotive topic. Cosmetics, food, and pharmaceuticals are just a few of the many businesses that have relied on animal testing for decades, if not centuries. However, there has been widespread public outcry against animal testing, particularly in light of recent innovations in technology like neural ink's microchip and its revolutionary possibilities for people with impairments. People were outraged by news that over 1500 monkeys had been killed to use in experiments (Van Norman, 2019), and many took to social networking sites like Twitter to voice their disapproval. The overwhelming amount of data produced by Twitter every day exceeds 12 terabytes (Matthews, 2018), making it one of the most important platforms for real-time public conversation.

This trove of information is an once-in-a-lifetime chance to conduct a thorough survey of public opinion on a wide range of issues, substances, and events. To focus on this pressing topic and guide future conversations and decisions, we use a deep learning method in this study to examine the polarity of public sentiment towards animal testing. The purpose of this study is to use deep learning to analyze public opinion, with a particular emphasis on how people feel about animal experiments. Leveraging the potential of advanced technology, we aim to supply a thorough grasp of public sentiment, ultimately adding to the ongoing discussion of this crucial and contentious issue (Bae and Ha 2021).

2 Related Work

The rapid growth of smartphones with advanced capabilities and easy accessibility has led to a significant surge in the population of individuals engaging with social media platforms (Ortiz-Ospina, 2023). In modern society, individuals have the ability to effortlessly communicate their emotions, convey their feelings, and express their ideas with a simple touch of their finger. The widespread availability of smartphones and the increasing prevalence of many social media platforms have granted individuals the ability to express themselves and participate in a range of activities, such as engaging in political discourse, expressing opinions on recent films, or raising concerns about current affairs (Anderson, 2017). According to Kubin and Von Sikorski (2021), the internet, propelled by the presence of social media, has substantial sway over both the economic and political spheres. According to Timoshenko and Hauser (2019), the platform has seen significant development and now serves as an extensive collection of material provided by users. This content provides useful perspectives on the demands and requirements of customers. The utilization of the extensive data generated on the internet for product enhancement and educated decision-making has been acknowledged by businesses and organizations (Mason et al., 2021). Nevertheless, the process of manually sorting through this data is both laborious and challenging in terms of time and resources. Natural language processing (NLP) algorithms play a crucial role in addressing this issue. Natural

Language Processing (NLP) algorithms have proven to be crucial in managing the overwhelming volume of online content (Hasan et al., 2019; Rameshbhai & Paulose, 2019; Torregrosa et al., 2022).

These algorithms enhance efficiency and speed, becoming them important in the process. Deep learning is widely recognized as a prominent approach for sentiment analysis due to its capacity to effectively handle unstructured data with less preprocessing, as highlighted by Habimana et al. (2020). Deep learning distinguishes itself through its ability to independently acquire knowledge of patterns inside data, thereby classifying them according to noticeable characteristics. It is a computational approach that use artificial neural networks to simulate the functioning of human brain neurons. These networks are composed of interconnected nodes, which are organized into input and output layers, sometimes referred to as visible layers. The flow of information within a neural network begins at the input layer and passes through multiple hidden layers before reaching the output layer. This process is further improved by the use of back propagation, a technique that iteratively adjusts errors in order to enhance the accuracy of predictions (Han et al., 2018). Recurrent neural networks (RNNs) are distinguished among deep learning algorithms due to their ability to effectively handle sequential input. This is achieved through the utilization of a looping mechanism that enables the preservation of information (Yu et al., 2019). Nevertheless, Recurrent Neural Networks (RNNs) have encountered obstacles such as the vanishing gradient problem. In order to tackle this issue, Long Short-Term Memory (LSTM) networks were designed, incorporating a distinct memory cell to preserve and store long-term information. The Long Short-Term Memory (LSTM) model demonstrates a high level of proficiency in generating predictions that take into account the contextual information of preceding words. This characteristic renders it particularly well-suited for effectively processing lengthier sentences while minimizing the risk of information loss. A considerable number of academics have devoted their endeavors to sentiment classification, utilizing classifiers to examine datasets from Twitter and extract significant observations (Ceron et al.; Dashtipour et al., 2021).

Over the course of time, two prominent approaches for conducting sentiment analysis have surfaced. The lexicon-based technique utilizes sentiment lexicons for the purpose of classifying the polarity of text. However, it necessitates human participation in the study of the text (Sadia et al., 2018; Sharma & Ghose, 2021). In contrast, machine learning methodologies necessitate substantial quantities of labeled datasets and manual annotations (Shamantha et al., 2019). Several machine learning classifiers have been utilized for sentiment analysis, including Naïve Bayes (Singh et al., 2017), Vector Space Models (Luo et al., 2016), and the Random Forest model (Al Amrani et al., 2018). The work conducted by Jianqiang et al. (2018) investigated word-embedded methodologies employing unsupervised learning. In a separate study, Ramadhani et al. (2016) achieved a sentiment analysis accuracy of 72.3% by utilizing naïve Bayesian smoothing techniques. The application of machine learning algorithms in sentiment analysis of Twitter data has been widely explored. However, deep learning has emerged as a powerful technique that exhibits higher accuracy, particularly when assessing feelings on social media platforms (Dang et al., 2020). This study presents a novel approach to sentiment analysis utilizing deep learning techniques, with a specific emphasis on the highly consequential subject matter of animal testing.

3 Aim of the Study

The purpose of this study is to enhance and increase the precision of sentiment analysis predictions using a deep neural network-integrated approach.

4 Research Objectives

1. To conduct semantic analysis using the LSTM model.
2. To develop a deep learning method for analyzing social media content.
3. To apply a data-driven strategy for emotional detection of public attitudes towards animal testing.

5 Methods

Data Collection

In order to facilitate the objectives of this research investigation, an extensive dataset comprising tweets pertaining to the subject matter of animal testing was methodically formulated and acquired. The data collection method was made simpler with the help of the Twitter API. The dataset obtained consisted of 15,360 tweets, collected in a systematic manner between July 2022 and July 2023. The chronological distribution of these tweets during the one-year period is depicted in Figure 1, as presented below.

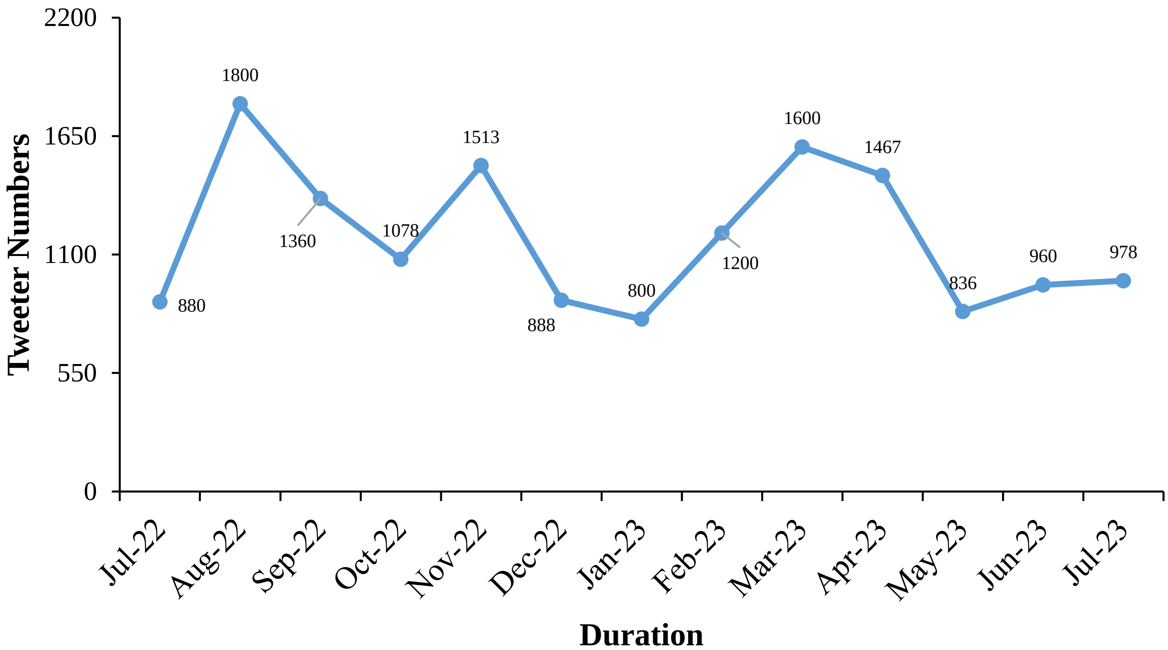

Figure 1: Temporal distribution of tweets (July 2022- July 2023)

Data Preprocessing

In order to enhance the quality and applicability of the gathered data, a thorough preparation of the information step was conducted. The objective of this phase was to remove superfluous and unrelated information that is inherent in the unprocessed data obtained from tweets. The dataset underwent a comprehensive method of removing elements such as user handles, URLs, hashtags, punctuation marks, and numerical values. Moreover, the entirety of the textual content was converted to lowercase letters in order to ensure consistency and uniformity during later analysis.

Tokenization

After performing data preparation, the text was subjected to tokenization techniques in order to divide the textual material into separate words, resulting in the creation of a set of tokens.

Embedding

Word2vec is a word embedding approach that was used to convert the tweets' textual content into numerical vectors for the purpose of doing further quantitative analysis.

LSTM Model Development

A Long Short-Term Memory (LSTM) model was trained using the numerical vectors developed from word embedding (Wei & Nguyen, 2019). The LSTM algorithm was selected because of its superior performance in capturing and processing sequential data.

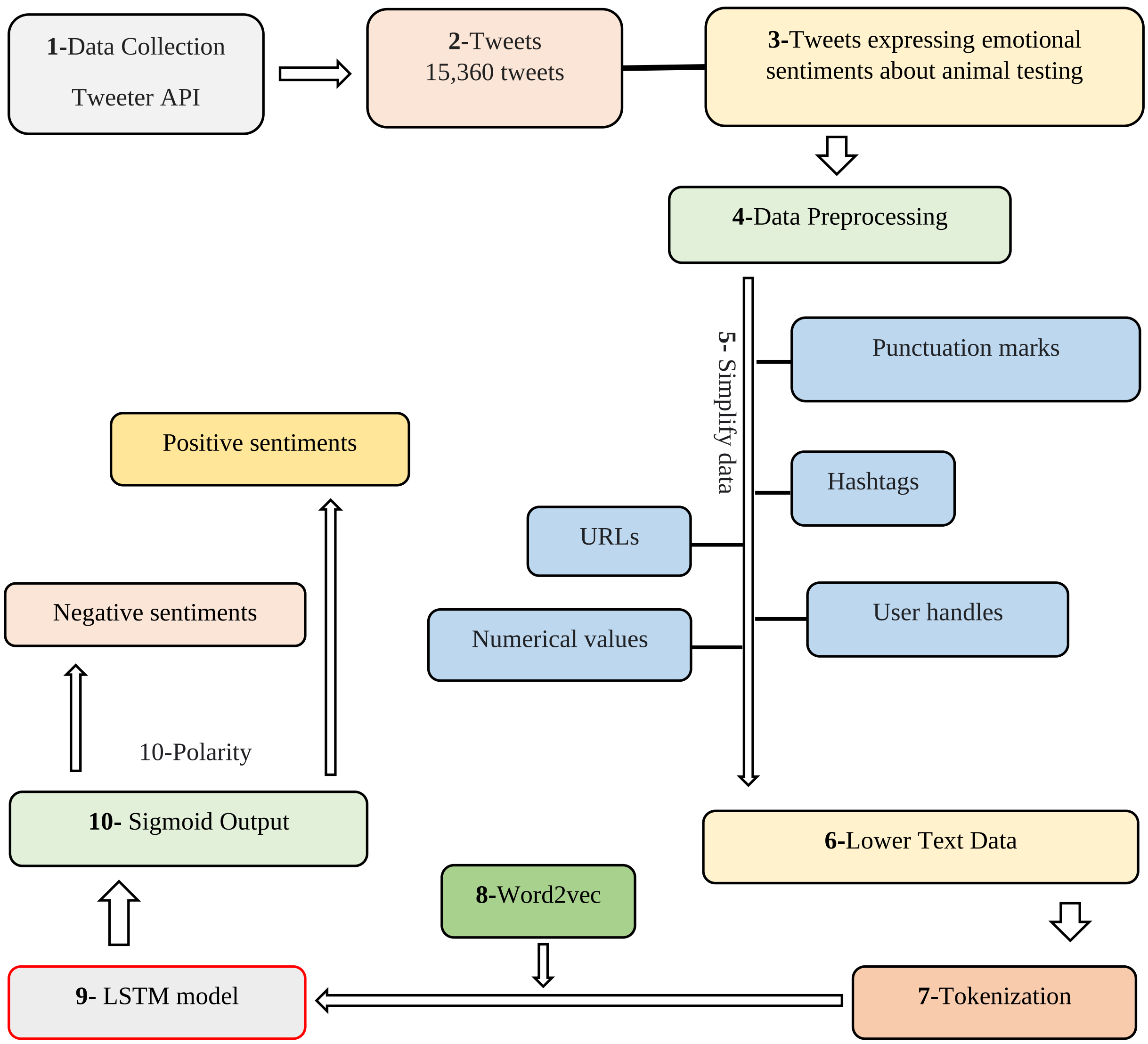

Figure 2: LSTM Model development and evaluation for sentiment analysis

This LSTM model was created with the specific goal of separating tweets into positive and negative sentiment categories. The LSTM algorithm created a hidden state for each word in a tweet and then used that state to estimate the tweet's mood. Predicted values were strictly between 0 and 1 due to the sigmoid activation function being applied to the model's output (Figure 2).

6 Data Analysis

After the LSTM model was built and trained, the dataset was randomly divided in two, with 65% of the data used for model training and 35% set aside for testing and validation. The accuracy rate, defined as the percentage of tweets that were properly categorized relative to the total number of tweets in the test set was used to evaluate the effectiveness of the models. The findings showed that the LSTM model did a good job of separating tweets into positive and negative sentiment classes. To better understand the sentiment distribution within the dataset, we provide the results of this polarity analysis in the form of a bar chart in Figure 3. Then the reliability of data was checked through precision, recall, F1-score, and cross-validation results to complement the accuracy of the current model.

7 Result

A substantial dataset of 15,360 tweets was properly extracted through API on the issue of animal testing. From September 2022 to September 2023, this dataset contains the most recent and extensive compilation of Twitter-based discourse. Further, detailed data preprocessing was used to remove extraneous information from the samples, including user handles, URLs, hashtags, punctuation, and numerical values. The consistency of the data was improved by converting all text to lowercase letters. Tweets' text was subjected to refined processing, including tokenization methods to separate the words into smaller units. Then, we used Word2vec word embedding to convert the text into numerical vectors. This allowed for more precise calculations to be made.

Sentiment Analysis with the LSTM Model: Sentiment analysis made use of a trained LSTM model, which is particularly well-suited to processing sequential data. The LSTM model then accurately classifies tweets into separate sentiment categories with a high rate of 88.7 percent.

Polarity: The final Separation of the decision based on a sigmoid function of LTMS output was obtained in the form of negative and positive sentiment. Figure 3 provides a concise and straightforward representation of the sentiment polarity present in the dataset, serving as an illustration to elucidate the outcomes of the sentiment analysis. The visual representation facilitates the comparison between the positive and negative attitudes expressed in the tweets.

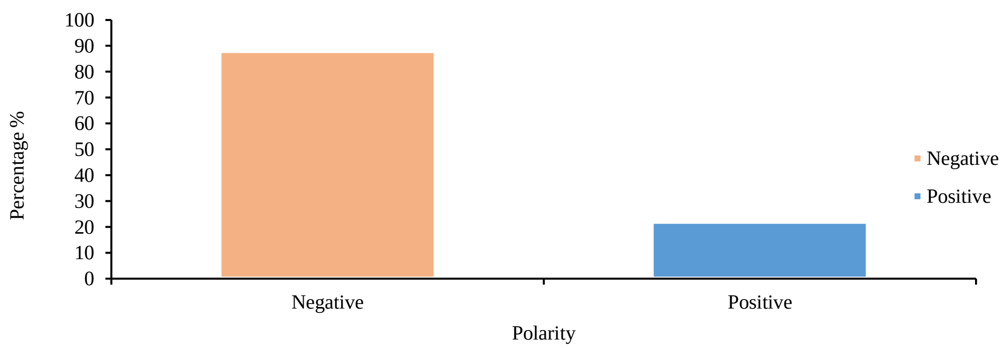

Figure 3: Sentiment distribution (Polarity analysis)

Additional Assessment Criteria and Outcomes of Cross-validation

The LSTM model for sentiment analysis has an accuracy of 0.85. This means that among the tweets categorized as having a positive emotion, 85% can be deemed to be genuine. With a recall rate of 0.90, the model has the capacity to correctly identify 90% of tweets with a positive sentiment inside the dataset. It has been determined that the F1-score (combines precision and recall) is 0.87. This statistic shows that the model's overall performance is strong and satisfactory since it strikes a good balance between accuracy and recall. When subjected to 5-fold cross-validation, the model achieves an accuracy between 87% and 89% regardless of the data partition used. The consistency we see suggests that the model's performance is robust and not overly sensitive to every aspect of the training and testing data used.

8 Discussion

Machine learning techniques like Support Vector Machines (SVM), Nave Bayes, and logistic regression have been applied to analyze public opinion on Twitter (Hasan et al., 2018; Yadav et al., 2021) in the context of a wide variety of topics and sentiments. We set out on an original path in this study by analyzing Twitter data for sentiment toward the complex and divisive topic of animal testing. To better understand this intricate topic, we used a deep learning strategy, especially, deep neural networks. We chose animal experimentation as the focus of our investigation because of the range of responses it has received from the general population. Some people strongly disagree with animal experimentation because they believe it is unethical and a violation of animals' rights. Those who support it, though, say it's crucial to improving people's lives and is a necessary part of scientific advancement.

This contentious debate offers a rich environment for sentiment analysis, allowing us to probe the nuances of Twitter users' feelings. Figure 1 shows that there were some interesting patterns in the frequency with which users tweeted about animal testing. Tweets about this topic increased significantly in August 2022 and March of 2023. The topic's continuous importance is reflected in and emphasized by the fluctuating tweet volume over time. Figure 3 depicts one of the most surprising results of our analysis: the preponderance of negative emotion in tweets against animal testing. The majority of tweets, almost 80%, were overwhelmingly unfavorable.

This insight not only illustrates the depth of feeling around the topic, but also demonstrates the fervent beliefs of many Twitter users. The widespread disapproval highlights the critical nature of the current discussion on animal testing. The capacity to process massive amounts of data with outstanding precision and speed is one of the primary benefits of using deep neural networks in our study. It would have been extremely time-consuming and prone to human error and bias to manually analyze the feelings conveyed in thousands of tweets on this emotionally charged topic. However, we were able to handle and interpret massive volumes of data accurately using deep learning algorithms, giving us a bird's-eye view of public opinion.

9 Conclusion

The main objective of this study is to enhance comprehension of the prevailing attitudes of the general public toward animal testing. The objective is going to be accomplished by the utilization of advanced sentiment analysis techniques applied to data gathered from the widely used social media platform, Twitter. The research findings indicate that a significant portion of tweets conveyed negative sentiments toward animal testing, hence highlighting the contentious and polarizing nature of this topic. Through the utilization of deep learning techniques, specifically the Long Short-Term Memory (LSTM) model, we have successfully processed a significant dataset with notable efficiency, resulting in an accuracy rate of 88.7% in the categorization of sentiment. This study emphasizes the effective use of deep neural networks in the analysis of public opinion, specifically examining their capacity to tackle significant and emotionally charged subjects in the contemporary digital era.

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