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Sentimental Analysis using Neural Network

Vishal Satpute, Vaibhav Singh, Dhananjay Gayke, Rushikesh Kamod
Prof. (Dr) Amol Potgantwar, Prof. Rais Shaik
Department of Computer Engineering
Sandip Institute of Technology and Research Centre, Nashik, India

Abstract*: This paper presents a comprehensive exploration of sentiment analysis using neural networks, focusing on architectures like RNNs, LSTMs, and transformers. Key findings include an in-depth analysis of model effectiveness, challenges in training data, and ethical considerations. The survey showcases the prominence of RNNs in capturing nuanced sentiment patterns, offering valuable insights for researchers and industry practitioners. Methodologically, dataset curation, preprocessing, and ethical considerations are discussed, culminating in a systematic approach to sentiment analysis. The model's applications span customer feedback, brand monitoring, market research, political sentiment analysis, healthcare feedback, content moderation, financial sentiment analysis, and educational feedback analysis. The paper concludes with a significant contribution to the evolving landscape of sentiment analysis, emphasizing the integration of neural networks for a deeper understanding of human sentiment.*

Keywords: Sentiment analysis

I. INTRODUCTION

Sentiment analysis, a sub-domain of natural language processing, plays a pivotal role in understanding public sentiment across diverse platforms. With the rise of social media and online communication, the need for effective sentiment analysis tools has become more prominent. In this context, neural networks have emerged as powerful tools for extracting nuanced sentiments from textual data.

This survey focuses on the application of neural networks, particularly Recurrent Neural Networks (RNNs), in sentiment analysis. RNNs, with their ability to capture sequential dependencies, offer a promising framework for understanding the context and temporal dynamics inherent in sentiment-laden text. By leveraging the strengths of RNNs, we aim to enhance the accuracy and contextual awareness of sentiment analysis models.

The following sections delve into the current landscape of sentiment analysis, exploring the challenges, advancements, and ethical considerations associated with the use of neural networks. We assess various neural network architectures, including RNNs, Long Short-Term Memory Networks (LSTMs), and transformer models, and discuss their effectiveness in deciphering complex sentiment patterns.

Additionally, this survey addresses critical aspects of sentiment analysis model training, such as the choice of datasets and the mitigation of biases. Ethical considerations, transparency, and interpretability of the models are also highlighted, underlining the importance of responsible deployment in real-world applications.

As we dive into this survey, our main goal is to give you a thorough look at the current state of sentiment analysis, honing in on how we use RNNs in particular. The findings presented herein aim to contribute valuable insights to both researchers and practitioners in the evolving landscape of sentiment analysis using neural networks.

The motivation for choosing RNNs stems from their distinctive ability to capture sequential dependencies within textual data. In the context of sentiment-laden text, accurate analysis hinges on understanding the context and temporal dynamics. RNNs, with their sequential processing capabilities, provide a promising framework for achieving this, thereby improving both the accuracy and contextual awareness of sentiment analysis models. As we progress through the paper, the rationale for selecting RNNs becomes apparent in the pursuit of deciphering the intricate patterns inherent in sentiments expressed across diverse textual sources.

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II. RELATED WORK

[1] The paper proposes a hybrid approach to sentiment analysis using 1D-CNN, LSTM, and CNN with an improved Support Vector Machine (SVM) for non-domain-specific data sets. The CNN architecture is used to learn sentiment incorporated vectors and obtain sentiment classification, with a supported vector machine (SVM) replacing the soft-max function in the output layer. The hybrid model improves the CNN's classification capabilities. The proposed method yielded better accuracy values for Kindle, Fire Tablet, and Fire TV data classes, with F1 scores of 83, 82, and 85 respectively. The paper focuses on research into RNN deep learning methods and incorporating existing data from urban areas, such as social and political information. [2] Novel CNN uses deep learning to detect human emotions through facial expression recognition. This method uses large filters and large filters to analyses images, resulting in high accuracy. Techniques used in training CNN include data augmentation, kernel recurrence, and batch normalization. The model categorizes images into six groups: poor, fair, average, good, best, and excellent. The determinant of emotion analysis is recognized as a dependent and independent variable. The proposed model improves the number of covenants for finding emotions based on customer reviews. In the training and testing variables, normalization occurs based on review comments, and feature extraction is done using vector variables. The model uses binary trees to split comments into dimensions, mapping to feature labels connected to the six groups of classes. Customer reviews are crucial for building commercial businesses, and machine learning models can improve results in selling and customer-related issues. The proposed Novel-CNN model outperforms existing CNN models in customer reviews with 98.3% accuracy, making it more reliable. [3] Their proposed system analyses reviews to identify sentiment expressions. The dataset is collected from ai.standfor.edu and noise is removed by eradicating noisy chunks of data, such as emojis and least important words. Words are then reduced to their root form to reduce the number of features. This task is part of the Natural Language Processing (NLP) of text data, which can be achieved using NLP Tool Kits. The raw data undergoes pre-processing, making it noise-free and tokenizing to form lists of tokens or words. Words like prepositions, articles, and helping verbs are treated as non-subjective, and root words are used to calculate IDF. TFIDF values are normalized to the range [0, 1] to create a sparse matrix. Four classification algorithms are compared to decide the finest model for sentiment analysis. The Logistic Regression Classifier shows the best accuracy at a learning rate of 0.5, while the SVM Classifier has the highest accuracy at 89.4%. The study reveals that the sentiment of a review is dependent on the words used, with logistic regression classifier showing better performance than other classification algorithms. The Gini index and entropy factors contributed to the maximum accuracy of the Decision Tree model. Negation handling significantly improved sentiment analysis results, and this research can be extended to identify sentiment polarity at higher precision. [4] This paper presents a CNN model that was tested using a single standard dataset from Stanford AI Lab. The underlying arrangement of characteristics, i.e., vector, weights, and bias, are selected indiscriminately after a progressive cycle, and the underlying parameters achieve optimality after an iterative preparation procedure. The CNN model is tested according to the following criteria: minimal LOSS, accuracy, gradient descent, precision, recall, and f1-score. The results states that, the CNN model performs better in terms of classification accuracy and also provides an optimal balance of weights and biases. [5] A Deep Learning Model for Live Tweet Analysis has been developed, which generates sentiment scores for recent tweets of a search query. The model uses a large dataset from the Sentiment140 dataset for training. The model achieved training accuracy of 86.33%, validation accuracy of 79.61%, and test accuracy of 79.73%. This project aims to develop software that can obtain user sentiment on specific topics from Twitter. Further research is needed to train more advanced models for higher accuracy and ease of integration.

These studies highlight the versatility of neural networks in sentiment analysis, employing hybrid models, novel architectures, and varied preprocessing methods. However, there exists a notable gap in synthesizing these approaches into a unified framework. The absence of a comprehensive comparative analysis across diverse datasets and domains impedes a clear understanding of the most effective strategies.

III. METHODOLOGY

- **Dataset Selection:** The first step in our methodology involved the careful curation of datasets suitable for sentiment analysis. We aimed to include diverse sources, such as social media posts, product reviews, and

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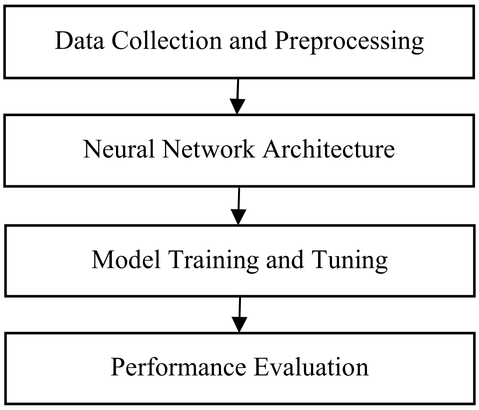
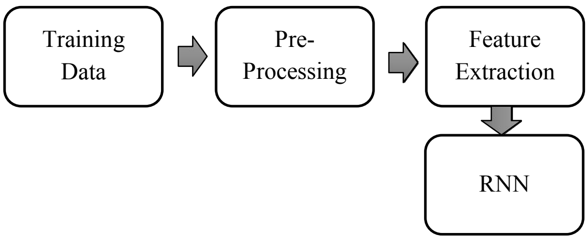
news articles, to ensure a comprehensive representation of sentiment expressions. Noteworthy consideration was given to the balance between positive and negative sentiments within the datasets.

- **Preprocessing:** Prior to training the sentiment analysis model, we subjected the datasets to rigorous preprocessing. This involved tasks such as text normalization, removal of stop words, and tokenization. The goal was to prepare the textual data in a standardized format, ensuring optimal model performance.
- **Model Architecture:** For the sentiment analysis task, we opted for Recurrent Neural Networks (RNNs) due to their intrinsic ability to capture sequential dependencies in textual data. The architecture comprised layers of recurrent cells, allowing the model to retain memory of previous words in a sentence. This sequential context preservation is particularly beneficial in discerning sentiment nuances.
- **Training Procedure:** The RNN model underwent a training process using a carefully partitioned dataset. We employed a standard training-validation-test split to assess the model's performance. Training parameters, such as learning rate and batch size, were fine-tuned through iterative experimentation to achieve optimal results.
- **Evaluation Metrics:** To assess the performance of the sentiment analysis model, we employed widely recognized evaluation metrics such as accuracy, precision, recall, and F1 score. These metrics provided a comprehensive understanding of the model's ability to correctly classify sentiments across various categories.
- **Comparison with Other Architectures:** In addition to RNNs, we explored alternative neural network architectures commonly used in sentiment analysis, including Long Short-Term Memory Networks (LSTMs) and transformer models. Comparative analysis was conducted to highlight the strengths and limitations of each architecture in capturing sentiment patterns.
- **Ethical Considerations:** Throughout the methodology, ethical considerations were paramount. We ensured that our dataset selection avoided perpetuating biases and that the training process adhered to ethical standards. Transparency and fairness were central to our approach to mitigate any unintended consequences in sentiment analysis outcomes.

3.1 Implementation Plan



3.2 Training



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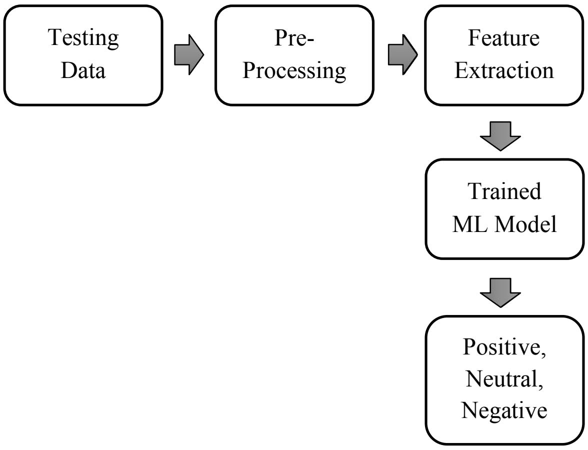
3.3 Testing



By meticulously following this methodology, we aimed to provide a robust and comprehensive evaluation of sentiment analysis using RNNs, contextualized within the broader landscape of neural network architectures.

IV. APPLICATIONS AND USE CASES

- **Customer Feedback Analysis:** One primary application of our sentiment analysis model is in analyzing customer feedback. By employing RNNs, our model excels in understanding the sentiment behind customer reviews, helping businesses gain valuable insights into customer satisfaction, identify areas for improvement, and make informed decisions for product and service enhancements.
- **Brand Monitoring on Social Media:** In the realm of social media, our sentiment analysis model proves instrumental in brand monitoring. By processing and analyzing social media posts, the model can gauge public sentiment toward a brand or product. This application is crucial for businesses to manage their online reputation, address customer concerns promptly, and strategize marketing efforts.
- **Market Research:** Our sentiment analysis tool contributes to market research by analyzing sentiments expressed in news articles, blogs, and forums. This application aids researchers and analysts in understanding market trends, consumer preferences, and emerging issues, facilitating more informed decision-making in various industries.
- **Political Sentiment Analysis:** In the political domain, our sentiment analysis model finds utility in gauging public opinion on political figures, policies, and events. This application is valuable for political analysts, pollsters, and policymakers seeking to understand and respond to the sentiment of the electorate.
- **Healthcare Feedback and Patient Satisfaction:** In the healthcare sector, our sentiment analysis model can be applied to analyze patient feedback and satisfaction surveys. This application assists healthcare providers in understanding patient sentiments, identifying areas for improvement in services, and enhancing overall patient experience.
- **Online Content Moderation:** Our sentiment analysis model plays a crucial role in content moderation on online platforms. By automatically detecting and categorizing sentiments in user-generated content, it helps in identifying and mitigating potentially harmful or inappropriate material, contributing to a safer online environment.
- **Financial Sentiment Analysis:** In the financial industry, our sentiment analysis tool can be employed to analyze news articles, social media discussions, and market reports. This application aids investors and financial analysts in gauging market sentiment, predicting market trends, and making data-driven investment decisions.
- **Educational Feedback Analysis:** Within the education sector, our sentiment analysis model can be used to analyze student feedback and evaluations. This application assists educational institutions in understanding student sentiments, evaluating teaching methodologies, and implementing improvements for an enhanced learning experience.

V. CONCLUSION

In summary, this survey provides a thorough examination of sentiment analysis within natural language processing, focusing on the application of Recurrent Neural Networks (RNNs). RNNs, with their ability to capture sequential dependencies, stand out in deciphering complex sentiment patterns when compared to other architectures.Our methodology, encompassing dataset selection, preprocessing, and ethical considerations, offers a systematic approach to implementing sentiment analysis using RNNs. The discussed applications highlight the practical relevance of our model in various domains, from customer feedback analysis to political sentiment analysis.As sentiment analysis continues to play a pivotal role in decision-making processes, our findings contribute insights into the evolving landscape of natural language processing and sentiment analysis. The integration of RNNs in sentiment analysis marks a significant advancement, inspiring further research in understanding human sentiment across diverse communication channels. In conclusion, the insights provided aim to propel advancements in this dynamic field, fostering a deeper understanding of sentiment in the context of artificial intelligence.

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