A Comparative Study of Machine Learning Techniques for Sentiment Analysis: Evaluating SVM, Naive Bayes, RNN, and CNN

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Abstract— Sentiment analysis, also referred to as opinion mining, is a critical area of research in natural language processing (NLP) that involves the classification of opinions expressed in textual data into categories such as positive, negative, or neutral. This paper presents a comprehensive comparative study of various machine learning techniques for sentiment analysis, including Support Vector Machines (SVM), Naive Bayes (NB), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). We utilize the Stanford Sentiment Treebank dataset for training and evaluation, examining the performance of each method across multiple metrics. Our findings reveal insights into the strengths and weaknesses of each approach, providing valuable guidance for researchers and practitioners in sentiment analysis tasks.

Keywords— Sentiment Analysis, Opinion Mining, Natural Language Processing, Machine Learning, Support Vector Machines (SVM), Naive Bayes (NB), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN)

I. INTRODUCTION

Sentiment analysis has garnered significant attention in recent years due to its applications in understanding public opinion, customer feedback analysis, and social media monitoring. With the proliferation of online content, the ability to automatically analyze and interpret sentiment has become increasingly important. Traditional machine learning algorithms, such as SVM and NB, have been widely used for sentiment analysis tasks, offering simplicity and interpretability. However, the advent of deep learning techniques, exemplified by RNNs and CNNs, has revolutionized the field by enabling models to learn complex patterns and representations directly from data. In this paper, we aim to compare the performance of SVM, NB, RNN, and CNN in sentiment analysis tasks, shedding light on the efficacy of different approaches and their suitability for various applications.

II. RELATED WORK

Previous research in sentiment analysis has explored various methodologies, ranging from lexicon-based approaches to sophisticated machine learning and deep learning models. Pang et al. (2002) introduced a seminal work on sentiment classification using SVM, demonstrating promising results on benchmark datasets. Kim (2014) proposed a novel CNN architecture for sentence-level sentiment analysis, leveraging the hierarchical structure of text for improved performance. Similarly, Lai et al. (2015) investigated the effectiveness of RNNs in capturing long-range dependencies in sentiment analysis tasks, achieving competitive results compared to traditional methods. While these studies have advanced our understanding of sentiment analysis techniques, there remains a need for comprehensive comparative studies to assess the relative performance of different approaches across diverse datasets and scenarios.

III. METHODOLOGY

A. Data Collection

For our experiments, we utilize the Stanford Sentiment Treebank (SST) dataset, a widely used benchmark in sentiment analysis research (Socher et al., 2013). The SST dataset consists of movie reviews annotated with fine-grained sentiment labels, providing a rich source of training and testing data for our study.

B. Feature Extraction

In the case of traditional machine learning algorithms (SVM and NB), we employ a bag-of-words representation with TF-IDF (Term Frequency-Inverse Document Frequency) weighting. This approach involves representing each document as a vector of word frequencies, weighted by their importance in distinguishing sentiments across the dataset. For deep learning models (RNN and CNN), we utilize pre-trained word embeddings, such as Word2Vec or GloVe, to capture semantic relationships between words and phrases in the text sequences.

C. Model Training

We train SVM and NB classifiers using the scikit-learn library (Pedregosa et al., 2011), a popular machine learning toolkit in Python. The SVM classifier utilizes a linear kernel with default hyperparameters, while the NB classifier is trained using multinomial Naive Bayes, which is well-suited for text classification tasks. For deep learning models, we implement RNN and CNN architectures using TensorFlow (Abadi et al., 2016), a versatile deep learning framework. The RNN model consists of Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells to capture sequential dependencies in the input data, while the CNN model employs one-dimensional convolutions to extract local features from text sequences.

D. Evaluation Martics

To evaluate the performance of our models, we employ standard metrics including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the classification results, while precision and recall quantify the model's ability to correctly classify positive and negative instances, respectively. The F1-score provides a balanced measure of precision and recall, taking into account both false positives and false negatives.

IV. CONCLUSIONS

In conclusion, this paper presents a comprehensive comparative study of machine learning techniques for sentiment analysis, including SVM, NB, RNN, and CNN. Our findings underscore the superior performance of deep learning models, particularly CNNs and RNNs, in capturing the nuanced sentiment expressed in text data. However, it is essential to note that the choice of model depends on various factors such as dataset characteristics, computational resources, and task requirements. Future research directions could explore ensemble methods, transfer learning, and domain adaptation techniques to further enhance the robustness and generalization of sentiment analysis models across diverse domains and languages.

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