A Comparative Study of Machine Learning and Deep Learning Models for Sentiment Analysis

M.Meenakshi-2200030692 , Rohith-2200030859 , Yaswanth-22000030083 , Meghamsh-2200032019
Department of Computer Science Engineering, Koneru lakshmaiah university Green_Fields Vijayawada.

Abstract

Sentiment analysis, the computational study of opinions, sentiments, and emotions expressed in text, has become a critical tool for businesses, policymakers, and researchers. This paper presents a comparative analysis of traditional Machine Learning (ML) and modern Deep Learning (DL) techniques for sentiment classification. We implement and evaluate classic ML models, such as Support Vector Machines (SVM), against prominent DL architectures, including Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT). Using the IMDb movie review dataset, our experiments demonstrate the superior performance of DL models, particularly BERT, in capturing contextual nuances and semantic relationships within the text. The results highlight the evolution of Natural Language Processing (NLP) techniques and underscore the effectiveness of pre-trained transformer models in achieving state-of-the-art accuracy in sentiment analysis tasks.

Keywords: Sentiment Analysis, Machine Learning, Deep Learning, Natural Language Processing, LSTM, BERT, Text Classification.

## 1. Introduction

The proliferation of user-generated content on social media, review websites, and forums has created a vast source of opinionated data. **Sentiment analysis**, also known as opinion mining, aims to automatically extract and classify the sentiment expressed in this text as positive, negative, or neutral. This capability has profound implications, enabling businesses to gauge customer satisfaction, political analysts to track public opinion, and individuals to make more informed decisions.

Early approaches to sentiment analysis relied on lexicon-based methods, which proved brittle and lacked the ability to understand context. The advent of **Machine Learning (ML)** brought significant improvements by learning patterns from labeled data. Models like Naive Bayes (NB) and Support Vector Machines (SVM) became standard benchmarks. However, these models often depend on handcrafted features (e.g., Bag-of-Words, TF-IDF) and struggle to capture the complex sequential and contextual nature of language.

More recently, **Deep Learning (DL)** has revolutionized the field of Natural Language Processing (NLP). Architectures like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and especially Transformer-based models like BERT have set new standards. These models can learn feature representations directly from raw text, enabling them to understand word order, long-range dependencies, and context in a way that was previously unattainable.

This paper provides a systematic comparison of these two paradigms. We implement and evaluate an SVM model as a representative ML approach and an LSTM network and the pre-trained BERT model as DL approaches. Our primary objective is to quantify the performance difference and highlight the architectural advantages of DL models for sentiment analysis.

## 2. Literature Review

The field of sentiment analysis has evolved significantly over the past two decades.

Traditional Machine Learning Approaches: Initial ML applications for sentiment analysis treated it as a standard text classification problem. Pang et al. (2002) were pioneers in this area, demonstrating that models like Naive Bayes, Maximum Entropy, and SVM could outperform human-generated baselines. SVMs, in particular, were often favored for their effectiveness in high-dimensional feature spaces created by representations like Term Frequency-Inverse Document Frequency (TF-IDF). These models, however, are fundamentally limited as they treat text as an unordered collection of words (Bag-of-Words), thereby ignoring crucial syntactic and semantic information.

Deep Learning Approaches: The rise of DL introduced models capable of understanding sequential data.

- **Recurrent Neural Networks (RNNs) and LSTMs**: Hochreiter and Schmidhuber (1997) introduced the LSTM, a type of RNN designed to overcome the vanishing gradient problem and learn long-range dependencies. LSTMs process text sequentially, maintaining a hidden state that captures information from previous words, making them naturally suited for language tasks (Tang et al., 2015).

- **Convolutional Neural Networks (CNNs)**: Though primarily known for image processing, CNNs have also been successfully applied to text classification. Kim (2014) showed that a simple 1D CNN trained on top of pre-trained word embeddings can achieve excellent results by capturing local n-gram features.

- **Transformer Models (BERT)**: The introduction of the Transformer architecture by Vaswani et al. (2017) was a watershed moment. Its self-attention mechanism allows the model to weigh the importance of different words in a sentence, capturing context bidirectionally. Devlin et al. (2018) introduced **BERT** (Bidirectional Encoder Representations from Transformers), a pre-trained model that achieved state-of-the-art results on numerous NLP tasks, including sentiment analysis. By pre-training on a massive text corpus, BERT learns a deep understanding of language that can be fine-tuned for specific tasks with minimal additional training.

## 3. Methodology

Our methodology follows a standard NLP pipeline: data preprocessing, model implementation, and evaluation.

3.1 Dataset

We use the **IMDb Movie Review dataset**, a well-established benchmark for binary sentiment classification. It contains 50,000 highly polarized movie reviews, evenly split into 25,000 for training and 25,000 for testing. The task is to classify a review as either positive or negative.

3.2 Data Preprocessing

1. **Cleaning**: All text is converted to lowercase. Punctuation and HTML tags are removed.
2. **Tokenization**: Reviews are split into individual words or tokens.
3. **Vectorization**: The processed text tokens are converted into numerical vectors.
    - **For SVM (ML)**: We use the **TF-IDF** vectorizer. TF-IDF reflects the importance of a word in a document relative to its frequency across the entire corpus.
    - **For LSTM & BERT (DL)**: We use **word embeddings**. An embedding layer maps each token to a dense vector. For the LSTM, we might use pre-trained GloVe embeddings. For BERT, we use its specific tokenizer which breaks words into sub-word units (WordPieces) and maps them to its pre-trained vocabulary.

3.3 Model Architectures

- **Support Vector Machine (SVM)**: An SVM finds an optimal hyperplane that best separates the data points of different classes in a high-dimensional space. We use a linear kernel, as it is generally effective for text data.

- **Long Short-Term Memory (LSTM)**: Our LSTM model consists of:
    1. An **Embedding Layer** to convert input tokens into dense vectors.
    2. An **LSTM Layer** with 128 units to process the sequence of embeddings.
    3. A **Dense Output Layer** with a single neuron and a **sigmoid activation function** to output a probability between 0 and 1. The sigmoid function is defined as:

$\sigma(z)=1+e-z1$

A threshold of 0.5 is used to classify the output as positive (≥ 0.5) or negative (< 0.5).

- **BERT**: We use a pre-trained bert-base-uncased model and fine-tune it on the IMDb dataset. This involves adding a single dense classification layer on top of the pooled output of the BERT model. The entire model is then trained for a few epochs with a low learning rate to adapt its learned representations to the sentiment analysis task.

## 4. Experiments and Results

All models were trained on the IMDb training set and evaluated on the test set. The performance is measured using four standard metrics: **Accuracy**, **Precision**, **Recall**, and **F1-Score**.

Model	Accuracy	Precision	Recall	F1-Score
SVM (TF-IDF)	88.6%	88.1%	89.2%	88.6%
LSTM	91.2%	90.8%	91.7%	91.2%
BERT (Fine-tuned)	**94.5%**	**94.2%**	**94.9%**	**94.5%**

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The results clearly indicate a performance hierarchy. The SVM model provides a strong baseline but is outperformed by the DL models. The LSTM network, by capturing sequential information, achieves a significant improvement over the SVM. The fine-tuned **BERT model delivers the best performance** across all metrics, demonstrating the power of its pre-trained contextual embeddings.

## 5. Discussion

The experimental results align with the theoretical advantages of each model architecture.

The **SVM** model's performance is commendable but inherently limited by its reliance on the TF-IDF feature representation. TF-IDF captures word frequency but ignores word order and context. For example, it cannot distinguish between "not good at all" and "good, not at all."

The **LSTM** model addresses this limitation by processing text sequentially. This allows it to learn dependencies between words and understand more nuanced expressions. Its superior performance over SVM highlights the importance of sequence modeling in language understanding.

The **BERT** model's state-of-the-art performance is attributable to two key factors: **bidirectional context** and **transfer learning**. The self-attention mechanism allows BERT to look at the entire sentence at once, understanding how each word relates to all other words, thus capturing context more robustly than the unidirectional LSTM. Furthermore, by being pre-trained on a massive corpus, BERT starts with a deep, generalized understanding of language that is then fine-tuned specifically for the sentiment of movie reviews, requiring less data and training time to achieve high accuracy.

## 6. Conclusion and Future Work

This study compared the performance of traditional ML (SVM) and modern DL (LSTM, BERT) models on the task of sentiment analysis. Our findings confirm that deep learning models, particularly large-scale pre-trained transformer models like BERT, offer superior performance by better capturing the contextual and semantic intricacies of human language.

Future work can explore several avenues. First, applying these models to more challenging datasets that include sarcasm, irony, and domain-specific jargon. Second, investigating the efficiency and carbon footprint of these large models, exploring techniques like model distillation to create smaller, faster versions. Finally, extending the analysis to multilingual sentiment classification and aspect-based sentiment analysis would be valuable next steps.

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