SENTIMENT ANALYSIS USING MACHINE LEARNING TECHNIQUES

Project report submitted in partial fulfillment
of the requirements for the degree of

Bachelor of Technology
in
Communication and Computer Engineering

by

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CERTIFICATE

This is to certify that the project entitled "**Sentiment Analysis Using Machine Learning Techniques**" , submitted by Rashika Jain (23ucc591) and Vidushi Sharma (23ucc614) in partial fulfillment of the requirement of degree in Bachelor of Technology (B. Tech), is a bonafide record of work carried out by them at the Department of Communication and Computer Engineering, The LNM Institute of Information Technology, Jaipur, (Rajasthan) India, during the academic session 2025-2026 under my supervision and guidance and the same has not been submitted elsewhere for award of any other degree. In my/our opinion, this report is of standard required for the award of the degree of Bachelor of Technology (B. Tech).

21-11-2025	Dr. Rahul Sharma
Date	Adviser: Name of BTP Supervisor

Acknowledgments

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Abstract

Sentiment Analysis has become a widely used Natural Language Processing (NLP) technique due to the massive growth of user-generated content on social media, review websites, and online platforms. This project aims to classify IMDb movie reviews as **positive** or **negative** using different machine learning algorithms and feature extraction methods.

We use a complete pipeline consisting of text preprocessing, tokenization, vectorization using **Bag of Words (BoW)**, **TF-IDF**, and **Word2Vec**, and classification using **Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest**. A detailed comparative analysis is performed based on accuracy, precision, recall, and F1-score.

Results show that **TF-IDF with Logistic Regression** performs the best with an accuracy of **88%**, proving that classical ML models combined with strong feature engineering are effective for sentiment classification tasks.

Contents

Chapter 1

Introduction

1.1 The Area of Work

Sentiment Analysis—also known as opinion mining—is an important NLP task that extracts emotional tone or polarity (positive/negative) from text. With the exponential rise of online reviews, user comments, and social media posts, automated sentiment classification has become highly significant for industries such as:

- E-commerce
- Marketing & brand monitoring
- Customer feedback systems
- Recommendation engines
- Content moderation

In this project, we target **movie review sentiment classification** using the IMDb dataset. Movie reviews are expressive and subjective, making them ideal for benchmarking NLP classification methods.

1.2 Problem Addressed

Manual analysis of 50,000+ reviews is time-consuming and inconsistent. The challenges include:

- Large volume of unstructured text
- Noisy data with slang, spelling errors, HTML tags
- Need for an efficient automated classifier
- Identifying the best combination of vectorization and ML algorithm

Thus, we aim to design a **full ML pipeline** that performs accurate sentiment classification using classical machine learning models.

1.3 Existing System

Existing methods for sentiment analysis fall into two main categories:

(1) Traditional ML + Feature Engineering

Models like Logistic Regression, SVM, and Naïve Bayes work on handcrafted features such as BoW or TF-IDF.

Advantages:

- Fast and interpretable
- Works well for sparse text data

Limitations:

- Cannot capture deep semantic relationships
- Vocabulary-based

(2) Deep Learning-based Models

LSTM, GRU, and Transformers learn contextual patterns directly from text.

Advantages:

- Captures semantics and long-range dependencies

Limitations:

- High computational cost
- Requires large datasets

Our project focuses on **classical ML**, which still performs strongly for binary review classification

CHAPTER 2

LITERATURE REVIEW

A brief summary of relevant research:

1. Pang & Lee (2002) – Machine Learning for Sentiment Classification

Introduced BoW-based sentiment classification using Naïve Bayes and SVM.

2. Maas et al. (2011) – IMDb Dataset

Introduced the 50K labeled IMDb dataset used internationally.

3. Liu (2012) – Sentiment Analysis Survey

Discussed challenges of lexical ambiguity and context.

4. Mikolov et al. (2013) – Word2Vec

Introduced neural embeddings capturing semantic relationships.

5. Medhat et al. (2014) – Sentiment Analysis Techniques Review

Compared ML and DL approaches.

Gaps identified:

- No single model works best for all datasets
- Performance highly depends on preprocessing + vectorizer

This motivates our comparative study using different feature extraction methods.

Chapter 3

Proposed Work

3.1 Overview of the System

Our system converts raw IMDb reviews into structured numerical vectors and evaluates multiple ML models.

Pipeline

Raw Review → Preprocessing → Tokenization → Vectorization (BoW / TF-IDF / Word2Vec) → Model Training (LR / NB / DT / RF) → Performance Comparison → Best Model Selection

This modular design ensures flexibility and reproducibility.

3.2 Dataset Details

Source: **IMDb Movie Review Dataset (HuggingFace)**
Labels:

- 0 → Negative
- 1 → Positive

Dataset Size:

- **50,000 reviews**
- 25K training
- 25K testing

This dataset is balanced and commonly used for sentiment analysis benchmarking.

3.3 Preprocessing Pipeline

Based on the steps from file

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:

- Lowercasing
- Removing HTML tags & special characters
- Tokenization
- Removing stopwords (NLTK)
- Lemmatization (WordNetLemmatizer)
- Rejoining cleaned tokens

3.4 Feature Extraction Methods

We compare three feature types:

- **Bag of Words (BoW)**
- **TF-IDF**
- **Word2Vec Embeddings**

Each has different strengths—TF-IDF captures importance, while Word2Vec captures semantics.

3.5 Machine Learning Models

Evaluated with each vectorizer:

- Logistic Regression
- Naïve Bayes
- Decision Tree
- Random Forest

Total models = **12 combinations**

3.6 Training Strategy

- Train/Test split: Provided by dataset
- Hyperparameters: Random State = 42
- Models trained on BoW, TF-IDF, Word2Vec

- Evaluation on accuracy, precision, recall, F1-Score

3.7 Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

Chapter 4

Simulation and Results

Logistic Regression (TF-IDF)

	precision	recall	f1-score	support
0	0.88	0.87	0.88	12500
1	0.87	0.88	0.88	12500
accuracy			0.88	25000
macro avg	0.88	0.88	0.88	25000
weighted avg	0.88	0.88	0.88	25000

Naïve Bayes
(TF-IDF)

	precision	recall	f1-score	support
0	0.84	0.84	0.84	12500
1	0.84	0.84	0.84	12500
accuracy			0.84	25000
macro avg	0.84	0.84	0.84	25000
weighted avg	0.84	0.84	0.84	25000

Decision Tree (TF-IDF)

	precision	recall	f1-score	support
0	0.71	0.72	0.72	12500
1	0.72	0.71	0.71	12500
accuracy			0.71	25000
macro avg	0.71	0.71	0.71	25000
weighted avg	0.71	0.71	0.71	25000

Random Forest (TF-IDF)

	precision	recall	f1-score	support
0	0.83	0.86	0.84	12500
1	0.85	0.83	0.84	12500

accuracy			0.84	25000
macro avg	0.84	0.84	0.84	25000
weighted avg	0.84	0.84	0.84	25000

Logistic Regression (BoW)

	precision	recall	f1-score	support
0	0.83	0.85	0.84	12500
1	0.85	0.82	0.84	12500
accuracy			0.84	25000
macro avg	0.84	0.84	0.84	25000
weighted avg	0.84	0.84	0.84	25000

Naïve Bayes (BoW)

	precision	recall	f1-score	support
0	0.83	0.85	0.84	12500
1	0.85	0.83	0.84	12500
accuracy			0.84	25000
macro avg	0.84	0.84	0.84	25000
weighted avg	0.84	0.84	0.84	25000

Decision Tree (BoW)

	precision	recall	f1-score	support
0	0.71	0.72	0.72	12500
1	0.72	0.71	0.71	12500
accuracy			0.71	25000
macro avg	0.71	0.71	0.71	25000
weighted avg	0.71	0.71	0.71	25000

Random Forest (BoW)

	precision	recall	f1-score	support
0	0.84	0.85	0.84	12500
1	0.85	0.84	0.84	12500
accuracy			0.84	25000
macro avg	0.84	0.84	0.84	25000
weighted avg	0.84	0.84	0.84	25000

Logistic Regression (Word2Vec)

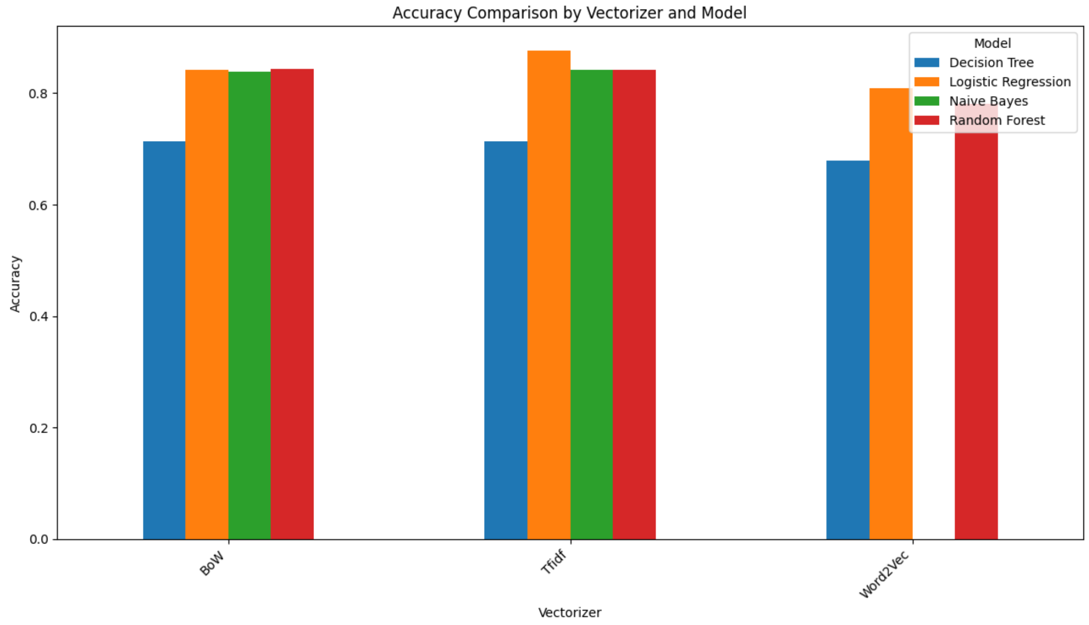
	precision	recall	f1-score	support
0	0.82	0.81	0.81	12500
1	0.81	0.82	0.81	12500
accuracy			0.81	25000
macro avg	0.81	0.81	0.81	25000
weighted avg	0.81	0.81	0.81	25000

Decision Tree (Word2Vec)

	precision	recall	f1-score	support
0	0.67	0.68	0.68	12500
1	0.68	0.66	0.67	12500
accuracy			0.67	25000
macro avg	0.67	0.67	0.67	25000
weighted avg	0.67	0.67	0.67	25000

Random Forest (Word2Vec)

	precision	recall	f1-score	support
0	0.79	0.77	0.78	12500
1	0.78	0.79	0.78	12500
accuracy			0.78	25000
macro avg	0.78	0.78	0.78	25000
weighted avg	0.78	0.78	0.78	25000



RESULTS :

Best overall model: **Logistic Regression + TF-IDF**
Accuracy: **88%**

We summarize key insights:

- TF-IDF consistently outperforms BoW
- Logistic Regression is the strongest baseline
- Naïve Bayes performs well but slightly lower
- Decision Trees overfit
- Random Forest performs stable but not superior
- Word2Vec requires deep networks for better performance

CHAPTER 5

CONCLUSION & FUTURE WORK

This project successfully implemented a complete sentiment classification framework. With detailed preprocessing and feature engineering, classical ML models performed strongly.

TF-IDF with Logistic Regression achieved the best performance (88%), proving its effectiveness for text classification tasks.

Future Work

- Use LSTM, GRU, or Transformer-based models
- Try contextual embeddings (BERT, RoBERTa)
- Add review summarization
- Deploy as a web app for real-time sentiment detection

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