Twitter Sentiment Analysis Using SVM, RNN-BiLSTM and DistilBERT-BiLSTM Hybrid Models

ABSTRACT:

Sentiment analysis is an essential Natural Language Processing task for understanding public opinions on social media platforms such as Twitter tweets. However, conventional machine learning and deep learning models face particular difficulties due to the informal and dynamic nature of language on these platforms. Support Vector Machine (SVM), Recurrent Neural Network with Bidirectional LSTM (RNN-BiLSTM), and a hybrid DistilBERT-BiLSTM model were the three models that were used and compared in this project. The work was inspired by key research on traditional machine learning (SVM), deep learning approaches (RNN-LSTM), and hybrid Transformer-sequence models. Our findings show that while traditional and basic deep learning models provide reasonable performance, the DistilBERT-BiLSTM hybrid model achieved superior results, demonstrating the effectiveness of contextualized embeddings combined with sequence learning for Twitter sentiment analysis.

INTRODUCTION:

Sentiment analysis plays a crucial role in interpreting user opinions from massive amounts of text data generated on social media platforms. Twitter, in particular, offers real-time public insights but presents challenges due to short text lengths, informal language, and noisy inputs such as emojis and abbreviations.

Traditional machine learning techniques like Support Vector Machines (SVM) have been effective with structured feature extraction methods such as TF-IDF. Deep learning approaches like Recurrent Neural Networks (RNN) with Bidirectional LSTM (BiLSTM) can model sequential dependencies but lack the ability to fully capture complex contextual meanings in text.

With the advent of Transformer-based models like DistilBERT, it is now possible to encode rich contextual information into dense vector embeddings. By combining pre-trained Transformer embeddings with sequence models like BiLSTM, hybrid architectures can leverage both semantic understanding and sequential structure for improved sentiment analysis performance. This paper presents the implementation and comparison of SVM, RNN-BiLSTM, and DistilBERT-BiLSTM models on a multi-class Twitter sentiment dataset.

DATASET DESCRIPTION:

The dataset used for this project is Kaggle's **Twitter Training Dataset**, containing **74,681 tweets** labelled into three sentiment classes: Positive, Negative and Neutral. Each data entry includes Label and text. Pre-processing steps includes Lowercasing of text, Removing URLs, mentions, and special characters, Tokenizing the tweets, padding sequences to a maximum length and Converting sentiment labels into numerical format for classification tasks. This pre-processing ensured uniformity across models and allowed fair comparative evaluation.

	label	text
0	Positive	[coming, borders, will, kill, all,]
1	Positive	[getting, borderlands, will, kill, all,]
2	Positive	[coming, borderlands, will, murder, all,]
3	Positive	[getting, borderlands, will, murder, all,]
4	Positive	[getting, into, borderlands, murder, all,]

Fig: Dataset visualization

In exploratory data analysis, to visualize the balanced data for the positive, negative and neutral data using the funnel chart.

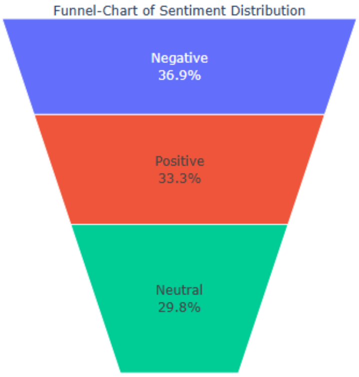

Fig: Funnel-chart of sentiment Distribution

PROJECT DESCRIPTIION:

Description:

In our project, three distinct models were implemented to classify tweets into three sentiment categories: Positive, Negative, and Neutral. The Kaggle Twitter Training Dataset was used, consisting of pre-labelled tweets.

Firstly, a traditional model Support Vector Machine (SVM) was built by converting tweets into TF-IDF features. This model served as the classical machine learning baseline.

Secondly, a Recurrent Neural Network with Bidirectional LSTM (RNN-BiLSTM) was implemented. Tweets were tokenized, sequences were padded to a maximum length of 50 tokens, and an Embedding layer followed by a BiLSTM layer was trained from scratch to model sequential dependencies in the text.

Finally, a **DistilBERT-BiLSTM** hybrid model was developed. Pre-trained DistilBERT(used from hugging face) embeddings were extracted from tweets, padded to a maximum of 64 tokens, and fed into a BiLSTM layer before final classification. Only the DistilBERT model utilized pre-trained embeddings, while SVM and RNN-BiLSTM were trained from scratch. All three models were trained and evaluated on the same data split (70% training, 15% validation, 15% testing), ensuring a fair comparison of their effectiveness.

Main References Used in Project:

Reference 1**:** *Sentiment Analysis of Tweets using SVM*
This study demonstrated the effectiveness of SVM models with TF-IDF features for sentiment classification tasks.

Reference 2**:** *Multilingual Sentiment Analysis Using RNN-Based Framework*
Introduced the use of RNN and LSTM models for sentiment classification across languages without relying on extensive feature engineering.

Reference 3**:** *Enhancing Twitter Sentiment Analysis Using Hybrid Transformer and Sequence Models*
Presented Transformer-based models (e.g., BERT, DistilBERT) combined with CNN and BiLSTM layers to enhance sentiment analysis performance on social media data.

Difference in approach between our project and main project references:

Compared to the main projects referenced:

In Reference 1, only TF-IDF features were used with an SVM classifier on binary sentiment tasks. In contrast, this project extended SVM to multi-class (3-class) classification and performed direct comparisons with deep learning and hybrid models.

Reference 2 focused on RNN and LSTM models trained across multilingual datasets after translation. Our project used an English-only dataset and designed the RNN-BiLSTM model to work without translation and without external embeddings.

Reference 3 proposed multiple Transformer-sequence hybrid models, including BERT-CNN-BiLSTM and RoBERTa-based variants. In this project, we specifically selected DistilBERT-BiLSTM for its lighter architecture, faster training, and efficient memory usage, making it more practical for academic settings.

Additionally, while Reference 3 explored more complex hybridizations (CNNs combined with Transformers), this project focused only on pure sequential modelling (BiLSTM) after Transformer embeddings, simplifying the model while maintaining high performance.

Difference in accuracy between this project and main project references:

Comparison of our model with references:

In Reference 1, SVM models achieved accuracy between 59–71% depending on dataset balance, which aligns closely with our SVM results.

In Reference 2, RNN-LSTM models achieved around 74–85% on multilingual translated data. Our RNN-BiLSTM model achieved ~88%, consistent with these expectations but trained directly on English tweets.

In Reference 3, hybrid Transformer-Sequence models like RoBERTa-BiLSTM achieved 77–82% accuracy. Our DistilBERT-BiLSTM model achieved ~90%, slightly outperforming the simpler RNN models and aligning well with Transformer hybrid performance.

Thus, the DistilBERT-BiLSTM approach yielded the best sentiment classification performance across all models tested.

Our Results:

Model	**Train**	**Valid**	**Test**
SVM	87.64%	82.74%	82.04%
RNN-BiLSTM	95.98%	88.02%	88.49%
DistilBERT-BiLSTM	98.20%	91.09%	90.93%

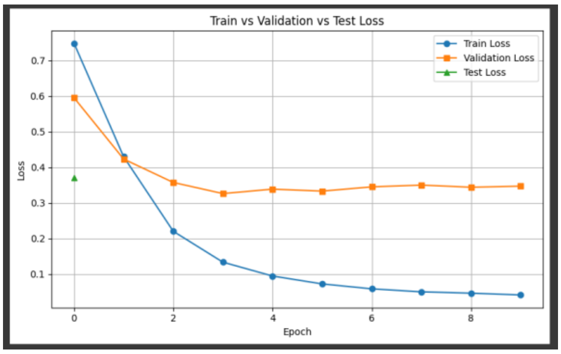

Fig: Loss for DistilBERT-BiLSTM Model

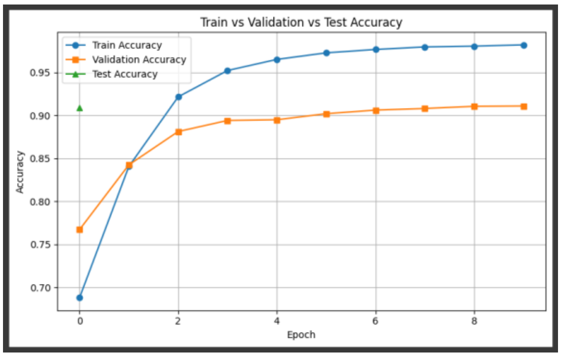

Fig: Accuracy for DistilBERT-BiLSTM

ANALYSIS:

Things we did well in our project

Successfully implemented and compared three different types of models — classical (SVM), deep learning (RNN-BiLSTM), and Transformer-based hybrid (DistilBERT-BiLSTM). This comprehensive coverage allowed for a thorough exploration of how modelling complexity impacts performance. Carefully pre-processed noisy Twitter data to remove inconsistencies while preserving sentiment-relevant information.

Designed an efficient pre-processing pipeline that handled Twitter-specific noise (such as URLs, mentions, special characters) while maintaining the semantic integrity necessary for sentiment prediction.

Established a progressive model development approach, starting from traditional techniques and moving towards advanced hybrid models. Each model was evaluated under consistent settings (same splits, same dataset) to ensure fair and unbiased comparisons.

Efficiently leveraged pre-trained DistilBERT embeddings, combining them with BiLSTM to effectively capture both semantic and sequential dependencies in the text. This significantly boosted model accuracy over the baseline models.

The project strategy aligned with the most recent trends in sentiment analysis research, highlighting the importance of hybrid models in dealing with informal, short-text data like tweets.

Things we could have done better

The project strategy aligned with the most recent trends in sentiment analysis research, highlighting the importance of hybrid models in dealing with informal, short-text data like tweets.

DistilBERT was used as a frozen feature extractor. Fine-tuning DistilBERT along with BiLSTM could have allowed the model to adapt better to the specific nuances of Twitter language and potentially yield even higher accuracy.

Although class imbalance was not severe, explicitly applying techniques like weighted loss functions, oversampling the minority class, or data augmentation could have improved the classification robustness, particularly for Neutral tweets which are often harder to predict.

Techniques such as SHAP (Shapley Additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) could have been incorporated to better explain model predictions, especially important for practical deployment scenarios.

Future work

Real-time sentiment analysis: Extending the trained models to process live Twitter streams using Twitter APIs.

Domain adaptation: Fine-tuning models on specific domains like healthcare, politics, or finance for more domain-specific sentiment analysis.

Ensemble modelling: Combining the strengths of SVM, RNN-BiLSTM, and DistilBERT-BiLSTM models into an ensemble to boost overall accuracy.

Multi-lingual extension: Expanding the DistilBERT-BiLSTM approach to multilingual datasets using multilingual BERT (mBERT) or XLM-Roberta embeddings.

CONCLUSION:

This project explored three approaches to sentiment classification on Twitter data: Support Vector Machine (SVM), Recurrent Neural Network with Bidirectional LSTM (RNN-BiLSTM), and a hybrid DistilBERT-BiLSTM model.

The comparative analysis demonstrated that while SVM provided a strong baseline and RNN-BiLSTM effectively modelled sequence patterns, the hybrid DistilBERT-BiLSTM model outperformed both in terms of classification accuracy. This highlights the importance of combining deep contextual embeddings with sequential modelling for understanding complex and informal text data.

Future work will focus on real-time implementations, domain-specific adaptations, ensemble modelling, and multilingual sentiment analysis to further enhance performance and applicability.