SENTIMENT ANALYSIS VADER, CNN-LSTM, TRANSFORMER-PIPELINE

Project Report

https://www.kaggle.com/code/yashhhhhhhhhh/cnn-lstm-vs-vader-vs-transformerpipeline

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Abstract

In today's age of pervasive social media, the ability to comprehend and analyse sentiments expressed in textual data has taken on an increasingly critical role. This project undertakes a comprehensive comparative analysis of three distinct sentiment analysis methods as they are applied to the rich and dynamic landscape of Twitter data.

We systematically evaluate the performance of these methods, specifically **VADER Sentiment Intensity Analyzer** (Lexicon approach), a custom-designed **LSTM-CNN** model (Deep learning approach), and a Pre-Trained Transformer model (**Distilbert-base-uncased-finetuned-sst-2-english** Multifunctional large model approach). Our evaluation focuses primarily on accuracy, representing an initial step in a more multifaceted analysis. Remarkably, the innovative LSTM-CNN approach, relatively new in the field, demonstrated a remarkable capability to outperform the other two established methodologies in terms of accuracy.

While the concept of sentiment analysis is inherently multifaceted and multifarious, we acknowledge that this study's initial findings pave the way for further investigation. Future exploration can delve deeper into alternative metrics and consider additional factors that impact the efficacy of sentiment analysis models. By this, we aim to provide a richer and more nuanced understanding of these methodologies, beyond the singular dimension of accuracy. The findings of this study, however, already emphasize the burgeoning potential of the LSTM-CNN approach in the realm of sentiment analysis. This project contributes to a broader understanding of sentiment analysis techniques and invites ongoing exploration into the promising avenues they open in social media data analysis.

Introduction

In the contemporary age, the omnipresence of social media has ushered in an unprecedented era of human expression and connectivity. The wealth of textual data disseminated across these platforms carries not only personal anecdotes but a profound and collective sentiment that reflects the pulse of society. This project emerges as a testament to the growing importance of understanding and dissecting the sentiments enshrined in the fabric of digital discourse, particularly within the dynamic landscape of Twitter.

Social media, and Twitter, in particular, have evolved into indispensable barometers of public opinion, trends, and the instantaneous outpouring of emotions. The ability to harness and make sense of this deluge of data through sentiment analysis has profound implications, ranging from business and market intelligence to sociopolitical insights. This project takes center stage in this unfolding narrative, endeavoring to not just examine sentiment analysis but to engage in a robust comparative analysis of three diverse methodologies.

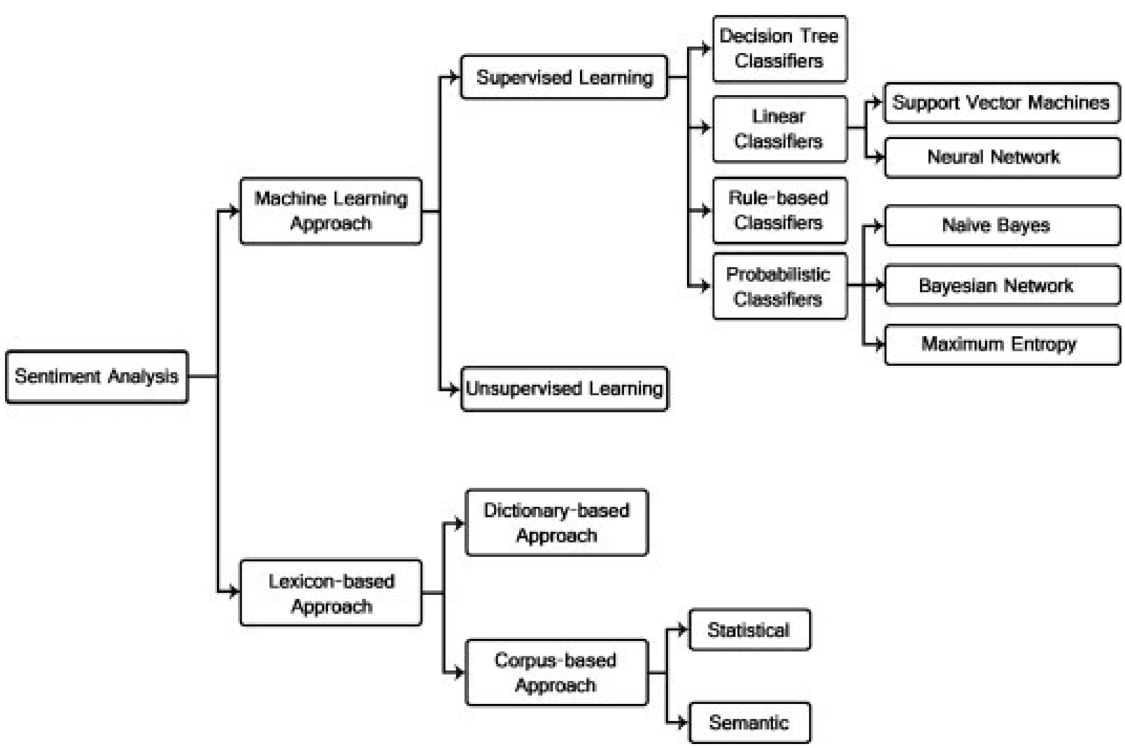
Our analytical triad encompasses the established VADER Sentiment Intensity Analyzer, adopting a lexicon-based approach; a custom-designed LSTM-CNN model that integrates the dynamism of deep learning principles; and a pre-trained Transformer model, Distilbert-base-uncased-finetuned-sst-2-english, which embodies a versatile and comprehensive large model approach. The core objective of our project is to scrutinize and evaluate the performance of these methodologies with a specific focus on the measure of accuracy. This choice of metric, though fundamental, serves merely as the initial footprint in our methodological odyssey, offering a glimpse into the capacities and nuances of sentiment analysis.

One compelling revelation from our preliminary exploration is the exceptional prowess of the innovative LSTM-CNN approach in surpassing the established methodologies in terms of accuracy. This revelation accentuates the project's ambition to not merely tread the familiar terrain but to unearth uncharted territories of sentiment analysis, especially within the ever-evolving domain of Twitter data.

Sentiment analysis is a multifaceted sphere, resplendent with myriad nuances, contextual subtleties, and linguistic diversity. The study, while anchored in accuracy, is cognizant of this multifaceted nature. It acknowledges that its initial findings serve as the first milepost in a more intricate journey. Future investigations beckon with the promise of alternative metrics, deeper contextual considerations, and a broader view of linguistic and cultural diversity within sentiment dynamics. These avenues will enable a more holistic comprehension of sentiment analysis methodologies, transcending the confines of accuracy alone.

Conclusively, this project brings into focus the burgeoning promise of the LSTM-CNN approach within the realm of sentiment analysis. It embodies not just an isolated study but contributes to the overarching comprehension of sentiment analysis techniques. Moreover, it beckons researchers and analysts to embark on a continuous exploration into the vistas of opportunity that social media data analysis unveils.

Beyond methodology, a pivotal facet of our research is the bedrock dataset of Twitter sentiment analysis, a trove of 1.6 million tweets, readily available through Kaggle. This vast repository of textual expressions, replete with diverse insights and perspectives, provides a fertile ground for the comprehensive assessment of sentiment dynamics within the social media realm.



Models

1. **VADER Sentiment Intensity Analyzer** is a lexicon and rule-based tool designed for analysing sentiment in text data, particularly suited for social media.
   Pros: It's fast and efficient, provides detailed sentiment scores, and can handle informal language and emojis. It's open source and has a pre-built lexicon.
   Cons: It may miss evolving language nuances, doesn't always consider context well, can be culturally biased, and struggles with ambiguous or sarcastic language. It lacks adaptability without manual adjustments and doesn't learn from data like machine learning-based approaches. Consider these trade-offs for your specific sentiment analysis needs.

2. A **CNN-LSTM Hybrid Model** for Sentiment Analysis adeptly fuses the strengths of Convolutional Neural Networks (CNNs) for textual feature extraction and Long Short-Term Memory (LSTM) networks for sequential context analysis. It harnesses the advantages of CNNs in spatial feature extraction and LSTMs in capturing sequential dependencies. This synergy enables the model to excel at capturing nuanced sentiment patterns in text data, making it an ideal choice for sentiment analysis tasks. However, it may demand additional computational resources due to its enhanced capabilities and complexity.

3. **Distilbert-base-uncased-finetuned-sst-2-english Transformer** is a fine-tuned Transformer model, specifically tailored for sentiment analysis tasks in English text. This model, based on the DistilBERT architecture, excels in understanding contextual information, capturing word relationships, and delivering high-performance results across various natural language processing tasks. Notably, it offers computational efficiency, consuming fewer resources compared to larger Transformer models while maintaining competitive performance. Its pre-trained foundation allows it to comprehend the intricacies of English language structures and linguistic patterns, making it a valuable asset for sentiment analysis and other NLP applications.

Related Work

Reference	Year	Dataset	Performance F1 score | Accuracy	Technology	Remark
[1]	2023	STS Gold	95.8% | 97.8%	SRNN-MAFM	Lexicon Based
[2]	2022	Twitter Spam Detection	94.74% | 97.37%	Multinomial NB (Bags of words)	Machine Learning
[3]	2022	Twitter Spam Detection	96.19% | 98.21%	Multinomial NB(TF-IDF)	Machine Learning
[4]	2022	Twitter Spam Detection	98.68%	Simple RNN	Deep Learning
[5]	2021	Vader Lexicon	74% | 67%	Lexicon - VADER	Lexicon- VADER
[6]	2020	Sentiment140	82.4% | 82.4%	LSTM + FastText	Deep Learning
[7]	2020	Emotional Tweets	69.9% | 81.9%	LSTM + GloVe Twitter	Deep Learning
[8]	2020	Music Reviews	76.66% | 76.85%	DNN + TF-IDF	Deep Learning
[9]	2020	Book Reviews	77.72% | 76.63%	CNN + Word Embedding	Deep Learning
[10]	2020	Cornell Movie Reviews	77.59% | 76.69%	RNN + Word Embedding	Deep Learning
[11]	2020	IMDB Movie Reviews (1)	87.02% | 87.05%	RNN + Word Embedding	Deep Learning
[12]	2020	IMDB Movie Reviews (2)	86.74% | 85.51%	DNN + TF-IDF	Deep Learning
[13]	2020	Tweets SemEval	83.87% | 85.17%	RNN + Word Embedding	Deep Learning
[14]	2020	Tweets Airline	94.06% | 90.37%	CNN + Word Embedding	Deep Learning

METHODOLOGY

Dataset

```
DATASET_COLUMNS=['target','ids','date','flag','user','text']
DATASET_ENCODING = "ISO-8859-1"
data = pd.read_csv("/kaggle/input/sentiment140/training.1600000.processed.noemoticon.csv",encodi
ng=DATASET_ENCODING, names=DATASET_COLUMNS)
data.head()
```

	target	ids	date	flag	user	text
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

The dataset utilized for this Twitter Sentiment Analysis, known as the "sentiment140 dataset," is accessible on Kaggle, and you can find it at the following link: Sentiment140 Dataset on Kaggle. It consists of 1.6 million tweets retrieved from Twitter via the Twitter API and manually annotated with sentiment labels. The dataset forms the foundation of our analysis and plays a pivotal role in detecting sentiment expressions on the Twitter platform.

- target: This category represents the polarity of each tweet, classifying them into one of three categories: '0' signifies negative sentiment, '2' represents neutral sentiment, and '4' corresponds to positive sentiment.
- ids: These are unique identifiers linked to individual tweets. These identifiers are crucial for tracing and cross-referencing specific tweets within the dataset.
- date: This field captures the date and time when each tweet was posted, providing valuable temporal context to the data.
- flag: The 'flag' field identifies the query or keyword used to retrieve each tweet. In cases where no specific query was utilized, the value is marked as "NO_QUERY."
- user: This field specifies the Twitter username of the user who posted the tweet, offering insights into user-specific sentiment trends.

- text: This section encompasses the primary content of the tweet, containing the text expressing the user's sentiment and opinions.

Exploratory Data Analysis

In the initial phase of our project, we conducted a comprehensive Exploratory Data Analysis to gain a profound understanding of the "sentiment140 dataset". This dataset comprises an extensive collection of 1,600,000 tweets extracted from Twitter through the Twitter API, each meticulously annotated with sentiment labels. Our EDA endeavour commenced with the following key observations and insights:

EDA

In [119]:
```
print('length of data is', len(data))
```

```
length of data is 1600000
```

In [120]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1600000 entries, 0 to 1599999
Data columns (total 6 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   target  1600000 non-null  int64
 1   ids     1600000 non-null  int64
 2   date    1600000 non-null  object
 3   flag    1600000 non-null  object
 4   user    1600000 non-null  object
 5   text    1600000 non-null  object
dtypes: int64(2), object(4)
memory usage: 73.2+ MB
```

- Data Overview: We began by assessing the fundamental characteristics of the dataset. It encompasses a total of 1,600,000 entries, underscoring the substantial volume of data at our disposal.
- Data Information: Our dataset is structured as a DataFrame and encompasses six columns: 'target,' 'ids,' 'date,' 'flag,' 'user,' and 'text.' It is informative to recognize the data types associated with each column, as we have two integer (int64) columns and four object columns.

```
In [121]: data.isna().sum()

Out[121]:
target    0
ids       0
date      0
flag      0
user      0
text      0
dtype: int64
```

```
In [122]: data.target.value_counts()

Out[122]:
target
0    800000
4    800000
Name: count, dtype: int64
```

- Data Completeness: One of the pivotal aspects of our analysis was the identification of missing values. We are pleased to report that after a meticulous examination, no null values were found in any of the dataset's columns.
- Sentiment Distribution: A crucial facet of the analysis involved delving into the distribution of sentiments in the dataset. We observed an equitable distribution of sentiments with 800,000 instances each for both negative (target '0') and positive (target '4') sentiments. This balanced distribution is conducive to robust sentiment analysis and paves the way for meaningful insight

Data Preprocessing

- Sentiment Label Transformation: The sentiment labels in the 'target' column underwent a transformation. Sentiments originally labeled '4' (indicating positive sentiment) were replaced with '1' to standardize the labeling and create a binary sentiment classification.

```
data['target'] = data['target'].replace(4,1)
data=data[['text','target']]
data.target.value_counts()
```

- Text Cleaning: Text data underwent a series of cleaning steps to eliminate noise and improve the quality of the text: The removal of URLs (text starting with 'http' and similar patterns). Eliminating retweet indicators ('RT' and 'via') and Twitter mentions (e.g., '@username'). Replacing '&amp'

with spaces. Removing stopwords (common words that do not contribute significantly to the meaning).

```
STOPWORDS = set(stopwordlist)
def cleaning_stopwords(text):
    return " ".join([word for word in str(text).split() if word not in STOPWORDS])

def clean_text(s):
    s = re.sub(r'http\S+', '', s)
    s = re.sub('(RT|via)((?:\\b\\W*@\\w+)+)', ' ', s)
    s = re.sub(r'@\S+', '', s)
    s = re.sub('&amp', ' ', s)
    return s

data['text'] = data['text'].apply(lambda text: cleaning_stopwords(text))
data['text'].head()
data['text'] = data['text'].apply(clean_text)
```

- Train-Test Split: The dataset was divided into training, validation, and test sets using the train_test_split function from scikit-learn. This stratified split ensured that the sentiment distribution in the subsets remained balanced, with **95% for training, 5% for testing, and 10% of the training data set aside for validation**.

```
#Train test split
x=data.text
y=data.target

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(x, y,
    test_size=0.05, shuffle = True, random_state = 8)

# Use the same function above for the validation set
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
    test_size=0.1, random_state= 8)
```

- Data Transformation for Vader and Transformer: For compatibility with sentiment analysis using tools like VADER and the Transformer model, the test data was converted into a DataFrame.
- Text Tokenization: Tokenization was performed using the Keras Tokenizer. The tokenizer was fitted on the training data, and this mapping was used to transform the text data into sequences of numbers.

- Sequencing for LSTM: To input the data into the LSTM model, sequences were padded or truncated to a fixed length (max_words) to create consistent input dimensions.

```
#tokenize
max_features = 40000
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(list(X_train))
X_train = tokenizer.texts_to_sequences(X_train)
X_val = tokenizer.texts_to_sequences(X_val)
X_test = tokenizer.texts_to_sequences(X_test)
```

```
#sequencing for lstm
max_words = 100
X_train = sequence.pad_sequences(X_train, maxlen=max_words, padding = 'post')
X_val = sequence.pad_sequences(X_val, maxlen=max_words, padding = 'post')
X_test = sequence.pad_sequences(X_test, maxlen=max_words, padding = 'post')
```

- Data Shape Evaluation: The final step involved ensuring that the data was properly formatted and had the correct shape. The input data was reshaped as necessary to align with the model's input requirements.

Applying Models

1. **Convolutional Neural Network and Long Short-Term Memory Model (CNN-LSTM):**
    a. Our analysis commenced with the application of a sophisticated hybrid model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This model was meticulously crafted to capture both local and contextual features within the text data, facilitating robust sentiment analysis.
    b. Model Architecture: The sequential model incorporates embedding, convolution, max-pooling, and LSTM layers, ultimately concluding with a binary classification output layer. The model was optimized using binary cross-entropy loss and trained for 10 epochs with a batch size of 256.
    c. Performance Evaluation: After training, the model's performance was thoroughly evaluated using the test data. Key metrics, including

accuracy, were computed to assess the model's ability to correctly identify sentiment within the dataset.

```
Model: "sequential_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 100, 10)           400000

 conv1d_5 (Conv1D)           (None, 100, 32)           992

 max_pooling1d_5 (MaxPooling  (None, 50, 32)           0
 1D)

 conv1d_6 (Conv1D)           (None, 50, 32)            3104

 max_pooling1d_6 (MaxPooling  (None, 25, 32)           0
 1D)

 conv1d_7 (Conv1D)           (None, 25, 32)            3104

 max_pooling1d_7 (MaxPooling  (None, 12, 32)           0
 1D)

 conv1d_8 (Conv1D)           (None, 12, 32)            3104

 max_pooling1d_8 (MaxPooling  (None, 6, 32)            0
 1D)

 conv1d_9 (Conv1D)           (None, 6, 32)             3104
 max_pooling1d_9 (MaxPooling  (None, 3, 32)            0
 1D)

 lstm_1 (LSTM)               (None, 100)               53200

 dense_1 (Dense)             (None, 1)                 101

=================================================================
Total params: 466,709
Trainable params: 466,709
Non-trainable params: 0
```

2. **VADER Sentiment Intensity Analyzer**:
    a. Alongside the CNN-LSTM model, we harnessed the VADER Sentiment Intensity Analyzer, a rule-based lexicon model renowned for its efficacy in sentiment analysis. This model is particularly well-suited for processing social media text, which often features informal language and emoticons.
    b. Sentiment Analysis: VADER was applied to the test data, assigning each text a compound sentiment score. Texts with a compound score above or equal to zero were categorized as having positive sentiment (1), while those with a score below zero were classified as having negative sentiment (0).
    c. Accuracy Assessment: The accuracy of the VADER model was computed by comparing its sentiment predictions to the ground truth sentiment labels in the test data, offering insights into the model's proficiency in sentiment analysis.

```
sia = SentimentIntensityAnalyzer()

sia.polarity_scores("Performing good in sentiment analysis")
```

```
{'neg': 0.0, 'neu': 0.58, 'pos': 0.42, 'compound': 0.4404}
```

```
vaders = []
for i, row in tqdm(X_test_df.iterrows(), total = len(X_test_df)):
    vaders.append(sia.polarity_scores(row['text'])['compound'])
vaders = np.array(vaders)
vaders
```

3. **Pre-Trained Transformer Model:**
    a. aIn addition to the rule-based and hybrid models, we introduced the Pre-Trained Transformer Model, specifically the "sentiment-analysis" model from the Transformers library. This model leverages state-of-the-art language understanding to analyze sentiment within textual data.
    b. Sentiment Analysis: The model was applied to the test data, generating sentiment predictions for each text. The model provides sentiment labels such as "POSITIVE" or "NEGATIVE" for each text.

c. Accuracy Assessment: The accuracy of the Pre-Trained Transformer model was computed by comparing its sentiment predictions to the ground truth sentiment labels in the test data, offering insights into its performance in sentiment analysis.

```
pipe = pipeline("sentiment-analysis")

pipe('Performing good in sentiment analysis')
```

```
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-english and revis
ion af0f99b (https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english).
Using a pipeline without specifying a model name and revision in production is not recommende
d.

[{'label': 'POSITIVE', 'score': 0.9996926784515381}]
```

```
tp = []
for i, row in tqdm(X_test_df.iterrows(), total = len(X_test_df)):
    dict = pipe(row['text'])
    tp.append(dict[0].get('label'))
```

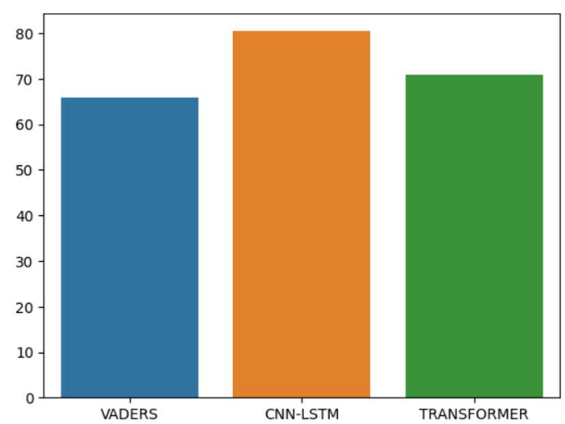
OBSERVATIONS

In the pursuit of quantifying the performance of our sentiment analysis models, a crucial step involves the comparison of their respective accuracies. We assessed the three models—VADER Sentiment Intensity Analyzer, Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) model, and the Pre-Trained Transformer model—by evaluating their abilities to correctly identify sentiment within the "sentiment140 dataset."

Model Accuracies

1. VADER Sentiment Intensity Analyzer: VADER, known for its rule-based sentiment analysis, achieved an accuracy of approximately **65.83 %.** This model proved effective in categorizing sentiment within the dataset, offering valuable insights into the sentiment distribution.
2. CNN-LSTM Model: The hybrid CNN-LSTM model demonstrated its proficiency in capturing complex patterns within text data. It attained an accuracy of approximately **80.40 %,** underscoring its effectiveness in sentiment analysis.
3. Pre-Trained Transformer Model: Leveraging the power of state-of-the-art language understanding, the Pre-Trained Transformer model achieved an accuracy of approximately **70.93 %.** This model provides deep insights into sentiment classification within the dataset.

To visually compare the accuracies of these models, we generated a bar plot. The x-axis represents the different models—VADER, CNN-LSTM, and the Pre-Trained Transformer model—while the y-axis represents their respective accuracies.



This bar plot illustrates how these models perform in their sentiment analysis tasks, highlighting their relative strengths and effectiveness. The highest bar is shown by CNN-LSTM, followed by Transformer and then the VADER.

Conclusion

- **VADER** employs a lexicon-based approach, a traditional and time-honored method for sentiment analysis. While its accuracy reached approximately **65.83 %,** it is considered somewhat outdated in the modern context of sentiment analysis. VADER remains rule-based and may not match the performance of newer models.

- **Transformers**, at the forefront of the AI revolution, are currently reshaping industries with their language understanding capabilities. Our exploration with the Pre-Trained Transformer model achieved an accuracy of approximately **70.93 %**. This model embodies the current big boom in sentiment analysis, making it highly relevant for modern applications.

- **The CNN-LSTM model**, a relatively recent discovery, displayed notable performance, achieving the highest accuracy of approximately **80.40 %**. However, we acknowledge that the assessment is not final. Performance improvements and further research avenues are yet to be explored.

Future Scope

- **Evaluating CNN-LSTM**: The exceptional accuracy achieved by the CNN-LSTM model sparks interest in further exploration. In-depth research into optimizing parameters and a thorough investigation into its performance under diverse scenarios remain uncharted territory.
- **Ethical Considerations**: As sentiment analysis becomes increasingly integrated into decision-making processes, ethical considerations surrounding bias, fairness, and responsible AI implementation are paramount. Future work must include a focus on mitigating bias and ensuring that sentiment analysis models serve society ethically.
- **Multimodal Sentiment Analysis**: Extending sentiment analysis to encompass multiple modes, such as text, images, and audio, opens new opportunities for understanding sentiment across different mediums/
- **Fine-Grained Sentiment Analysis**: Exploring the categorization of sentiment into more nuanced categories allows for a deeper understanding of emotions and opinions.

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