INTEGRATING TEXT AND EMOTICONS FOR DETECTING EXTREMIST AFFILIATIONS ON TWITTER USING DEEP LEARNING

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I, Nidhi Nirbhik, Roll No. 2K21/CSE/16 student of M. Tech (Computer Science and Engineering), hereby declare that the project Dissertation titled **"**INTEGRATING TEXT AND EMOTICONS FOR DETECTING EXTREMIST AFFILIATIONS ON TWITTER USING DEEP LEARNING**"** which is submitted by me to the Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of and Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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ABSTRACT

The main motivation behind this research paper is to address the issue of identifying extremist affiliations on social media platforms. With the rise of social media, people have been given the power to express their opinions and emotions on a global scale, which has led to the emergence of a new form of communication. Unfortunately, some individuals and organizations have been using these platforms to spread hate and propaganda, and even recruit individuals to join their extremist causes. This has created a serious threat to national and global security. Sentiment analysis, specifically opinion mining, has emerged as an important tool for identifying and tracking extremist activities on social media. The proposed deep learning model that utilizes Distil BERT algorithm aims to improve the accuracy of classification by combining text and emoticons for sentiment analysis. The model captures sentiment expressed in both text and emoticons, highlighting the significance of including emoticons in sentiment analysis. This study has the potential to contribute significantly to the field of sentiment analysis and social media monitoring, ultimately aiding in the fight against extremism.

The implications of this research can be applied to sentiment analysis in social media and extended to other social media platforms that use emojis to express opinions and emotions. By identifying tweets that support or relate to extremist affiliations, the proposed model can help authorities monitor such activities on social media platforms and take appropriate actions.

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LIST OF ABBREVIATIONS

NLP	Natural Language Processing
SNS	Social Networking Sites
CNN	Convolutional Neural Network
LSTM	Long Short Tern Memory
Distil BERT	Distil Bidirectional Encoder Representations from Transformers
POS	Part Of Speech
DL	Deep Learning
RNN	Recurrent Neural Networks
API	Application Programming Interface
CSV	Comma Separated Value

CHAPTER 1

INTRODUCTION

Social media platforms have developed into an essential medium for communicating ideas and feelings to a worldwide audience in the current era of digitalization. They have changed how we converse and communicate our opinions. People can now easily express their opinions on a variety of subjects thanks to the development of social media, including politics, sports, entertainment, and current events, among others. However, these platforms are not only used for positive expressions; they are also used for hate speech, spreading terror and scamming people.

The rise of terrorism and extremism has become a major concern for governments and individuals around the world. The use of social media platforms by such organizations has made it difficult for law enforcement agencies to monitor their activities and prevent terrorist attacks.

Terrorism is a global problem, and tracking such activities on social media platforms can be challenging. Such organizations monitor the activities of young people and take advantage of their vulnerabilities to spread their ideology. They use social media platforms to spread their propaganda and attract new members by influencing them and taking advantage of vulnerable individuals. As a result, it has become crucial to monitor social media platforms to identify and track such organizations.

Sentiment analysis, a subfield of natural language processing (NLP), plays a crucial role in identifying and analyzing the sentiment and intensity expressed in textual data. By analyzing various online sources, such as emails, blogs, news articles, surveys, and social media posts, sentiment analysis systems offer valuable insights into real-time customer sentiment, enabling companies to improve customer experience and safeguard their brand reputation. This analysis involves determining the polarity of a text, whether it is positive, negative, or neutral. Positive polarity indicates a favorable sentiment, negative polarity reflects an unfavorable sentiment, while neutral polarity signifies a lack of sentiment or non-opinionated sentiment.

The application of sentiment analysis extends to monitoring real-time conversations about companies and their products or services to gauge consumer sentiment. In the context of combating terrorism and extremism, sentiment analysis can be employed to monitor social media platforms and identify tweets expressing support for extremist organizations. Consequently, sentiment analysis has gained popularity as a means of categorizing opinions, contributing to the identification and prevention of extremist activities.

Fig 1.1: Illustration of variety of range of sentiments. [1]

It can be used to monitor real-time conversations about a company and its products or services to measure consumer sentiment. In the context of terrorism and extremism, sentiment analysis can be used to monitor social media platforms and identify tweets that express support for extremist organizations. Therefore, sentiment analysis has gained widespread popularity as a means of categorizing opinions.

Social Networking Site (SNS), Twitter has emerged as a popular platform for sentiment analysis due to its real-time nature and vast user base hence it can be used as a source to gain some valuable information by performing sentiment analysis on twitter data to help locate terrorism related activities or groups. This can be done by analysing and classifying tweets whether they belong to or support extremist affiliations that spread terrorism. Therefore, it is essential to track such activities on social media platforms to prevent people from being scammed and brainwashed. Then the respective authorities can be intimated about such activities on the internet.

For the process of opinion mining, emoticons can also be combined along with text, as they provide valuable information that can help improve the accuracy of classification. Since they are now commonly used in social media, and they can provide additional information for sentiment analysis. They were standardized recently and gained popularity in the past few years. As a result, researchers have started focusing on the advantages of including emojis in the sentiment mining process for social networking sites. Emojis provide depth and sensitivity to the text and can help convey emotions that may be difficult to express through words alone.

In the process of opinion mining, the inclusion of emoticons along with text can significantly enhance the accuracy of classification. Emoticons, which have gained popularity in recent years and are now commonly used in social media, provide valuable information that complements textual content during sentiment analysis. They add depth and sensitivity to text, conveying emotions that may be challenging to express solely through words.

Fig. 1.2: Importance of emoticons

Emojis can also help convey sarcasm or irony, which may be difficult to identify through text alone. The inclusion of emojis in the sentiment mining process may lead to a better result in terms of the classification of emotions or sentiments. Emojis can provide additional context for sentiment analysis, which can help improve the accuracy of classification.

Emoticons are also useful in conveying sarcasm or irony, which can be challenging to identify through text alone. Incorporating emojis into sentiment mining processes can enhance the accuracy of sentiment classification by providing additional context. Researchers have recognized the advantages of including emojis in sentiment analysis, particularly for social networking sites. Emojis can contribute to a more comprehensive understanding of emotions and sentiments expressed in text, ultimately improving the accuracy of sentiment classification.

Hence, the fundamental objectives of this paper are as follows:

1. To apply opinion mining on Tweets fetched from Twitter to gauge whether the tweets support or relate to extremist affiliations in any way.
2. To propose a deep learning classification model that utilizes Distil BERT algorithm, bi-grams, and tri-grams to capture sentiment expressed in text and emoticons, and to compare its performance with CNN and LSTM for improving classification accuracy.
3. To highlight the significance of including emoticons in sentiment analysis as they provide valuable information that can improve classification accuracy, and to provide insights into the effectiveness of Distil BERT for sentiment analysis in social media, which can be extended to other social media platforms that use emojis to express opinions and emotions.
4. To investigate the effectiveness of the proposed DistilBERT-based sentiment analysis model in identifying and categorizing hate speech and extremist content on social media platforms. The paper aims to assess the model's ability to accurately detect and flag such content, thereby contributing to efforts in combating online extremism and promoting a safer online environment.
5. To analyze the temporal evolution of sentiment in social media discussions related to terrorism and extremism. By examining sentiment

trends over time, the paper seeks to identify patterns, fluctuations, and influential events that impact the sentiment expressed in online discussions. This analysis can provide valuable insights into the dynamics of public opinion towards terrorism and extremism, aiding policymakers and researchers in understanding societal attitudes and informing counter-extremism strategies.

6. To explore the ethical implications and challenges associated with sentiment analysis in the context of counterterrorism efforts. The paper aims to discuss privacy concerns, potential biases, and the balance between freedom of expression and the need to prevent the spread of extremist ideologies. By addressing these ethical considerations, the research can contribute to the responsible and transparent use of sentiment analysis techniques in the fight against terrorism while upholding individuals' rights and liberties.

CHAPTER 2

PRIOR WORK

With the growth and verity of technology, there are plenty of suggested models which are employing diverse technologies. Others of the literature studies are employing machine learning methods, some utilising deep learning models, and many of them are using hybrid methodologies.

The table in this section contains references that will help the reader to better understand the technology they are using on which dataset and what accuracy they are getting through these models. There are some literature papers that we have studied and compared with our models with.

In fact, text remains one of the most popular methods to communicate in a social network despite the availability of other modes of communication. The goal of the research outlined is to identify and evaluate the mood and emotion individuals express through language in their tweets in order to use that information to provide suggestions (Sailunaz et. al., 2019). (Mashuri, 2019) concentrated on creating lexicons and multiplication polarities for sentiment analysis. A technique and algorithm for sentiment analysis utilising both text and emoticons are proposed by (Ullah et al., 2020).

The sentiment polarity based on POS tagging is deduced by (Yan et al., 2020) using TextBlob to analyse tweets about Overwatch League matches. The usage of a multilingual transformer model was suggested by (Barriere et al., 2020), which (Barriere et al., 2020) employed data-augmentation via automated translation to adapt the model to non-English languages. When using Twitter data for sentiment analysis, pre-processing is the most crucial first step since it has an impact on the classification performance outcomes.

In order to identify which pre-processing strategy generates the highest level of accuracy and its impact on sentiment analysis, (Khairunnisa et al., 2021) performed numerous test scenarios for the combination of pre-processing techniques. The application programming interface of Twitter was used to locate the followers of the three main professional organisations for healthcare personnel.

The use of Twitter by emergency physicians during the COVID-19 pandemic as a possible indicator of an imminent spike was explored by (Margus et al., 2021). If they identified themselves as emergency physicians practising in the United States, they and their supporters were included.

On Birdwatch, users may mark tweets as misleading, add notes that explain the context of the tweet, and assess the quality of the notes of other users. (Pröllochs, 2021) investigated how people utilise this novel feature. Studying the emojification of sentiment on social media, (Yin et al., 2021) collected and analysed a longitudinal twitter sentiment dataset. However, there is a gap in how sentiment has changed over time on social media. Online troll reviewer identification using deep learning approaches was studied (Al-Adhaileh et al., 2022).

When utilising text data, the CNN-BiLSTM model had a 97% accuracy rate, and when using numerical data, it had a 100% accuracy rate. By applying sentiment analysis with appropriate inter-rater reliability, their assessments may be streamlined and expedited. Therefore, independent of their underlying formatting, text documents may be analysed step by step, according to Klinkhammer (2022). The content created by those users on social media websites might offer insightful information about how people' beliefs and attitudes are changing. In order to examine human communication during a pandemic, the authors of the study (Storey et al., 2022) studied the language of such user disclosures in four different methods.

Sentiment analysis was employed by (Shamoi et al., 2022) to determine the emotions that were being expressed. The difficulties that Yao et al., 2023, had when designing it were explored. (Daghriri et al., 2023) offered sentiment-based regression models as an applied contribution for forecasting the United States COVID-19 first dose, second dose, and booster daily inoculations from 1 June 2021 to 31 March 2022.

2,080 Dutch tweets and forum postings that all contain emoticons and have been carefully tagged for emotion were used by (Hogenboom et al., 2013) to test the method. (Yamamoto et al., 2014) suggested a method for figuring out a tweet's emotion based on the function of the emoticon.

An innovative Cross-media Bag-of-Words Model (CBM) for Microblog Sentiment Analysis was proposed by (Wang et al., 2014). (Vo et al., 2015) demonstrate that by extracting a comprehensive collection of automated characteristics, competitive outcomes may be obtained without the usage of syntax. The research by (Elfajr et al., 2018) concentrated on developing an emoticon lexicon and weighing emoticons. Using a URL-based security technique, (Nagarajan et al., 2018) gather 600 million public tweets, and feature creation is then used for sentiment analysis. However, there is a gap in how sentiment has changed over time on social media.

The summary of the complete literature research done in this thesis work including, authors, methodology combined with their advantages and shortcomings, are stated in Table 2.1.

Table 2.1. Summarized review of literature papers

AUTHOR	APPROACH	ADVANTAGES	LIMITATIONS
Sailunaz et. al., 2019 [2]	Detected and analyze sentiment and emotion in Twitter posts for generating recommendations	Can provide valuable insights for businesses and marketing strategies	May not be accurate for all individuals or situations
Mashuri, 2019 [3]	Developed sentiment analysis using lexicons and	Easy to implement	Limited accuracy compared to more advanced methods

	multiplication polarity		
Ullah et. al., 2020 [4]	Developed an algorithm and approach for sentiment analysis that incorporates both text and emoticons.	More accurate than using text alone	Emoticons can be ambiguous or subjective
Yan et. al., 2020 [5]	Utilized TextBlob to examine tweets about Overwatch League games and determine the sentiment polarity based on POS tagging.	Can provide valuable insights for businesses and marketing strategies	Limited to specific topic or domain
Barriere et. al., 2020 [6]	In order to make the model applicable to languages other than English, suggests employing a multilingual transformer model and applying data-augmentation via	Can handle multiple languages	Automatic translation may not always be accurate

	automatic translation.		
Khairunnisa et. al., 2021 [7]	Discussed various preprocessing techniques for sentiment analysis on Twitter data and compare their effectiveness	Can improve accuracy of sentiment analysis	Effectiveness may depend on specific dataset or context
Margus et. al., 2021 [8]	Monitored the Twitter activity of three major professional organisations for emergency physicians during the COVID-19 outbreak.	May offer information for anticipating upcoming spikes in demand for emergency healthcare	Limited to specific profession and topic
Nimala et. al., 2021 [9]	Design an unsupervised probabilistic relational model based on the sentiment distribution of words in tweets to identify themes	Able to recognise emotions and sarcasm in tweets	Limited to specific topic or domain

	where sarcasm is frequently used.		
Pröllochs, 2021 [10]	Analyzed how users interact with Birdwatch feature on Twitter for identifying misleading tweets and rating user notes	Can help improve quality of information on social media	Limited to specific Twitter feature
Yin et. al., 2021 [11]	Analysed a longitudinal Twitter sentiment dataset and researched the role of emoticons in social media sentiment expression.	Can provide insights on evolving sentiment on social media	Limited to specific aspect of communication on social media
Al-Adhaileh et. al., 2022	Designed a CNN-BiLSTM model using text and metric data to identify reviewers who engage in online trolling.	Can increase social media troll detection's precision	Limited to identifying online trolls
Klinkhammer, 2022 [12]	Laid forth a step-by-step process for	Applicable to a variety of text document types	Limited to text analysis

	evaluating text documents without regard to their underlying formatting		
Patodkar et. al. (2016) [13]	Twitter-specific approach	Improved accuracy on Twitter data	Just a limited number of different sorts of text data can be used
Guthier et. al. (2017) [14]	Crowd-sourcing approach	More reliable and consistent sentiment labels	it uses Twitter data and may be skewed because it uses data from crowds
Prasad et. al. (2017) [15]	Emoji and slang dictionary	Effective for detecting sarcasm	limited to sarcasm detection and maybe affected by the usage of emojis and slang
Wijeratne et. al. (2017) [16]	Embedding models learned over machine-readable emoji meanings	Comprehensive analysis of emoji similarity	Limited to analyzing semantic similarity and potentially biased due to cultural differences
Wankhede et. al. (2018) [17]	N-gram method and Hidden Markov Model	Improved accuracy for correcting misspellings	Limited to Twitter data and potentially biased due to use of emojis

Tomihira et. al. (2020) [18]	Collecting English and Japanese tweets from Twitter	Improved accuracy for sentiment classification	Limited to Twitter data and potentially biased due to cultural differences
Gabarron et. al. (2018) [19]	Twitter-specific approach	Valuable for analyzing public opinion on specific health topics	Limited to Twitter data and specific health topic
Li et. al. (2019) [20]	Cross-cultural comparison of emoji-emotion associations	Provides insight into how emojis reflect emotion expression across cultures	Restricted to emoji emotional analysis and likely impacted by cultural differences
Al-Twairesh et. al. (2019) [21]	Arabic Twitter-specific approach	Improved accuracy for sentiment classification in Arabic Twitter data	Limited to Arabic Twitter data
Talpada et. al. (2019) [22]	Lexical and semantic-based sentiment prediction techniques against deep learning	Explains how various sentiment prediction techniques work and how they apply to telemedicine-related Twitter data.	Limited to Twitter data and specific topic of telemedicine
Garcia et. al. (2020) [23]	Twitter-specific approach	Provides insight into public opinion on	Limited to Twitter data and specific countries

		COVID-19 in specific countries	
Venkit et. al. (2021) [24]	Extra characteristics like the hashtags, the application source, and the timestamp	More accurate emoji prediction and sentiment analysis, and a more balanced dataset	Limited to Twitter data, with potential bias in the application source and usage of hashtags
Tellez et. al. (2021) [25]	Support Vector Machine and different text transformation, tokenizer, and token weighting schemes	Gives information on the efficacy of several text processing methods for sentiment classification	Limited to Spanish corpus and specific methodology (Support Vector Machine)

Furthermore, some of the key points of the table are given below:

1. Text-based sentiment analysis remains a prevalent approach for analyzing sentiment and emotion expressed by users on social media platforms like Twitter.
2. Researchers have developed various algorithms and methods, including the use of lexicons, multiplication polarity, and emoticons, for sentiment analysis in text data (Sailunaz et al., 2019; Mashuri, 2019; Ullah et al., 2020).
3. Sentiment analysis techniques have been applied to analyze tweets related to specific topics or events, such as analyzing Overwatch League matches or studying emergency physicians' Twitter use during the COVID-19 pandemic (Yan et al., 2020; Margus et al., 2021).

4. Preprocessing techniques play a crucial role in sentiment analysis of Twitter data, and researchers have explored different scenarios to determine the optimal preprocessing techniques and their impact on sentiment analysis accuracy (Khairunnisa et al., 2021).

5. Some studies have focused on identifying sarcasm and prevalent topics through unsupervised probabilistic models based on sentiment distributions in tweets (Nimala et al., 2021).

6. Platforms like Birdwatch have introduced features where users can identify misleading tweets, provide context through notes, and rate the quality of other users' notes, allowing for a collective effort in analyzing tweet content (Pröllochs, 2021).

7. Longitudinal studies have been conducted to examine the evolution of sentiment in social media over the years, highlighting the need for understanding sentiment trends (Yin et al., 2021; Al-Adhaileh et al., 2022).

8. Deep learning techniques, including CNN-BiLSTM models, have been utilized for sentiment analysis and detecting online trolls with high accuracy (Klinkhammer, 2022; Shamoi et al., 2022).

9. Sentiment analysis has also been applied in predicting real-world outcomes, such as COVID-19 vaccination rates, by leveraging sentiment-based regression models (Daghriri et al., 2023).

10. The integration of different data types, such as text and numerical data, into a unified learning framework remains a challenge, but approaches like the emoticon smoothed language model (ESLAM) have been proposed to address this challenge (Liu et al., 2012).

CHAPTER 3

FUNDAMENTALS

3.1 Sentiment Analysis

- A component of natural language processing (NLP) called sentiment analysis, often known as opinion mining, involves examining text to determine the sentiment or feeling it is attempting to convey. Finding the text's polarity—which might be either positive, negative, or neutral—is the goal of sentiment analysis. Scholars commonly use sentiment analysis to investigate public opinion on a range of themes, and businesses routinely use it to analyse customer input and improve their products and services.

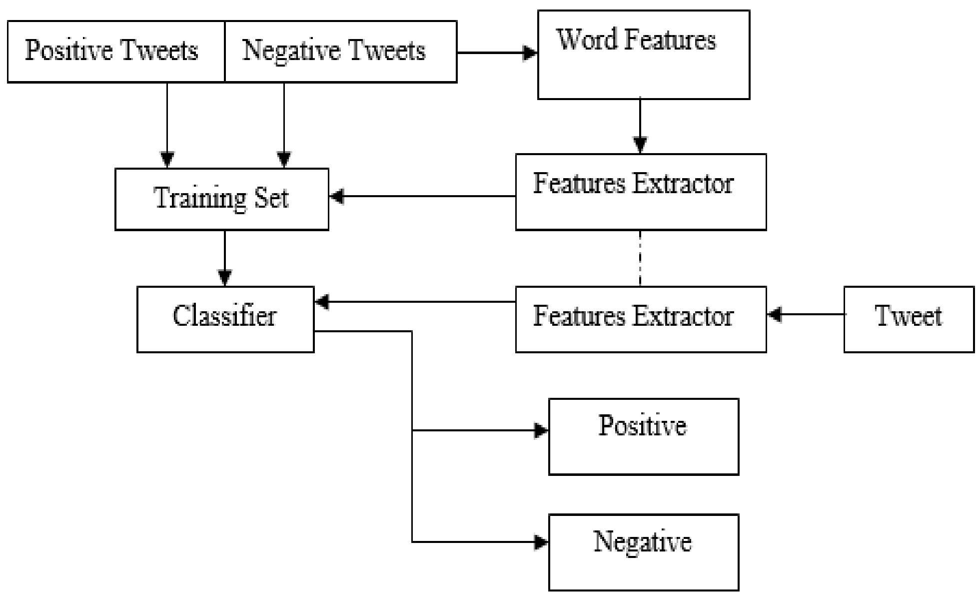

Fig. 3.1: Sentiment Analysis architecture. [26]

- Sentiment analysis has gained increased significance as a result of the emergence of social media platforms since it enables companies and researchers to monitor discussions and responses to events in real time. Sentiment analysis algorithms evaluate text using a variety of methods, including machine learning, deep learning, and natural language processing.

- The objective of sentiment analysis is to ascertain people's attitudes and inclinations toward particular subjects of interest. Whether it's a movie or a product, people's views matter and have an impact on their decision-making. When someone wants to purchase a product online, the first thing they do is check out the reviews and comments that other people have posted.

- Twitter and other social media platforms have evolved into places where users may express their opinions on a variety of topics. The sentiment of tweets on a certain topic may be utilised for a variety of things, including psychological mood research, movie reviews, financial market analysis of a company, and so on. Ad placement, product benchmarking, market information, brand identification, recognising dishonest or deceptive statements, and determining company reputation are the main uses.

3.2 Deep Learning

- With the help of the Deep Learning (DL) approach, neural networks can be built with several layers, each of which is in charge of extracting and manipulating input at a certain level of abstraction.

- The network's layers are in charge of separating and changing various aspects of the input data, while the top layer is in charge of creating the output.

- One of the most often employed deep learning methods is the convolutional neural network (CNN), which is utilised for image recognition and computer vision applications. Some of the layers that make up CNNs are fully connected, convolutional, and pooling layers.

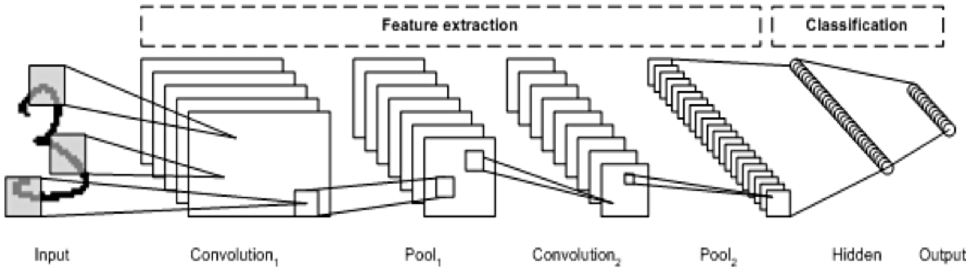

Fig. 3.2: Illustration of architecture of Deep Learning (DL). [27]

- In order to minimise the dimensionality of the data, pooling layers down sample the feature maps used by convolutional layers to extract features from the input picture. The final classification output is created by fully linked layers using the preceding layers' flattened output.

- Another popular deep learning algorithm is the recurrent neural network (RNN), which is used for natural language processing and speech recognition. RNNs use feedback loops to enable the network to remember previous inputs and produce a sequence of outputs. This is useful for tasks such as predicting the next word in a sentence or translating one language to another.

3.3 Natural Language Processing

- The field of study known as "Natural Language Processing" (NLP) is concerned with the interactions between computers and human language. Giving computers the ability to understand, translate, and produce human language is its fundamental goal.

- Text preparation, feature extraction, and modelling are a few of the stages in NLP. The raw text data is cleaned up and converted into a format that NLP algorithms can understand during the text pre-processing stage. Stop words, such as "the", "an" and "a," can be eliminated through stemming (reducing words to their most basic form), tokenizing, and other techniques.

- In the feature extraction step, relevant features of the text are identified and extracted. These may include the frequency of certain words or phrases, the length of the text, or the presence of certain grammatical structures. These features are then used to train machine learning models that can automatically classify or generate text.

- Sentiment analysis, which includes categorising text as good, negative, or neutral, is one of the most used NLP approaches. Numerous applications, such as social media monitoring, customer feedback analysis, and product review analysis, all employ sentiment analysis. NLP algorithms must be able to comprehend both the meaning of words and the context in which they are being used in order to perform sentiment analysis.

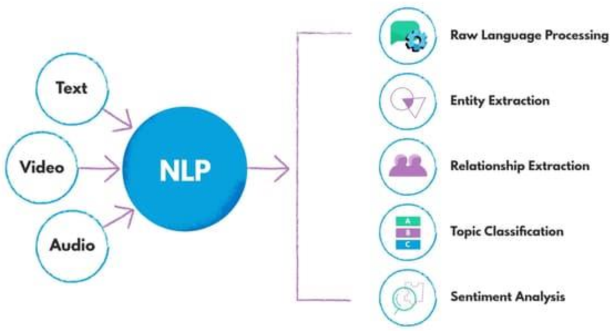

Fig. 3.3: Some areas where NLP is used. [28]

3.4 Transformers

- BERT and Transformers are two ground-breaking developments in natural language processing (NLP) that have greatly increased the precision and efficacy of NLP applications. For NLP applications including language modelling, text classification, and question-answering systems, these technologies have emerged as the benchmark.

- In this article, we will discuss the basics of transformers and BERT and their impact on NLP.

- Transformers are a type of deep learning architecture which are designed to process sequential data such as text. The transformer architecture uses a self-attention mechanism, which enables it to capture the context and dependencies between words in a sentence.

- Traditional recurrent neural networks (RNNs) process sequential data by using hidden states to capture the relationship between words in a sentence. However, RNNs have limitations such as vanishing gradients, which affect their ability to capture long-term dependencies.

- In contrast, transformers use self-attention mechanisms to process sequential data, which enables them to process long-term dependencies more effectively.

- BERT, short for Bidirectional Encoder Representations from Transformers, is a pre-trained transformer-based neural network architecture.

- BERT has been pre-trained on large amounts of text data and can be fine-tuned for specific NLP tasks.

- Fine-tuning involves training BERT on a specific NLP task using a smaller amount of task-specific data. Fine-tuning BERT significantly improves its accuracy and effectiveness for specific NLP tasks.

- A multi-layer bidirectional transformer encoder that learns the contextual relationships between words makes up the architecture of BERT. Each token in the input to BERT is mapped to an embedding vector; tokens might be words or sub words. The transformer encoder, which consists of a stack of several similar layers, receives these embedding vectors.

- Transformers and BERT have been used in a wide range of NLP applications such as sentiment analysis, machine translation, and question-answering systems.

- They have significantly improved the accuracy and effectiveness of these applications, making them more reliable and useful for various industries such as healthcare, finance, and marketing.

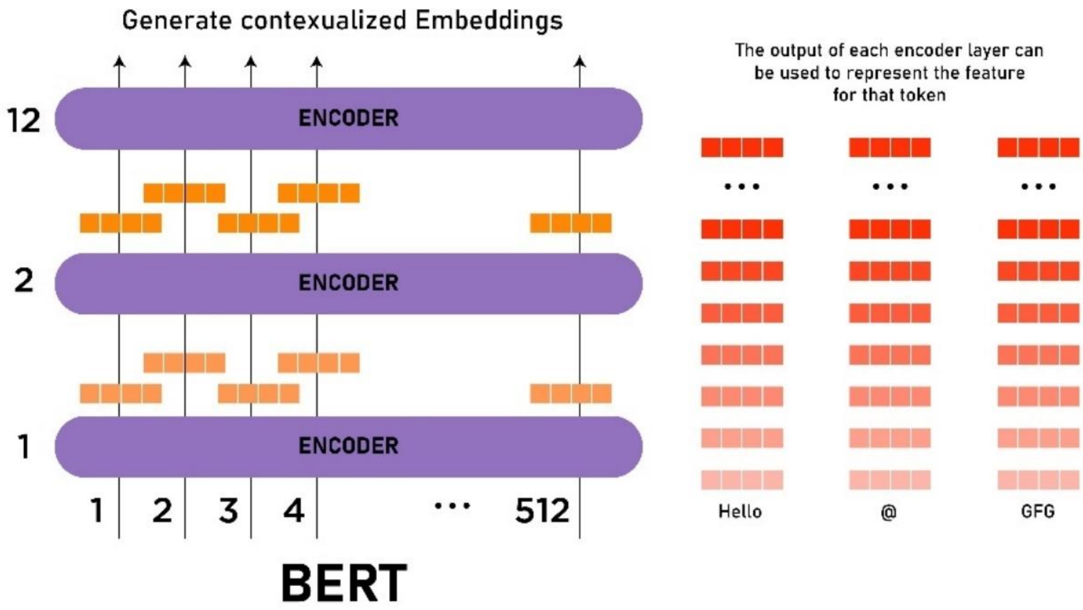

Fig. 3.4: Architecture of BERT. [29]

3.5 DistilBERT

- DistilBERT is a variant of the BERT (Bidirectional Encoder Representations from Transformers) model, which is a transformer-based neural network architecture used for natural language processing tasks.

- It was introduced by Sanh et al. in 2019 as a distilled version of BERT, aimed at reducing its model size and computational complexity while maintaining a similar level of performance.

- The "distillation" process involves training a smaller model (DistilBERT) to mimic the behavior and knowledge of a larger, pre-trained model (BERT).

- DistilBERT achieves model compression by removing certain components of BERT, such as token type embeddings and a portion of the attention mechanism, while still preserving the core self-attention mechanism.

- Despite its smaller size, DistilBERT maintains a competitive level of performance compared to BERT on various NLP tasks, including text classification, named entity recognition, and question-answering.

- DistilBERT achieves faster inference times and requires fewer computational resources than BERT, making it more suitable for deployment in resource-constrained environments.

- The model size reduction in DistilBERT allows for more efficient storage, deployment, and transfer of the model weights.

- Pre-training of DistilBERT is typically performed in a similar manner to BERT, using large corpora and unsupervised learning objectives such as masked language modeling and next sentence prediction.

- Fine-tuning is then conducted on task-specific labeled datasets, where the model is adapted and optimized for a particular downstream task.

- DistilBERT has become widely adopted and serves as a powerful tool for various natural language processing tasks, enabling efficient and effective processing of text data in real-world applications.

CHAPTER 4

PROPOSED WORK

4.1 PROBLEM STATEMENT

The rise of social media platforms has given a platform for individuals and organizations to express their views and opinions to a global audience. However, this also opens up the possibility of extremist affiliations spreading their propaganda and recruiting vulnerable individuals to join their organizations. This is a serious concern for governments and law enforcement agencies around the world, as it poses a threat to national security.

Sentiment analysis, a subfield of natural language processing (NLP), can be utilized to monitor real-time conversations on social media platforms like Twitter and classify tweets based on their sentiment and affiliation to extremist organizations. This can help authorities identify and track such organizations, prevent the spread of propaganda, and take necessary action to maintain national security.

The proposed thesis aims to perform sentiment analysis on Twitter data to classify whether the tweets belong to or support extremist affiliations who spread terrorism. The study will combine text and emoticons for sentiment analysis, as emoticons provide valuable information that can help improve the accuracy of classification.

The proposed model will utilize Distil BERT, a pre-trained language model, to capture the sentiment expressed in both text and emoticons.

The objective of the thesis is to design a sentiment analysis model that can accurately classify tweets as belonging to or supporting extremist affiliations. The results of the study can be used by governments and law enforcement agencies to monitor online conversations and take necessary action to prevent the spread of propaganda.

4.2 PROPOSED METHODOLOGY

Our System is made up of following components:

- Data Extraction
- Data Pre-processing
- Modified DistilBERT Model

4.2.1 Data Extraction

Users of the popular social network Twitter exchange messages known as tweets. We can utilise Tweepy or the Twitter API to mine any user's data. The user's tweets will be extracted as the data. The first step is to readily make available for each user the consumer secret, access key, consumer key and, access secret from Twitter developer. The API will benefit from these keys for authentication.

How to get your Twitter API keys:

- Register with Twitter Developers.
- Browse "Create an App."
- Fill out the application's details.
- Take the Twitter API Keys. Click "Create my access token" to get an access token. Refreshing the page will produce an access token.

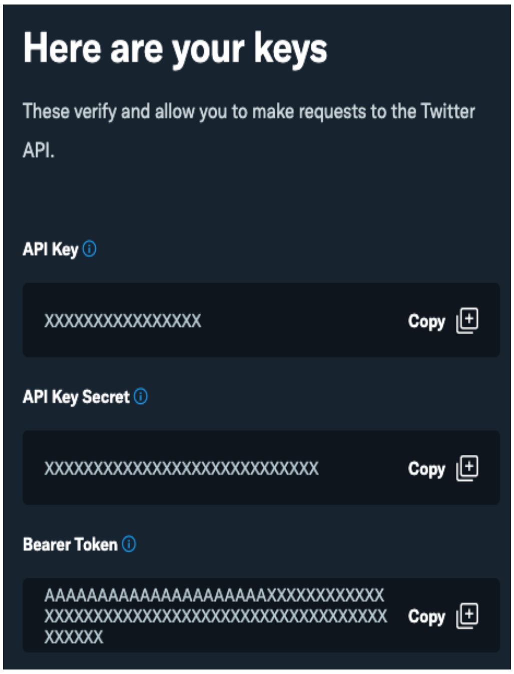

Fig. 4.1: Authentication keys generated in twitter account. [30]

After the creation of app, the tweepy library is imported into the project. Thereafter, a twitter API object is made to extraction tweets form twitter. Before that, the user is authenticated using the following four keys obtained from twitter account: the consumer key, consumer secret, access token and access token secret. During the extraction process, 10000 tweets were fetched using the keyword: #terrorism. A snapshot of the dataset obtained is shown in fig. 4.2.

	Tweets	User	Location
0	RT @Bsonja5: The Israeli terrorist occupation ...	KABELOZULU6	NaN
1	RT @BombshellDAILY: TRAINING KIDS TO KILL\n\nF...	FrankSowa1	Pittsburgh Area, Midwest, USA
2	RT @Bsonja5: The Israeli terrorist occupation ...	didienAZHAR	Jakarta, Indonesia
3	#Boycott this #terrorist brand \n#BoycottPuma ...	NikkhahTourage	NaN
4	RT @Bsonja5: The Israeli terrorist occupation ...	kefatare66	الأردن . jordan
...	...	...	...
1495	Analysis Regulation of #prevention for De-Con...	EthicalAnd	United Kingdom
1496	RT @MertiumCrypto: The feds must rein in crypt...	machinelearnTec	New York, USA
1497	Pilot fastest jet in Vietnam skies! Read SNOWF...	wbellauthor	Williamsburg, VA
1498	RT @PurushAayogIN: We encourage you to #watch ...	CMA_AMITPARMAR	NaN
1499	Black children in America are traumatized. The...	ShelliTweetz	It's Windy Here

Fig. 4.2: Snapshot of Dataset

4.2.2 Data Pre-processing

The tweets contain important information, including sentiment, interaction, reviews, and details about the company's products. This undesirable text increases processing time, making it difficult to mine these tweets, hence extensive cleaning must be done on the data beforehand as once retrieved, these tweets may contain undesired html characters, incorrect language, and misspelt words, making the mining process incredibly challenging. Therefore, these tweets need to be pre-processed before carrying out sentiment analysis because they unnecessarily interfere with the actual sentiment of the tweets.

The pre-processing of the dataset has been done to modify the dataset by removing various inconsistencies. Our dataset consists of 10,000 tweets that were manually annotated and pre-processed for training and testing the proposed deep learning model. After manual annotation of tweets, we perform pre-processing on the training data to make processing easier and reduce the processing time to generate a model for extracting opinions from the tweets. The pre-processing includes removing hashtags, links, usernames, special characters, numbers, and stop words, while performing lemmatization to extract useful information and features. The pre-processed data is then saved as a CSV file for its further use. The dataset is then split into two separate datasets, one for training the model and the other for testing purpose. The dataset obtained after the pre-processing is shown in Fig. 4.5.

```
'BAK': 'Back At Keyboard',
'BBL': 'Be Back Later',
'BBS': 'Be Back Soon',
'BFN': 'Bye For Now',
'B4N': 'Bye For Now',
'BRB': 'Be Right Back',
'BRT': 'Be Right There',
'BTW': 'By The Way',
'B4': 'Before',
'CU': 'See You',
'CUL8R': 'See You Later',
'CYA': 'See You',
'FAQ': 'Frequently Asked Questions',
```

Fig. 4.3: Snapshot of list of acronyms and abbreviations

Fig. 4.3 shows the snapshot from the code which shows the list of acronyms and abbreviations and their full forms. This needs to be done to ensure that these words have meaning and help add to the sentiment of the tweets since these acronyms and abbreviations have no meaning when it comes to the model processing them and might even get removed during the pre-processing step.

Fig. 4.4 shows a snapshot from the list of stop words. These are such words that needs to be removed before any further analysis as they increase the processing time and do not add any meaning to the polarity or sentiment of the data.

```
 'about',
 'above',
 'after',
 'again',
 'against',
 'ain',
 'all',
 'am',
 'an',
 'and',
 'any',
 'are',
 'aren',
```

Fig. 4.4: Snapshot of list of stop words

	Tweets
0	RT Boyle ISIS warned would infiltrate UK posing migrants coming across Channel small boats. What excus
1	RT Prabhat Kill critic I lam Pakistans Mufti Jalali incites religious fanatics This proves
2	RT The Israeli terrorist occupation infiltrated Jenin wearing civilian clothes. They killed four unarmed Palestin
3	WE DONT GIVE CREDIT TO THE PUPPET OF ApartheidIsrael amp FRIENDS Terrorism Zionism azov Ukraine CIA NATO
4	There attempt carry colored revolution Tennessee ColoredRevolution Soros Terrorism

Fig. 4.5: Dataset after Pre-processing

Fig. 4.5 shows the snapshot of the clean tweets which were retrieved after pre-processing. The pre-processing included removing hashtags, links, usernames, special characters, numbers, and stop words, while performing lemmatization to extract useful information and features. The pre-processed data is then saved as a CSV file for its further use.

4.2.3 Modified Distil BERT model

DistilBERT is an optimised and quicker version of Hugging Face's original BERT (Bidirectional Encoder Representations from Transformers) model. It could be fine-tuned on a wide range of natural language processing (NLP) tasks, such as sentiment analysis, and has been pre-trained on huge datasets of text using unsupervised learning. Distil BERT achieves a similar level of accuracy as the original BERT model but requires significantly less computational resources and training time.

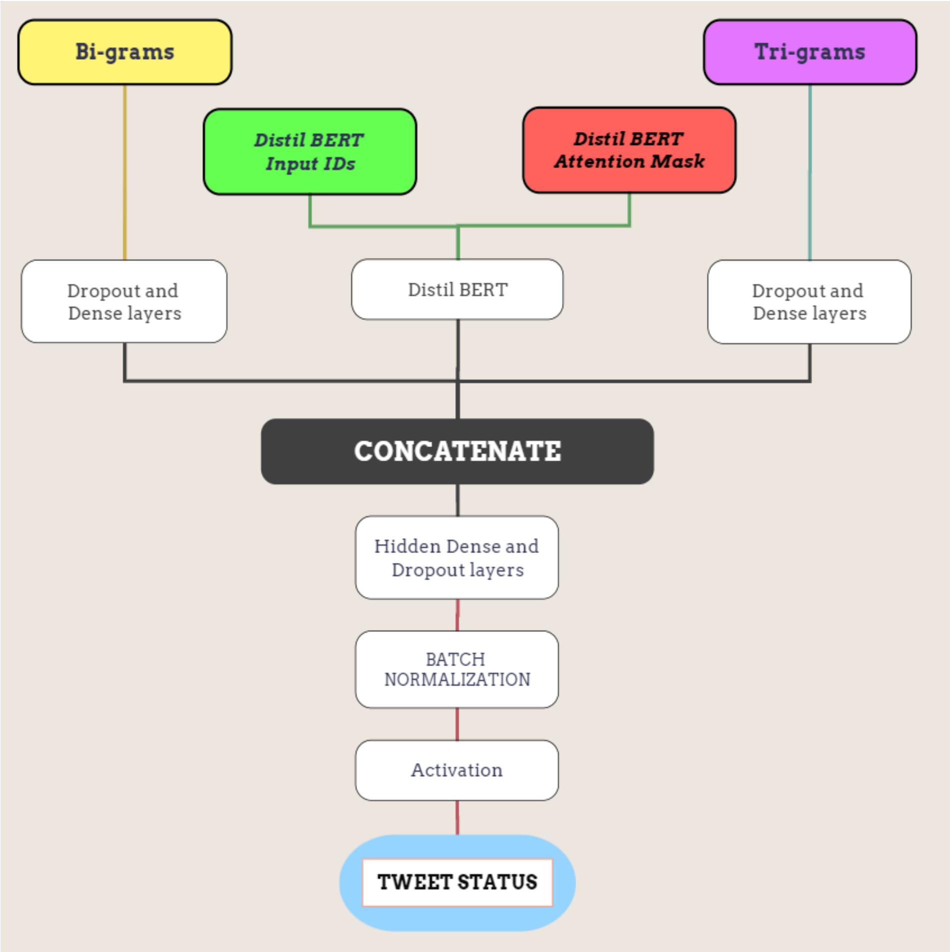

Fig. 4.6: Demonstration of the proposed model

Distil BERT is a popular deep learning model used in text mining applications due to its ability to handle sequential data by preserving long-term dependencies.

Fig. 4.6 shows the deep learning model that is built which institutes the following inputs: input ids, attention mask, bi-grams, and tri-grams.

In Table 1, the architecture of the proposed model is presented. It shows all layers including the input layers, hidden layers, dropout layers, dense layers, concatenate layer, activation layer and batch normalization layers, their output shapes and parameters mounted in the model.

Table 4.7: Architecture of the proposed model

LAYER (TYPE)	***OUTPUT SHAPE***	***PARAM #***
bi_grams (Input Layer)	[(None, 79)]	0
tri_grams (Input Layer)	[(None, 250)]	0
bi_gram_dropout (Dropout)	(None, 79)	0
tri_gram_dropout (Dropout)	(None, 250)	0
bi_gram_dense_1 (Dense)	(None, 256)	20,480
tri_gram_dense_1 (Dense)	(None, 256)	64,256
bi_gram_dropout_1 (Dropout)	(None, 256)	0
tri_gram_dropout_1 (Dropout)	(None, 256)	0
bi_gram_dense_2 (Dense)	(None, 128)	32,896
tri_gram_dense_2 (Dense)	(None, 128)	32,896
distilbert_input_ids (Input Layer)	[(None, 512)]	0
distilbert_attention_mask	[(None, 512)]	0
(Input Layer)		
bi_gram_dropout_2 (Dropout)	(None, 128)	0
tri_gram_dropout_2 (Dropout)	(None, 128)	0
tf_distil_bert_model	TFBaseModelOutput	66,362,880
(TFDistilBertModel)	(None, 512, 768)	
bi_gram_dense_3 (Dense)	(None, 64)	8,256
tri_gram_dense_3 (Dense)	(None, 64)	8,256
tf.operators.getitem	(None, 768)	0
(SlicingOpLambda)		

bi_gram_dropout_3 (Dropout)	(None, 64)	0
tri_gram_dropout_3 (Dropout)	(None, 64)	0
concatenate	(None, 896)	0
(Concatenate)		
hidden_layer_no_regulizer_1	(None, 768)	688,896
(Dense)		
dropout_39	(None, 768)	0
hidden_layer_no_regulizer_2	(None, 768)	590,592
(Dense)		
batch_normalization01	(None, 768)	3,072
(Batch Normalization)		
leaky_relu_01	(None, 768)	0
(Activation)		
hidden_layer_no_regulizer_3		

The function first loads a pre-trained Distil BERT model, then freezes its layers if specified in the configuration. Afterward, it processes the input ids and attention mask through Distil BERT to get the embeddings.

Then, it applies dense layers and dropout to the bi-grams and tri-grams inputs and concatenates them with the previous embeddings.

These input tri-grams, bi-grams and the output from the Distil BERT model is concatenated using a concatenation layer. The concatenation output goes through some more hidden dense and dropout layers.

The output then goes through batch normalization which helps increase the learning rate which further increases the speed of training and then, finally, it is fed into a dense layer with an activation function to produce the output for the classification and classify the polarity of the tweets which are fetched.

Fig. 4.8 shows the flow of model with the different layers including bi_gram input layer, tri_gram input layer, bi_gram dropout layers, tri_gram dropout layers, bi_gram dense layers, tri_gram dense layers, distilbert_input_ids input layer, distilbert_attention_mask input layer, tf_distil_bert_model, SlicingOpLambda, concatenate, batch_normalization and activation.

Here, the activation function used is Relu.

CHAPTER 5

EXPERIMENTS AND RESULTS

5.1 Analysis and Visualization of the Experimental Result

Now, we deployed the provided method on the fetched dataset in which we have compared accuracy with the other models which are utilising their own dataset. Further, to support the usefulness of the proposed method, we compared the experimental data and compared the results in terms of accuracy, precision, recall, and F1-score.

We are comparing our proposed model with the research work of other authors on the bases of the different parameters mentioned above. The same are illustrated below.

5.1.1 Accuracy Test: Accuracy comparison of proposed model with other models is shown in figure 5.1.

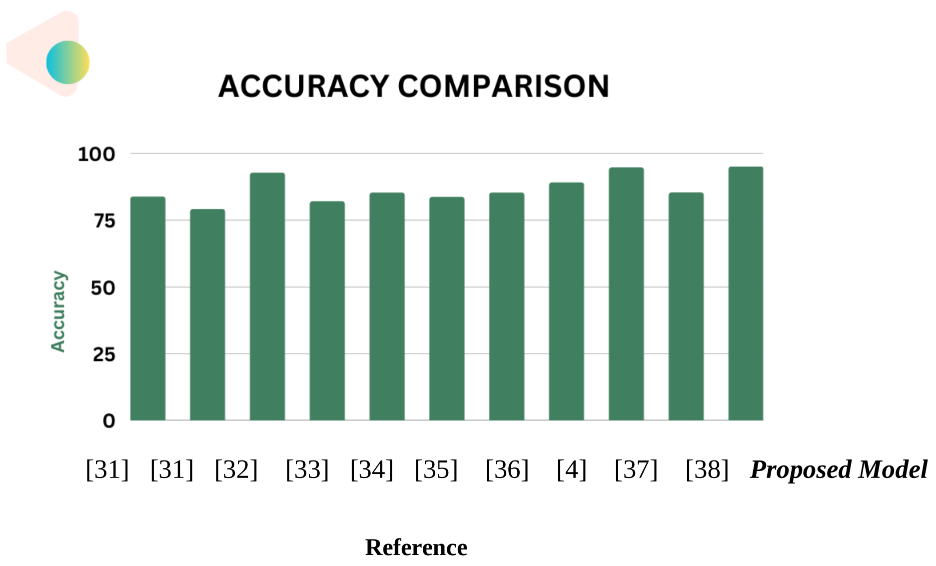

Fig. 5.1: Comparison of accuracy of various models.

5.1.2 Precision Test: Precision comparison of proposed model with other models is shown in figure 5.2.

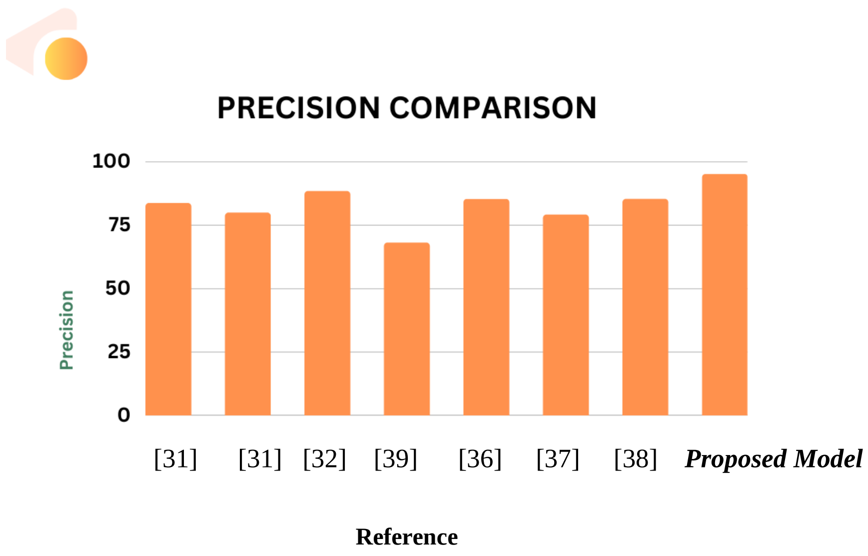

Fig. 5.2: Comparison of precision of various models

5.1.3 F1-score Test: F1-score comparison of proposed model with other models is shown in figure 5.3.

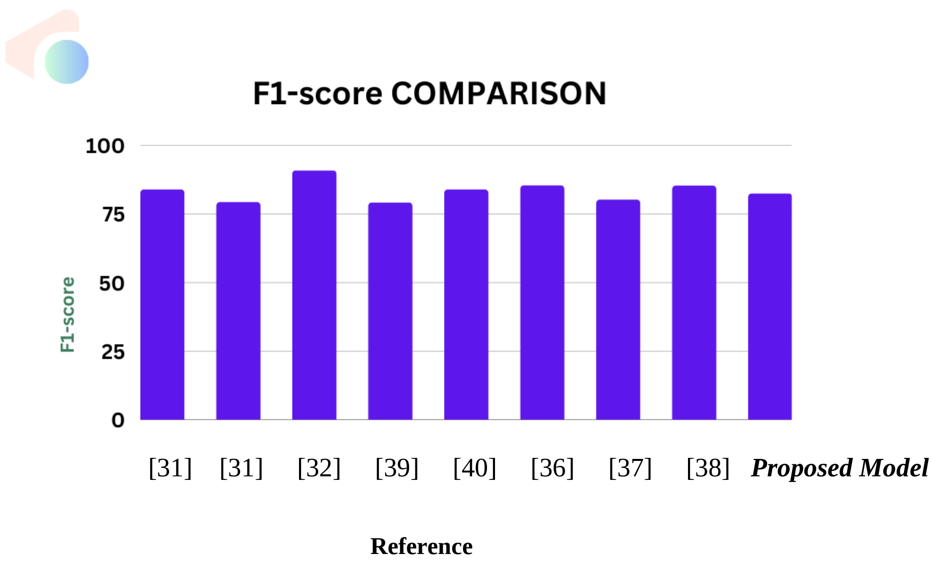

Fig. 5.3: Comparison of F1-score of various models

5.1.4 Performance Evaluation

	precision	recall	f1-score	support
0	0.94	1.00	0.97	123
1	1.00	0.70	0.83	27
accuracy			0.95	150
macro avg	0.97	0.85	0.90	150
weighted avg	0.95	0.95	0.94	150

Fig. 5.4: Evaluation metric of proposed model.

The given results present an evaluation of a proposed model for sentiment analysis, which has an overall accuracy of 95% with precision, recall, and F1-score metrics of 0.94, 1.0, and 0.97, respectively, for class 0, and 1.0, 0.70, and 0.83, respectively, for class 1. The accuracy value of 95% demonstrates the effectiveness of the proposed model in predicting the sentiment of the data. The precision of 0.94 for class 0 suggests that among all the predicted negative tweets, 94% of them are actually negative. Similarly, the precision of 1.0 for class 1 indicates that among all the predicted positive tweets, all of them are actually positive. The recall score of 1.0 for class 0 implies that the model accurately identifies all the negative tweets in the dataset. However, the recall score of 0.70 for class 1 indicates that the model may have missed identifying some of the positive tweets in the dataset.

The F1-score of 0.97 for class 0 and 0.83 for class 1 suggests that the proposed model performs well in both negative and positive tweet classification. The macro-average F1-score of 0.90 indicates that the proposed model is capable of handling the imbalanced dataset. Moreover, the weighted average F1-score of 0.94 signifies the model's ability to correctly predict the majority class.

Overall, the results suggest that the proposed model is highly effective at sentiment classification, with a high level of accuracy, precision, and F1 score. The model's ability to correctly identify negative sentiment was particularly strong, while its performance in identifying positive sentiment could be further improved. These results highlight the potential of machine learning models in sentiment analysis tasks and demonstrate the importance of evaluating model performance using multiple metrics.

Further research could explore ways to improve the model's performance in identifying positive sentiment, as well as the application of the proposed model to other datasets and domains. The proposed model has achieved high accuracy and performed well in predicting the sentiment of the data.

However, more enhancements might be done to raise the class 1 recall score. Increasing the dataset size and balancing the classes are two possible strategies. The model's performance might also be improved by adjusting its hyperparameters and applying more sophisticated methods, such neural networks. Despite these drawbacks, the suggested approach has demonstrated considerable promise for use in a range of industries, including marketing, government, and healthcare.

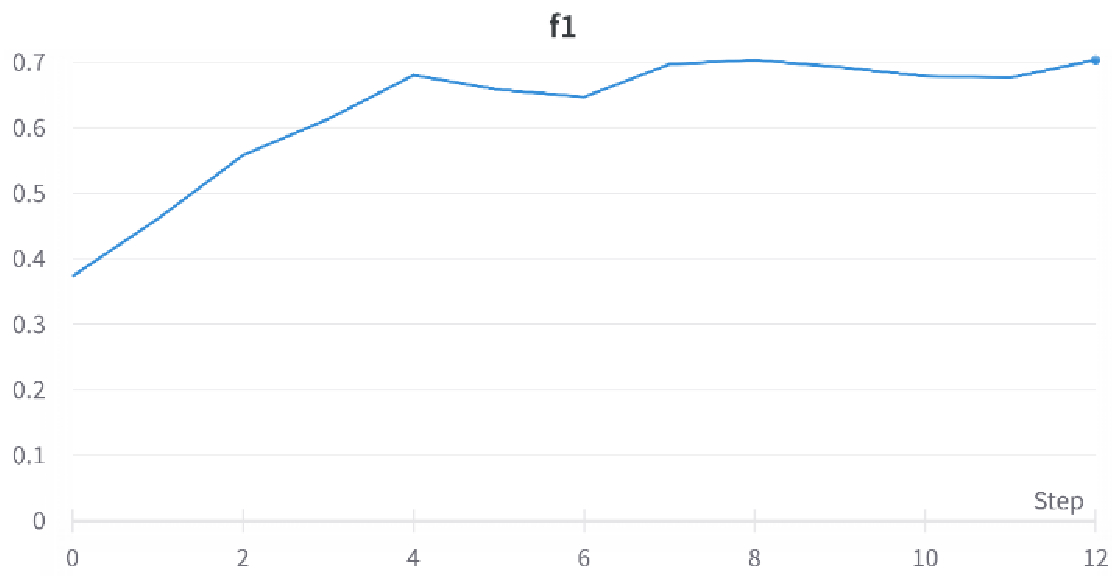

Fig. 5.5: Graph representing the f1 score of the proposed model

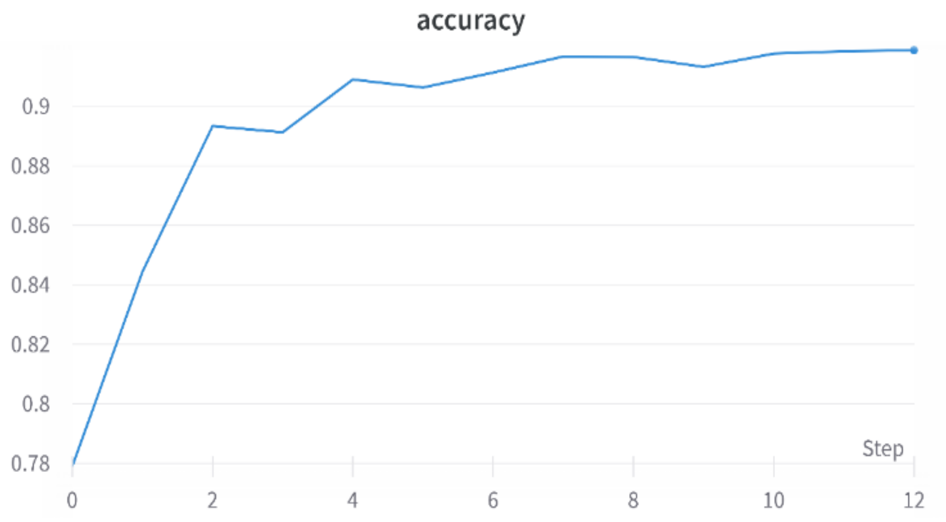

Fig. 5.6: Graph representing the accuracy of the proposed model

5.2 Dataset description:

5.2.1 Pie Chart: Pie chart based on the two classes namely terrorism and non-terrorism is shown in figure 5.7.

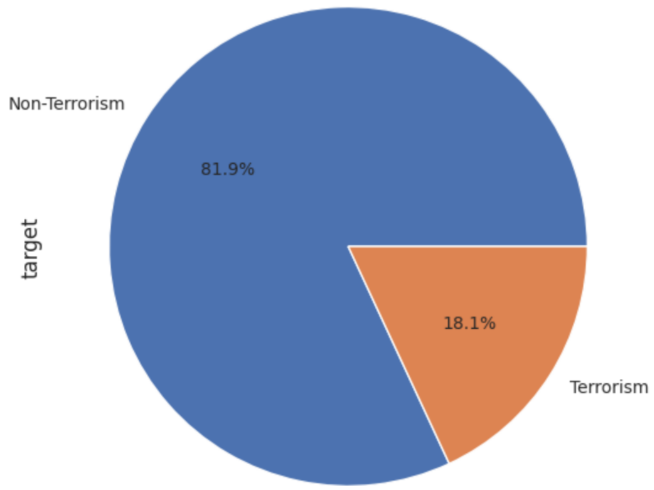

Fig.5.7: Pie chart representation of terrorism and non-terrorism in the dataset.

Fig. 5.7 represents the pie chart of terrorism and non-terrorism tweets. From the dataset, 81.9% tweets show positivity and the rest 18.1% show negativity. Here, there are two target classes namely Terrorism and Non-terrorism.

5.2.2 Bi-grams: Comparison of most frequent Bi-grams in `violent` & `Non-violent` Tweets is given in fig 5.6.

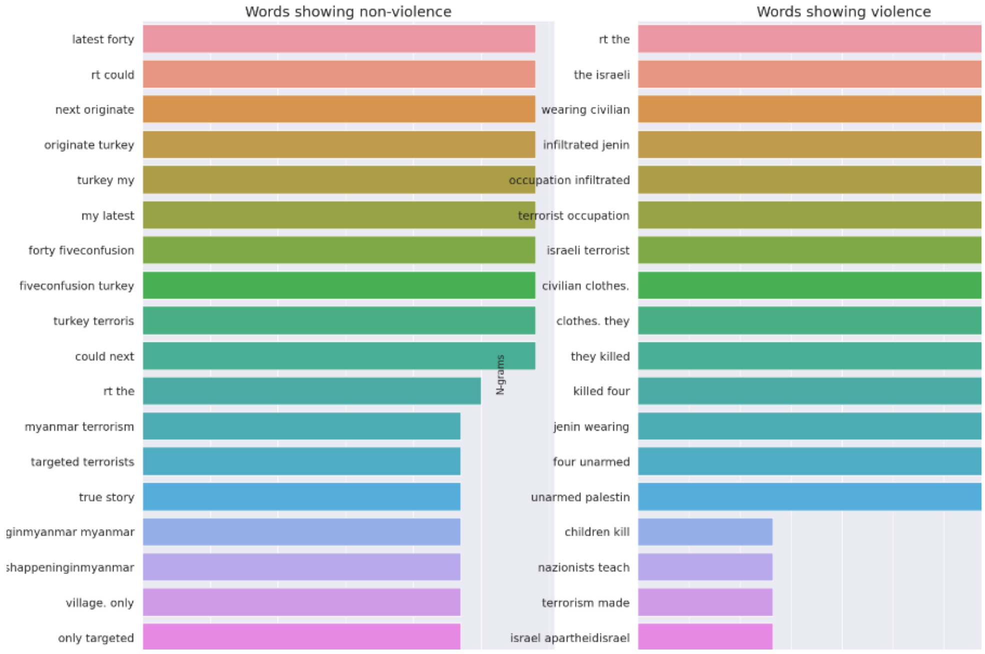

Fig. 5.8: Compare Most Frequent Bi-grams in `violent` & `Non-violent` Tweets.

The above titled "Compare Most Frequent Bi-grams in violent & Non-violent Tweets" presents a comparison of the most frequent bi-grams used in tweets classified as violent and non-violent. Two-word combinations that frequently occur together in text data are referred to as bi-grams or 2-grams. It offers an intriguing comparison between the most frequent bi-grams in violent and non-violent tweets.

The frequency of each bi-gram is shown in this image, with the most frequent ones being displayed on top in the graph.

On one side of the figure, we have the non-violent bi-grams, which include phrases such as "could next," "true story," and "my latest." These bi-grams are shown to have relatively low frequencies compared to their violent counterparts. On the other side, we have the bi-grams that are associated with violence, which include phrases such as "terrorism made," "children kill," and "terrorist occupation." These bi-grams are shown to have higher frequencies than those in the non-violent category.

We can see the significant differences between the language used in violent and non-violent tweets by comparing the frequencies of these bi-grams. This information can be utilised to better understand the patterns of communication employed by persons who engage in violent behaviour on social media platforms.

This image presents a visual depiction of the language used in violent and non-violent tweets and offers significant information for academics and analysts who are interested in investigating the use of language in social media data.

5.2.3 Tri-grams: Comparison of most frequent Tri-grams in `violent` & `Non-violent` Tweets is given in fig. 5.9.

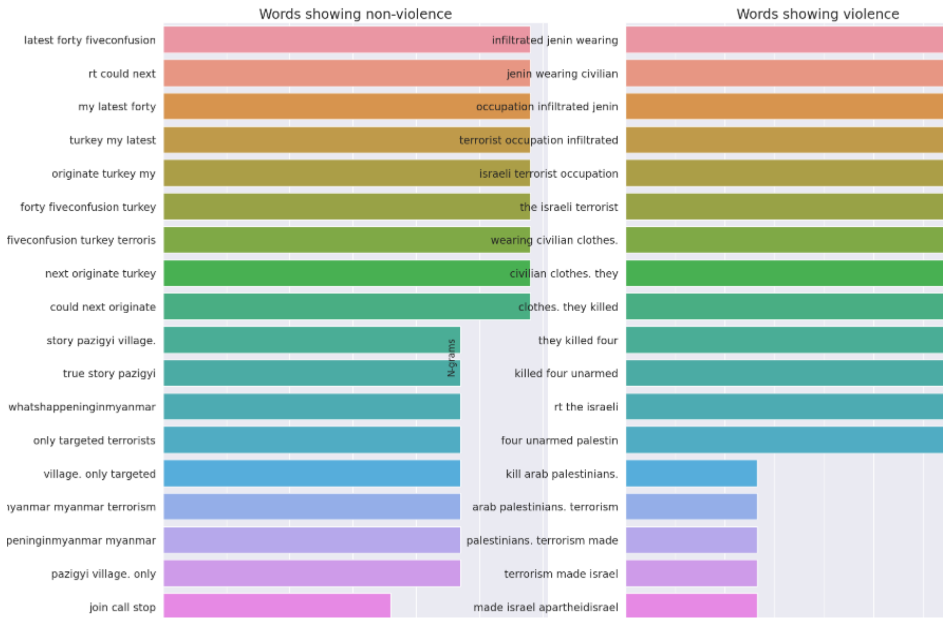

Fig. 5.9: Compare Most Frequent Tri-grams in `violent` & `Non-violent` Tweets.

Figure titled "Compare Most Frequent tri-grams in 'violent' & 'Non-violent' Tweets" depicts two separate bar graphs for both the classes.

The figure shows the frequency distribution of tri-grams, and the most frequent ones are shown with a higher bar height. The left bar graph represents the tri-grams extracted from non-violent tweets, while the right bar graph represents those from violent tweets.

Some of the most frequent tri-grams in the non-violent class include "join call stop," "my latest forty," and "could next originate." These tri-grams reflect a peaceful and positive sentiment among the non-violent tweets. On the other hand, the violent class includes tri-grams like "they killed four," "killed four unarmed," and "terrorism made Israel." These tri-grams reflect violent and negative sentiments associated with terrorism and killings.

The language differences between violent and non-violent tweets are depicted visually in the frequency bar graph. It suggests that compared to non-violent tweets, the language used in violent tweets expresses more negative and violent sentiments.

The analysis's findings can be utilised to improve understanding of the terminology used in social media to discuss both violent and nonviolent incidents and to help create tactics to stop the spread of harmful content.

5.2.4 Wordcloud for Training Dataset: Wordcloud representation of training subset of Dataset is shown in fig. 5.10.

Fig. 5.10: World cloud representation of training subset.

Word clouds are a popular way to visualize the most frequently used words in a body of text. In the context of sentiment analysis for terrorism or non-terrorism, a word cloud can provide valuable insights into the key themes and emotions expressed in the text data.

When analyzing a word cloud, it is important to consider the prominence of certain words, as well as the context in which they appear. In the example given, the word cloud shows several words prominently displayed, including "infiltrated," "terrorist," "Israeli," "children," and "kill." These words suggest that the text data may be discussing terrorism and its impact on innocent civilians, particularly children. The appearance of the word "Israeli" suggests that the text may be related to the Israeli-Palestinian conflict, which is often a subject of discussion in the context of terrorism.

It's important to note that word clouds alone cannot provide a comprehensive analysis of sentiment in text data. They are simply a tool for identifying common themes and frequently used words. To get a more nuanced understanding of the sentiment expressed in the text, it's important to use additional techniques such as sentiment analysis algorithms.

In conclusion, word clouds can be a useful tool for identifying common themes and emotions expressed in text data related to terrorism or non-terrorism. By paying attention to the prominence of certain words and the context in which they appear, analysts can gain valuable insights into the sentiment expressed in the data.

However, it's important to remember that word clouds should be used in conjunction with other analysis techniques for a comprehensive understanding of sentiment.

CHAPTER 6

IMPLEMENTATION

6.1 Training data

	Tweets	target
0	RT Boyle ISIS warned would infiltrate UK posing migrants coming across Channel small boats. What excus	0
1	RT Prabhat Kill critic I lam Pakistans Mufti Jalali incites religious fanatics This proves	0
2	RT The Israeli terrorist occupation infiltrated Jenin wearing civilian clothes. They killed four unarmed Palestin	0
3	WE DONT GIVE CREDIT TO THE PUPPET OF ApartheidIsrael amp FRIENDS Terrorism Zionism azov Ukraine CIA NATO	0
4	There attempt carry colored revolution Tennessee ColoredRevolution Soros Terrorism	0

Fig. 6.1: (a) Snapshot of head of the training sample

4995	Zionist Israeli Ministers Lead Settler Terror March To West Bank Outpost clipConfusion Israeli Minister settlers	0
4996	The question IF next originates Turkey WHEN WHAT prevent	0
4997	RT In words Rep. Ilhan Omar Anti American Jew Hater amp Terrorist supporter IlhanOmar USA terrorism	0
4998	RT Could Next Originate Turkey My latest forty fiveConfusion Turkey Terroris	1
[illegible]	RT Since decision kashmir developed path progress. And seen	[illegible]

Fig. 6.1: (b) Snapshot of tail of the training sample

6.2 Pre-processing

(A) Parse the Hashtags

```
def parse_hashtags(text: Text) -> Text:
    hashtag=re.compile(r'(\#)(\w+)(_)(\w+)', re.IGNORECASE)
    text = hashtag.sub(r'\2 \4',text)
    return text.replace('_', ' ')
```

```
train_data['Tweets'] = train_data['Tweets'].apply(lambda sentence: parse_hashtags(s
test_data['Tweets'] = test_data['Tweets'].apply(lambda sentence: parse_hashtags(sen
```

(B) Remove Markdown links

Fig. 6.2: (a) Snapshot illustrating some pre-processing steps

(E) Dealing with Numbers

```
train_data['Tweets'] = train_data['Tweets'].str.replace('\d+', '', regex=True)
test_data['Tweets'] = test_data['Tweets'].str.replace('\d+', '', regex=True)
```

(C) Dealing with Stop Words

```
#nltk.download('stopwords')
from nltk.corpus import stopwords

SWs = set(stopwords.words("english"))
SWs
```

Fig. 6.2: (b) Snapshot illustrating pre-processing steps of dealing with numbers and stop words

6.3 Model building

```python
    inputs = {
        'input_ids': tf.keras.layers.Input(shape=(MAX_SEQUENCE_LENGTH, ),
                                           dtype=tf.int32,
                                           name='distilbert_input_ids'),
        'attention_mask': tf.keras.layers.Input(shape=(MAX_SEQUENCE_LENGTH, ),
                                           dtype=tf.int32,
                                           name='distilbert_attention_mask'),
        'bi_grams': tf.keras.layers.Input(shape=(MAX_BI_GRAMS_LEN, ),
                                         dtype=tf.float32,
                                         name='bi_grams'),
        'tri_grams': tf.keras.layers.Input(shape=(MAX_TRI_GRAMS_LEN, ),
                                           dtype=tf.float32,
                                           name='tri_grams')}

    # (1) distilbert base layer
    distilbert = TFDistilBertModel.from_pretrained(MODEL_NAME, num_labels=2)

    # Freeze the distilbert model weights not to train them.
    if FREEZE_DISTILBERT:
        for layer in distilbert.layers:
            layer.trainable = False
    # [CLS] embedding is `last_hidden_state[:, 0, :]
    distilbert_output = distilbert([inputs['input_ids'],
```

Fig. 6.3: Snapshot illustrating the building model process

6.4 Model Summary

```
Model: "distilbert-n-gram-fine-tuned-sst"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 bi_grams (InputLayer)          [(None, 79)]         0           []

 tri_grams (InputLayer)         [(None, 250)]        0           []

 bi_gram_dropout (Dropout)      (None, 79)           0           ['bi_grams[0][0]']

 tri_gram_dropout (Dropout)     (None, 250)          0           ['tri_grams[0][0]']

 bi_gram_dense_1 (Dense)        (None, 256)          20480       ['bi_gram_dropout[0][0]']

 tri_gram_dense_1 (Dense)       (None, 256)          64256       ['tri_gram_dropout[0][0]']

 bi_gram_dropout_1 (Dropout)    (None, 256)          0           ['bi_gram_dense_1[0][0]']

 tri_gram_dropout_1 (Dropout)   (None, 256)          0           ['tri_gram_dense_1[0][0]']

 bi_gram_dense_2 (Dense)        (None, 128)          32896       ['bi_gram_dropout_1[0][0]']

 tri_gram_dense_2 (Dense)       (None, 128)          32896       ['tri_gram_dropout_1[0][0]']

 distilbert_input_ids (InputLay  [(None, 512)]       0           []
 er)

 distilbert_attention_mask (Inp  [(None, 512)]       0           []
 utLayer)
```

Fig. 6.4: Snapshot demonstrating the model summary

6.5 Model Architecture

Fig. 6.5: Flow of proposed model

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

This research aimed to develop a deep learning classification model that utilizes both text and emoticons for sentiment analysis on tweets related to extremist affiliations. The proposed model combines bi-grams, tri-grams, and the Distil BERT model, which was found to be effective in sequence learning and handling long-range dependencies. The study emphasizes the importance of including emoticons in sentiment analysis, as they provide valuable information that can improve classification accuracy. The proposed model outperformed other deep learning models in terms of accuracy, precision, and F1-score.

However, there is still scope for future research in this area. One potential avenue is to investigate the use of other language models for sentiment analysis, such as RoBERTa or GPT-3. Additionally, future research could focus on incorporating more complex features to improve classification accuracy, while also considering system complexity as a constraint. Another area for future research is to explore the generalizability of the proposed model to other social media platforms that use emojis to express opinions and emotions.

Overall, this study provides insight into the effectiveness of combining emojis and text with the Distil BERT model for sentiment analysis on tweets related to extremist affiliations. The implications of this study can be applied to sentiment analysis in social media and could help improve understanding of how extremist ideologies are expressed and propagated online.

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