Defending the Digital Domain: BERT-Powered Deep Learning for Aggression Detection in Text Streams

Submitted in partial fulfillment of the
requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **G.CHANDRA SEKHAR(40110398) AND A.BRAHMAIAH(40110091)** who carried out the Project Phase-1 entitled **"Defending the Digital Domain: BERT-Powered Deep Learning for Aggression Detection in Text Streams"** under my supervision from July 2023 to November 2023.

Internal Guide

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Submitted for Viva voce Examination held on________________________

Internal Examiner **External Examiner**

DECLARATION

I, **Gorantla Chandra Sekhar(40110398),** hereby declare that the Project Phase-1 Report entitled **“Defending the Digital Domain: BERT-Powered Deep Learning for Aggression Detection in Text Streams”** done by me under the guidance of **Dr. G KALAIARASI** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE: G.Chandra Sekhar

PLACE:Chennai **SIGNATURE OF THE CANDIDATE**

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I am pleased to acknowledge my sincere thanks to **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

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I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

Cyberbullying has become a growing concern in the digital age, affecting the well-being of its victims. To address this issue, a deep learning-based approach for cyberbullying detection using the Bidirectional Encoder Representations from Transformers (BERT) model was proposed in this paper. It has several advantages over the existing models in NLP, making it a powerful tool for various NLP tasks. Firstly, BERT is bidirectional it takes into account the context of a word from both the left and the right side in a sentence. This allows for a more comprehensive understanding of the meaning of a word in a given context. Additionally, BERT is pre-trained on a large corpus of text, providing a solid base for various NLP tasks. This pre-training allows it to perform well even without fine-tuning for specific tasks. Furthermore, BERT can be fine-tuned for specific NLP tasks, allowing for transfer learning from the pre-trained model to improve the performance for a particular task. BERT is a state-of-the-art pre-trained transformer-based deep learning model for natural language processing tasks. The pre-trained BERT model was finetuned on a large dataset of text messages annotated for cyberbullying. The aim of the fine-tuning process was to train the model to predict whether a given text message contains cyberbullying or not. This paper demonstrates the effectiveness of the BERT model for cyberbullying detection and highlights the potential of deep learning-based approaches for addressing this important problem. The proposed approach has the potential to be applied in real-world settings for the automatic detection of cyberbullying in online text messages.

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF THE PROJECT

Cyberbullying is a form of bullying that takes place using digital technologies, such as the internet, social media platforms, and mobile phones. It involves the use of technology to deliberately intimidate, harass, or harm others. This can take many forms, such as sending threatening messages, spreading rumors or false information, or sharing sensitive or embarrassing photos or videos. Cyberbullying can have a significant impact on its victims, including feelings of fear, anxiety, and depression. Unlike traditional forms of bullying, cyberbullying can reach a large audience, as the abusive messages and images can be easily shared and spread online. This can make it difficult for victims to escape the abuse, as it is always accessible through their digital devices. Cyberbullying is a growing concern, particularly among young people who are among the most frequent users of digital technologies. While the anonymity and distance provided by digital technologies can make it easier for individuals to engage in cyberbullying, it can also make it more difficult for authorities to identify and hold perpetrators accountable for their actions. As such, it is important for educators, parents, and policymakers to be proactive in addressing cyberbullying, through education and awareness programs, responsible use policies, and the development of effective interventions and support for victims. One effective approach to detecting cyberbullying is through monitoring of digital communications, such as social media accounts, texts, and other online interactions. This can be done by parents, educators, or the individuals themselves, and involves regularly checking for signs of cyberbullying, such as threatening messages, spreading of false information, or sharing of sensitive or embarrassing photos or videos. Another strategy for detecting cyberbullying is through reporting mechanisms provided by social media platforms and other digital technologies. Encouraging individuals to report instances of cyberbullying when they encounter it can help identify the problem and provide the necessary information for authorities to take action. Additionally, using sentiment analysis algorithms or machine learning models trained specifically for cyberbullying detection can help detect and classify abusive messages and images. Finally, detecting cyberbullying requires a combination of monitoring, reporting, and the use of advanced technologies. Cyberbullying on Twitter is a growing concern and can have serious impacts on the mental health and well-being of those who are targeted. It often takes the form of harassing or threating messages, spreading false or hurtful information, or targeting someone with insults and derogatory comments. The reach of Twitter means that these actions can have a wider impact, potentially causing harm to not only the individual targeted but also their friends, family, and followers. Twitter has policies in place to address cyberbullying and other forms of abuse. This includes the option to block or report accounts that engage in such behavior.

1.2 FEASIBILITY STUDY

A feasibility study is an analysis that considers all of a project's relevant factors-including economic, technical, social. In this we examine several feasibilities where existing and software equipment were sufficient for completing the project. The economic Feasibility determines whether doing the project is economically beneficial. The outcome of first phase was that the request and various studies are approved and it was decided that the project taken up will serve the end user. On developing and implementing this software saves a lot of amounts and sharing of valuable time

- Economic Feasibility
- Technical Feasibility
- Social Feasibility

1.2.1 Economical Feasibility

The study is accomplished to check the monetary effect that the gadget may have on the corporation. the quantity of fund pour in research and development of gadget is confined. The expenditure is justified.

1.2.2 Technical Feasibility

This is achieved to test the technical feasibility this is, the technical necessities of the system .Any system advanced must not have an excessive demand on available technical recourses. The evolved system needs to have tolerable necessities and are required for enforcing this machine. Our task has tolerable technical requirements.

1.2.3 Social Feasibility

The element of study is to check the extent of recognition of the machine with the aid of the person. This includes the technique of schooling the user to use the system efficaciously. The user has to not be threatened via the gadget. His/her degree of self belief must be accelerated in order that he/she is capable of make some constructive criticism which is welcomed.

1.3 Scope

Cyberbullying detection can help identify and prevent instances of online abuse, harassment, and intimidation. By analyzing text data, including social media posts, comments, and messages, machine learning models can be trained to recognize patterns and features that are associated with cyberbullying. This can help social media platforms and other organizations detect cyberbullying in real-time and take appropriate action to prevent further harm. Using BERT for cyberbullying detection has the potential to significantly improve the ability to detect and prevent cyberbullying in online platforms and social media networks. However, it is important to note that no algorithm can detect cyberbullying with maximum accuracy, and human review and intervention may still be necessary in some cases

CHAPTER 2

LITERATURE SURVEY

In a study by D. Rios and J. De La Rosa, the authors conducted a comparison of various machine learning techniques for detecting cyber bullying on online social networks. The techniques evaluated included logistic regression, decision trees, random forests, and SVMs. The results showed that SVM achieved the best performance among the tested algorithms. The aim of the study was to determine the most effective machine learning technique for detecting cyber bullying on social media platforms. In a research effort conducted by R. Tiwari, A. Aggarwal, and N. Goel, the authors examined the use of deep learning techniques for detecting cyber bullying on social media platforms. The deep learning models studied LSTM networks and CNNs. The results of the study showed that the LSTM model was the most effective among the models tested, with the highest accuracy and F1-score. This study aimed to provide insights into the performance of deep learning models for detecting cyber bullying in the context of social media. Overall, the study provides valuable information on the potential of deep learning models for detecting cyber bullying on social media platforms. It highlights the importance of selecting appropriate models and features for this task, and the potential for using deep learning to effectively detect and address the problem of cyber bullying. In a study by B. M. Alghamdi and M. Algarni, the authors explored the use of ensemble methods for detecting cyber bullying in social media. These methods combined the predictions of multiple models to improve the overall performance of the system. The authors also employed term frequency-inverse document frequency and sentiment analysis as features to represent the text data in their models. These features were used to capture the most important words in the text and the overall sentiment expressed. The results of the study indicated that the use of ensemble methods significantly improved the performance of the models in detecting cyber bullying on social media. This suggests that combining multiple models can help to address the challenges and limitations of individual models and enhance the overall accuracy and effectiveness of the system. In a study by R. Bhutani and P. Kanungo, the authors conducted a comparative study of various ML algo’s for detecting cyber bullying on the popular social media platform, Twitter. The algorithms included logistic regression, decision trees, random forests, and support vector machines. The results of the study revealed that support vector machines outperformed the other algorithms in terms of accuracy and performance. This suggests that SVM may be a suitable approach for detecting cyber bullying on Twitter and other similar platforms. Overall, the study provides valuable insights into the performance of different machine learning algorithms for detecting cyber bullying on social media. It highlights the importance of selecting appropriate algorithms and features for this task, and the potential for using machine learning to effectively detect and address the problem of cyber bullying. E. Demirtas, M. O. Toker, and M. Gokerconducted a study aimed at detecting cyber bullying on social media through the use of machine learning techniques.

2.1 Existing System & Drawbacks

Cyberbullying is a serious issue that has become increasingly prevalent with the increase in social media usage. To combat this problem, researchers have looked to using machine learning models to automatically detect instances of cyberbullying. This approach uses various ML algo's, including K-Nearest Neighbor, SVM, Naive Bayes,and Decision Tree, to classify text as either being or not being related to cyberbullying. The process begins by obtaining a dataset of labeled text data. After pre-processing, the data is split into testing and training sets. The training set is used to develop the ML models, and the testing set is used to assess them. To describe the text data and enhance the effectiveness of the models, features including TF-IDF, bag of words, and n-grams are used. Each machine learning algorithm has its own unique strengths and weaknesses, and the choice of algorithm is dependent on the specific needs of the problem.

For example, SVM is often utilized for text classification due to its ability to handle high-dimensional data and its resistance to overfitting. In conclusion, ML algo such as SVM, Naive Bayes, KNN, and Decision Trees can be used to detect cyberbullying in text data, and the best choice of algorithm depends on the specific needs of the problem.

Naive Bayes is a fast and straightforward algorithm that is frequently used for text classification. KNN is a non-parametric algorithm that is often used for text classification because it can handle a large number of features and has low computational costs.

Decision Trees are simple to understand and interpret, and they can handle non-linear relationships between features and target variables. In conclusion, ML algo such as SVM, Naive Bayes, KNN, and Decision Trees can be used to detect cyberbullying in text data, and the best choice of algorithm depends on the specific needs of the problem.

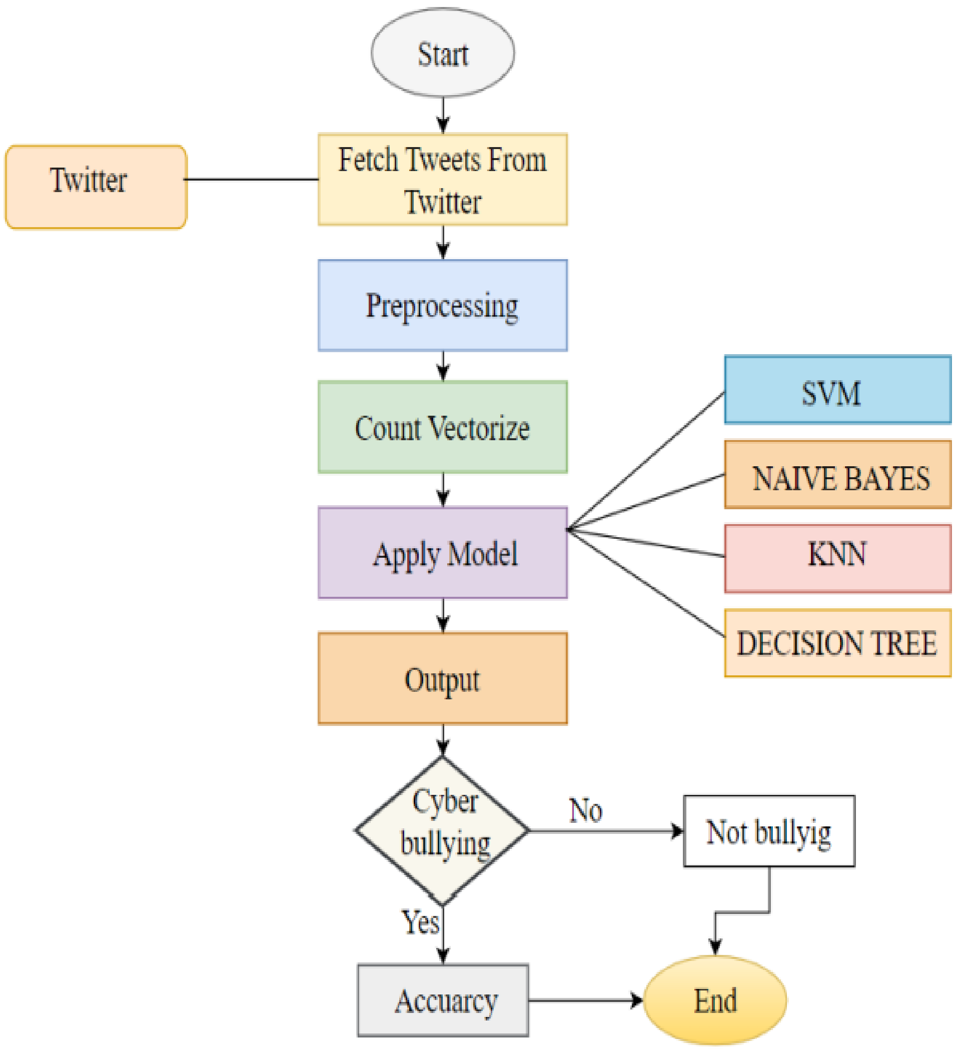

Fig.No.2.1.1 Existing System

Limitations

Limited ability to capture context: SVM, Naive Bayes, KNN and Decision Tree all rely on bag-of-words representations of text, which do not capture the context and meaning of words in a sentence. This can limit their ability to accurately classify text, particularly for complex or nuanced language.

Require feature engineering: Traditional machine learning algorithms require careful feature engineering to extract relevant information from text data. This can be time consuming and may require domain-specific knowledge.

Limited scalability: Traditional machine learning algorithms can become computationally expensive and slow when working with large datasets or complex models.

Limited adaptability: Traditional machine learning algorithms are generally trained on a specific dataset and may not generalize well to new datasets or tasks.

Limited accuracy on complex tasks: While traditional machine learning algorithms can perform well on simple text classification tasks, they may struggle with more complex tasks such as sentiment analysis, question answering, and natural language inference.

2.2 PROPOSED SYSTEM

BERT ARCHITECTURE

Bert is a transformer-based architecture that is trained on large amounts of text data, allowing it to learn the relationships between words and phrases in a given language. The bidirectional nature of the model means that it is able to consider the context of words in both directions, allowing for a more comprehensive understanding of the text data. Numerous tasks, such as sentiment, named entity identification, and text categorization, were used to train Bert.The pre-trained version of Bert can be fine-tuned for specific tasks using smaller amounts of labelled data, which is particularly useful for low-resource domains. The fine-tuning process involves updating the parameters of the pre-trained Bert model with additional data to learn the specific relationships that are relevant to a particular task. Bert has been shown to outperform previous state-of-the-art models in a wide range of NLP tasks and has become one of the most widely used models in the field. The pre-trained version of Bert is available for researchers and developers to use, making it easier to apply state-of-the-art NLP techniques to new and challenging problems. Overall, Bert is a highly flexible

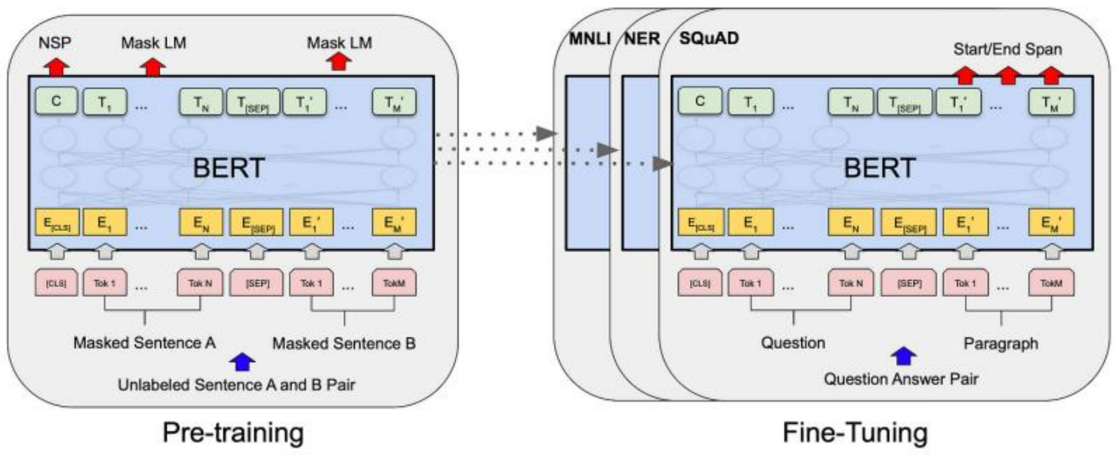

Fig No:2.2.1 Pre-training & Fine-Tuning for Bert model

Pre-training in BERT refers to the process of training a deep neural network language model on a large amount of text data before fine-tuning it on a specific NLP task.

Pre-training for BERT consists mostly of two tasks: next phrase forecasting and mask language modelling. During masked language modelling, BERT is trained to predict the masked words in a sentence given the context, with the aim of capturing the context-dependent relationships between words in a sentence. Next sentence prediction, on the other hand, trains BERT to predict whether two sentences are consecutive or not, with the goal of learning the relationship between sentences and the overall structure of the text.

After pre-training is finished, the pre-trained BERT model can be fine-tuned to execute a particular NLP job, such as text categorization, question answering, or named entity recognition on a smaller, mission dataset..

Methodology:

BERT is a pre-trained transformer-based neural network that is used for various NLP tasks, including sentiment analysis. The general flow of using a BERT model for sentiment analysis is as follows:

Pre-processing:

The input text data needs to be pre-processed to obtain a numerical representation that can be fed into the model. This typically involves tokenizing the text into words or sub words, converting the tokens into numerical indices, and padding the sequences to a fixed length.

Fine-tuning:

The pre-trained BERT model is fine-tuned on the task-specific training data. During finetuni the sentiment label for a given input text. The output from the last layer of the BERT model is fed into a linear layer with a sigmoid activation function to obtain the probability of the belonging to a positive or negative class.

Prediction:

After fine-tuning, the model can be used to predict the sentiment label for new, unseen text data. The model takes the pre-processed text data as input and outputs a sentiment label, either positive or negative

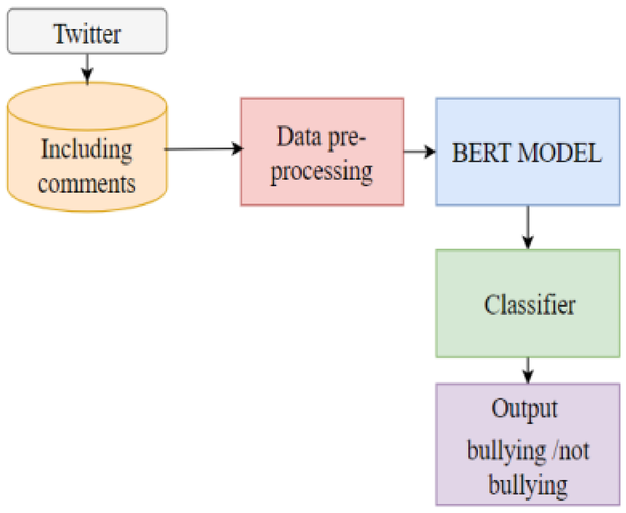

Fig No:2.2.2 Proposed System

Advantages:

Ability to capture context and meaning: BERT is a deep learning model that uses a transformer-based architecture to capture the complex context and meaning of words in a sentence. This allows it to perform better on tasks that require a deep understanding of language, such as sentiment analysis, natural language inference, and question answering.

No feature engineering required: Unlike traditional machine learning algorithms, BERT does not require any manual feature engineering. It can automatically extract features from raw text data, making it easier and faster to train and deploy.

Multilingual support: BERT can be trained on multiple languages and has shown to perform well on text classification tasks in different languages. This makes it a useful tool for multilingual applications.

Dataset

The "cyberbullying_tweets.csv" dataset contains tweets annotated as either containing cyberbullying behavior or not. The dataset is stored in a CSV format, which is a widely used file format for storing tabular data. Each row in the dataset represents a single tweet, and the columns contain various attributes related to the tweet, such as the tweet text, the user who posted the tweet, and the annotated label indicating whether the tweet contains cyberbullying behavior or not. It is likely used to train and evaluate machine learning models for cyberbullying detection. The dataset is used to train models to automatically detect and flag cyberbullying behavior, to create a safer online environment.

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CHAPTER 3

SYSTEM ANALYSIS

3.1 OVERVIEW OF SYSTEM ANALYSIS

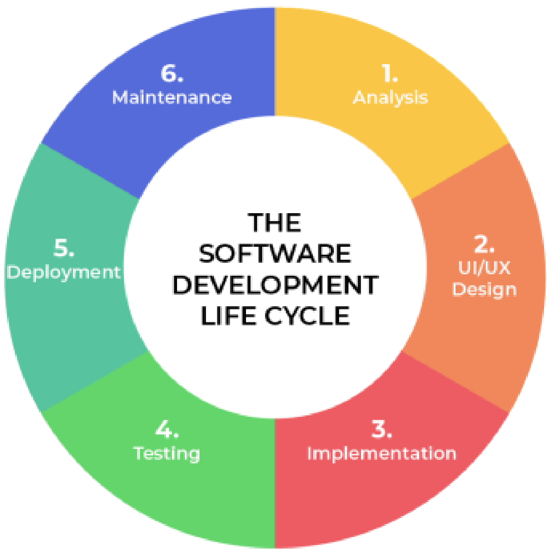


Fig No:3.1.1 Development Model

- Project Requisites Accumulating and Analysis
- System Design
- Implementation
- Testing
- Application Deployment of System
- Maintenance of the Project

3.1.1 Requisites Accumulating and Analysis

It's the first and foremost stage of the any project as our is an academic leave for requisites amassing, we followed of IEEE Journals and Amassed so many IEEE Related papers and final culled a Paper designated by setting and substance importance input and for analysis stage we took referees from the paper and did literature survey of some papers and amassed all the Requisites of the project in this stage.

3.1.2 System Design

During the Design Phase, the system is designed to satisfy the requirements identified in the previous phases .The requirements identified in the Requirements Analysis Phase are transformed into a System Design Document that accurately describes the design of the system and that can be used as an input to system development in the next phase.

3.1.3 Implementation

The Implementation is Phase where we endeavor to give the practical output of the work done in designing stage and most of Coding in Business logic lay comes into action in this stage its main and crucial part of the project

3.1.4Testing

Unit Testing

It is done by the developer itself in every stage of the project and fine-tuning the bug and module predicated additionally done by the developer only here we are going to solve all the runtime errors

3.1.5 Deployment of System

Once the project is total yare, we will come to deployment of client system. we did deployment in our laptop only with all needed Software's.

3.1.6 Maintenance

The Maintenance of our Project is one time process only

3.2 SOFTWARE USED IN THEPROJECT

3.2.1 Python

Python is a popular high-level programming language used for a wide range of applications, including web development, scientific computing, data analysis, artificial intelligence, and more Python is known for its simplicity, readability, and versatility. It has a large standard library and supports multiple programming paradigms, including procedural, functional, and object-oriented programming. Python code is often shorter and easier to read than code in other languages, making it a popular choice for beginners and experienced programmers alike.

Python is open source, meaning that its source code is available for anyone to view, modify, and distribute. It is also cross-platform, meaning that it can be run on multiple operating systems, including Windows, Mac, and Linux.

Some popular libraries and frameworks in Python include NumPy, Pandas, Matplotlib, TensorFlow, Django, and Flask. These libraries and frameworks make it easy to perform advanced calculations, analyze data, create visualizations, build web applications.

3.2.2 VS Code

VS Code is a powerful and flexible code editor that is well-suited for a wide range of programming tasks and projects.VS Code provides a lightweight and customizable code editing experience that includes features such as syntax highlighting, auto-completion, code refactoring, debugging, and Git integration. It also has a large and active community of users who develop and share extensions, themes, and other customizations to enhance the editor's functionality.

One of the key features of VS Code is its ability to support a wide range of programming languages and frameworks. It includes built-in support for popular languages such as Python, JavaScript, TypeScript, C++, and more. Additionally, developers can install extensions to support even more languages and frameworks.

It includes built-in support for popular languages such as Python, JavaScript, TypeScript, C++, and more. Additionally, developers can install extensions to support even more languages and frameworks.

3.2.3 Packages

Transformeres: The Transformers package in Python is a powerful and popular open-source library that provides state-of-the-art natural language processing (NLP) capabilities for a wide range of applications. The package is built on top of the PyTorch library and includes pre-trained models that can be fine-tuned for specific NLP tasks, as well as tools for training new models.

The Transformers package includes pre-trained models for a wide range of NLP tasks, such as sentiment analysis, named entity recognition, question answering, and language generation. These models are trained on large datasets such as Wikipedia, Common Crawl, and BookCorpus, and can be fine-tuned on smaller datasets for specific tasks.

In addition to pre-trained models, the Transformers package includes a wide range of tools for working with NLP data and models, such as tokenization, encoding, and decoding of text data, as well as methods for fine-tuning and evaluating models.

Torch:

The Torch package in Python is an open-source machine learning library that is widely used for building and training neural networks. It is built on top of the Lua programming language, but it also has a Python interface called PyTorch.

The main feature of the Torch package is the ability to construct and train neural networks using dynamic computational graphs. This means that neural networks can be built on the fly as data is processed, allowing for greater flexibility and ease of experimentation. The package also provides a wide range of built-in functions for constructing and manipulating tensors, which are multi-dimensional arrays that can be used to represent data in a neural network.

Numpy:

NumPy is a popular open-source Python library that is widely used for scientific computing and data analysis. The library provides support for multi-dimensional arrays, which are fundamental data structures for many scientific applications.

Pandas: Pandas software library written in the language of the Python program for cheating and analyzing data. In particular, it provides data structure and function for managing numerical tables and time series. pandas are widely used for machine learning in the form of data frames. Pandas allows importing data for various file formats such as csv, excel etc.

Matplotlib.pyplot: Provides a site-based API based on applications using standard GUI tools. pyplot shell-like interface in Matplotlib. Pyplot keeps status on all calls. It is useful for use in Jupyter or IPthon notebooks.

Seaborn: Seaborn is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures. Seaborn helps you explore and understand your data.

Demoji: Demoji is a Python library that provides an easy-to-use interface for working with emoji in text data. The library can be used to extract, replace, or remove emoji from text, as well as to identify the most common emoji used in a given dataset.It uses a pre-trained machine learning model to identify emoji in text, and can handle both Unicode and emoji short codes. The library also provides functionality for converting emoji shortcodes to their corresponding Unicode characters, and vice versa.

Nltk: NLTK (Natural Language Toolkit) is a Python library that provides a wide range of tools and resources for working with human language data. It is widely used for natural language processing (NLP) tasks, such as text preprocessing, tokenization, and part-of-speech tagging.

3.3 SYSTEMREQUIREMENTS

3.3.1 SOFTWARE REQUIREMENTS

- Software: PYTHON
- Version: 3.8

- Operating System: windows

3.3.2 HARDWARE REQUIREMENTS

- Processor: IntelcoreI5
- RAM:8GB
- Hard Disk:500GB

CHAPTER 4

SYSTEM DESIGN

4.1 OVERVIEW OF SYSTEM DESIGN

The System overview of Cyberbullying detection using BERT can identify instances of cyberbullying in online communication. BERT is a pre-trained language model that has been trained on large amounts of text data and can be fine-tuned for specific natural language processing (NLP) tasks, such as text classification.
The system design for cyberbullying detection using BERT typically involves the following components:

Data Collection: The first step in the process is to collect data that can be used to train and test the system. This data is collected from kaggle site.

Data Preprocessing: Once the data has been collected, it needs to be preprocessed to remove any irrelevant information, such as emojis, URLs, and hashtags. This is done to ensure that the system only focuses on the text and not on any metadata.

BERT Embedding: The next step is to encode the preprocessed text using BERT embeddings. BERT is a language model that can generate embeddings for each word in a sentence. These embeddings can be used to represent the semantic meaning of the text.

BERT Classification: In this section, we will load a pre trained BERT model from the Hugging Face library and fine tune it for our classification task.

Model Training and Evaluation: The classification algorithm needs to be trained using a labeled dataset. The labeled dataset consists of examples of cyberbullying and non-cyberbullying instances. Once the model has been trained, it can be evaluated using a separate dataset.

Algorithm:

```
BERT_Cyber_Bullying_Detection(text):

        # 1. Preprocess the text data
        # - Clean and tokenize the text data
        # - Pad the tokenized data to a fixed length
           tokenized_text = Preprocess(text)
        # 2. Load a pretrained BERT model
         bert_model = Load_BERT_Model ()
         # 3. Pass the tokenized text data to the BERT model
          # - Obtain the hidden states from the model
          hidden_states = bert_model(tokenized_text)
          # 4. Feed the hidden states to a classifier layer
          # - Obtain the predicted probability of the text being cyber bullying
            probability = Classifier(hidden_states)
          # 5. Threshold the predicted probability to obtain the final binary label
                   threshold = 0.5
                   if predicted_probability> threshold:
              is_cyber_bullying = 1
                  else:
              is_cyber_bullying = 0
                  return is_cyber_bullying
```

4.2 CODING & IMPLEMENTATION

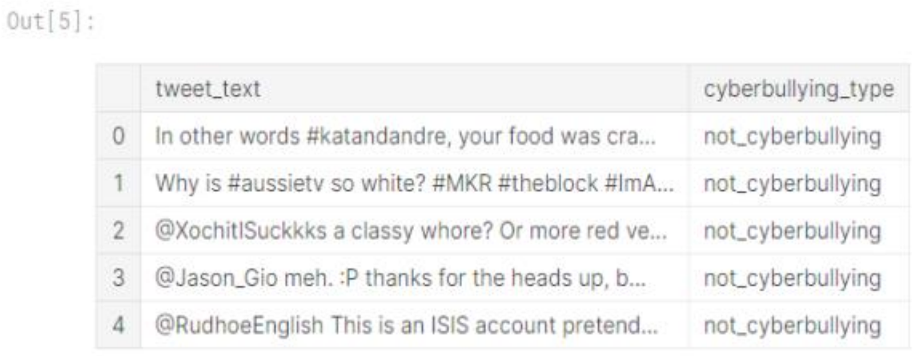
Import libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re, string
import demoji
import nltk
nltk.download('stopwords')
nltk.download('punkt')
from nltk.stem import WordNetLemmatizer,PorterStemmer
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
from sklearn import preprocessing from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler

import transformers
from transformers import BertModel
from transformers import BertTokenizer
from transformers import AdamW, get_linear_schedule_with_warmup
from sklearn.metrics import classification_report, confusion_matrix

import random
seed_value=42
random.seed(seed_value)
np.random.seed(seed_value)
torch.manual_seed(seed_value)
torch.cuda.manual_seed_all(seed_value)

import time
sns.set_style("whitegrid")
sns.despine()
```

```
plt.style.use("seaborn-whitegrid")
plt.rc("figure", autolayout=True)
plt.rc("axes", labelweight="bold", labelsize="large", titleweight="bold", titlepad=10)
```

Data Import

```
  df = pd.read_csv("cyberbullying_tweets.csv")
 df.head
```

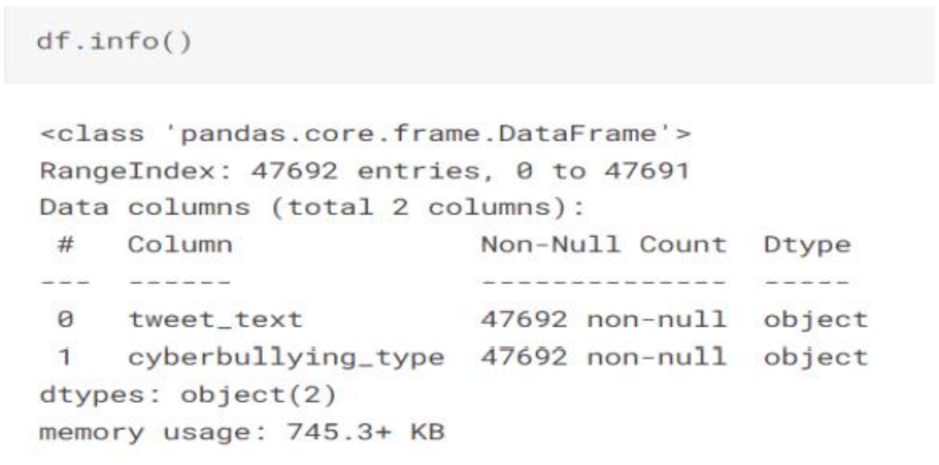


Out[5]:

	tweet_text	cyberbullying_type
0	In other words #katandandre, your food was cra...	not_cyberbullying
1	Why is #aussietv so white? #MKR #theblock #ImA...	not_cyberbullying
2	@XochitlSuckkks a classy whore? Or more red ve...	not_cyberbullying
3	@Jason_Gio meh. :P thanks for the heads up, b...	not_cyberbullying
4	@RudhoeEnglish This is an ISIS account pretend...	not_cyberbullying

Attributes information

```
df.info()
```

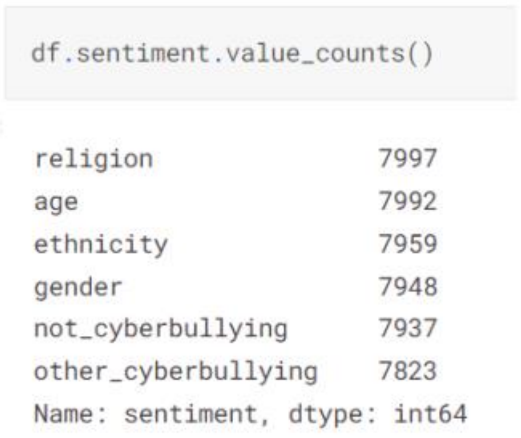


```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47692 entries, 0 to 47691
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   tweet_text          47692 non-null  object
 1   cyberbullying_type  47692 non-null  object
dtypes: object(2)
memory usage: 745.3+ KB
```

First we rename the columns using shorter words for easier reference

```
  df = df.rename(columns={'tweet_text': 'text', 'cyberbullying_type': 'sentiment'})
df.sentiment.value_counts()
```

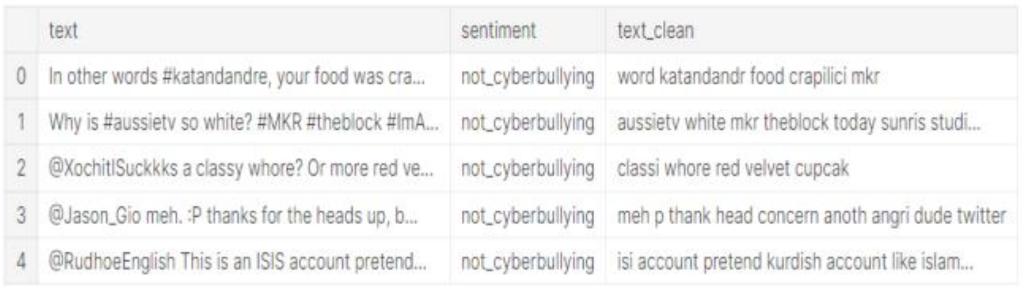


```
df.sentiment.value_counts()

religion               7997
age                    7992
ethnicity              7959
gender                 7948
not_cyberbullying      7937
other_cyberbullying    7823
Name: sentiment, dtype: int64
```

Tweets text deep cleaning

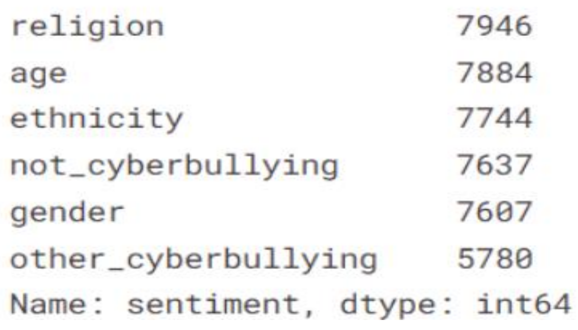
```
  def remove_emoji(text):
      return demoji.replace(text,'')

   def strip_all_entities(text):
   text = text.replace('\r', '').replace('\n', ' ').lower()
   text = re.sub(r"(?:\@|https?\://)\S+", "", text)
   text = re.sub(r'[^\x00-\x7f]',r'', text)
   banned_list= string.punctuation
   table = str.maketrans('', '', banned_list)
   text = text.translate(table)
   text = [wordforwordintext.split() if word not in stop_words]
   text = ' '.join(text)
   text =' '.join(word forword intext.split() if len(word) < 14)
   return text

def decontract(text):
   text=re.sub(r"can\'t","cannot", text)
   text = re.sub(r"n\'t", " not", text)
   text = re.sub(r"\'re",are", text)
   text = re.sub(r"\'s", " is", text)
   text = re.sub(r"\'d", " would", text)
```

```
    textre.sub(r"\'ll", " will", text)
    text = re.sub(r"\'t", " not", text)
    text = re.sub(r"\'ve", " have", text)
    text = re.sub(r"\'m", " am", text)
    return text

def clean_hashtags(tweet):
    new_tweet = " ".join(word.strip() for word in re.split('#(?!(?:hashtag)\b)[\w-
                    ]+(?=(?:\s+#[\w-]+)*\s*$)', tweet))
    new_tweet2 = " ".join(word.strip() for word in re.split('#|_', new_tweet))
    return new_tweet2
    def filter_chars(a):
      sent = []
      for word in a.split(' '):
        if ('$' in word) | ('&' in word):
            sent.append('')
        else: sent.append(word)
       return ' '.join(sent
def remove_mult_spaces(text):
       return re.sub("\s\s+" , " ", text)

 def stemmer(text):
       tokenized = nltk.word_tokenize(text)
       ps = PorterStemmer()
       return ' '.join([ps.stem(words) for words in tokenized])

       def lemmatize(text):
       tokenized = nltk.word_tokenize(text)
       lm = WordNetLemmatizer()
       return ' '.join([lm.lemmatize(words) for words in tokenized])

    def deep_clean(text):
         text = remove_emoji(text)
         text = decontract(text)
         text = strip_all_entities(text)
         text = clean_hashtags(text)
         text = filter_chars(text)
        text = remove_mult_spaces(text)

    texts_new = []
    for t in df.text:
        texts_new.append(deep_clean(t))
    df['text_clean'] = texts_new
    df.head()
```



	text	sentiment	text_clean
0	In other words #katandandre, your food was cra...	not_cyberbullying	word katandandr food crapilici mkr
1	Why is #aussietv so white? #MKR #theblock #ImA...	not_cyberbullying	aussietv white mkr theblock today sunris studi...
2	@XochitlSuckkks a classy whore? Or more red ve...	not_cyberbullying	classi whore red velvet cupcak
3	@Jason_Gio meh. :P thanks for the heads up, b...	not_cyberbullying	meh p thank head concern anoth angri dude twitter
4	@RudhoeEnglish This is an ISIS account pretend...	not_cyberbullying	isi account pretend kurdish account like islam...

```
df.shape

(47656, 3)
df["text_clean"].duplicated().sum() #duplicated values count
3058
df.drop_duplicates("text_clean", inplace=True) #remove duplicates
df.shape
(44598, 3)
df.sentiment.value_counts
```



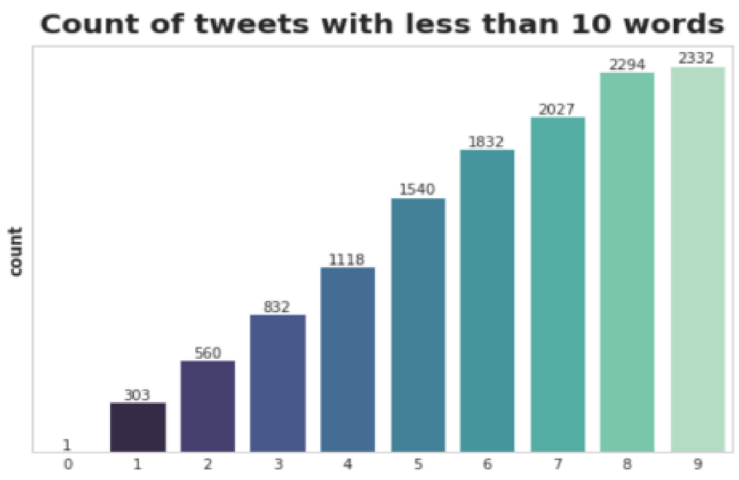
```
religion              7946
age                   7884
ethnicity             7744
not_cyberbullying     7637
gender                7607
other_cyberbullying   5780
Name: sentiment, dtype: int64
```

```
df.sentiment.value_counts
```

```
(df = df[df["sentiment"]!="other_cyberbullying"]
sentiments = ["religion","age","ethnicity","gender","not bullying"]
```

Tweets length analysis

```
  text_len = []
  for text in df.text_clean:
  tweet_len = len(text.split())
  text_len.append(tweet_len)
  df['text_len']     = text_len
  plt.figure(figsize=(7,5))
  ax = sns.countplot(x='text_len', data=df[df['text_len'] ] 10], palette='mako')
  plt.title('Count of    tweets with less than 10 words', fontsize=20)
  plt.yticks([])
  ax.bar_label(ax.containers[0])
  plt.ylabel('count')
  plt.xlabel('')
  plt.show()
```

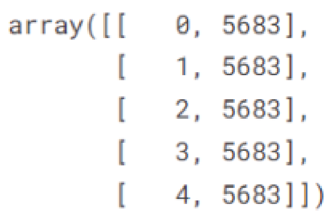


```
df = df[df['text_len'] > 3] #remove tweets with words less than 4
df = df[df['text_len'] < 100] #remove tweets with words greater than 100
max_len = np.max(df['text_len']) #length of longest tweet present
max_len

79

df.sort_values(by=["text_len"], ascending=False)
```

```
df['sentiment']= df['sentiment'].replace({'religion':0,'age':1,'ethnicity':2,'gender':3,
'not_cyberbullying':4})
```

Train - Validation - Test split

```
   X = df['text_clean'].values

   y = df['sentiment'].values

  X_train, X_test, y_train, y_test =  train_test_split(X,y,test_size=0.2,stratify=y,
random_state=seed_value)

X_train, X_valid, y_train, y_valid = train_test_split(X_train,y_train, test_size=0.1,
stratify=y_train, random_state=seed_value)

ros = RandomOverSampler()

X_train_os, y_train_os = ros.fit_resample(np.array(X_train).reshape(-
1,1),np.array(y_train).reshape(-1,1))

X_train_os = X_train_os.flatten()

y_train_os = y_train_os.flatten()

(unique, counts) = np.unique(y_train_os, return_counts=True)

np.asarray((unique, counts)).T
```



```
array([[   0, 5683],
       [   1, 5683],
       [   2, 5683],
       [   3, 5683],
       [   4, 5683]])
```

BERT Tokenization

```
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased', do_lower_case=True)

def bert_tokenizer(data):

    input_ids = []

   attention_masks = []
   for sent in data:

   encoded_sent = tokenizer.encode_plus

 ( text=sent, add_special_tokens=True,            # Add `[CLS]` and `[SEP]` special tokens
max_length=MAX_LEN,                               # Choose max length to truncate/pad
pad_to_max_length=True,                           # Pad sentence to max length
return_attention_mask=True                        # Return attention mask )
input_ids.append(encoded_sent.get('input_ids'))

 attention_masks.append(encoded_sent.get('attention_mask'))

# Convert lists to tensors

 input_ids = torch.tensor(input_ids)

attention_masks = torch.tensor(attention_masks) return input_ids, attention_masks
encoded_tweets = [tokenizer.encode(sent, add_special_tokens=True) for sent in X_train]

 max_len = max([len(sent) for sent in encoded_tweets])

print('Max length: ', max_len)

Max length: 126

MAX_LEN = 128 #let maxlen will be 128

train_inputs, train_masks = bert_tokenizer(X_train_os)

val_inputs, val_masks = bert_tokenizer(X_valid)

test_inputs, test_masks = bert_tokenizer(X_test)
```

Data preprocessing for PyTorch BERT model

```
train_labels = torch.from_numpy(y_train_os)

 val_labels = torch.from_numpy(y_valid)

 test_labels = torch.from_numpy(y_test)
```

Dataloaders

```
batch_size = 32

# Create the DataLoader for our training set

train_data = TensorDataset(train_inputs, train_masks, train_labels)

train_sampler = RandomSampler(train_data) train_dataloader = DataLoader(train_data,
sampler=train_sampler,

batch_size=batch_size)

# Create the DataLoader for our validation set

val_data = TensorDataset(val_inputs, val_masks, val_labels)

val_sampler = SequentialSampler(val_data)

 val_dataloader = DataLoader(val_data, sampler=val_sampler, batch_size=batch_size)


# Create the DataLoader for our test set

test_data = TensorDataset(test_inputs, test_masks, test_labels)

test_sampler = SequentialSampler(test_data)

test_dataloader = DataLoader(test_data, sampler=test_sampler, batch_size=batch_size)
```

BERT Modeling

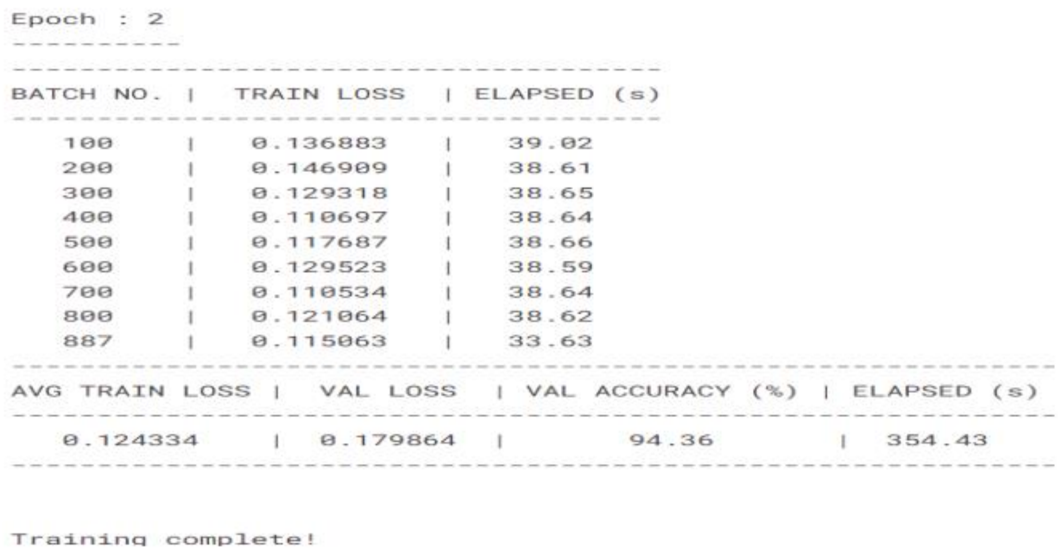
```
%%time

class Bert_Classifier(nn.Module):

    def __init__(self, freeze_bert=False):

    super(Bert_Classifier, self).__init__()
```

```
  n_input = 768

  n_hidden = 50

  n_output = 5

  self.bert = BertModel.from_pretrained('bert-base-uncased')

  self.classifier = nn.Sequential

  ( nn.Linear(n_input, n_hidden),

   nn.ReLU(),

   nn.Linear(n_hidden, n_output))

   if freeze_bert:

   for param in self.bert.parameters():

   param.requires_grad = False

  def forward(self, input_ids, attention_mask):

  outputs = self.bert(input_ids=input_ids,

                      attention_mask=attention_mask)

   last_hidden_state_cls = outputs[0][:, 0, :]

  logits = self.classifier(last_hidden_state_cls)

  return logits

def initialize_model(epochs=4):

 bert_classifier = Bert_Classifier(freeze_bert=False)

 bert_classifier.to(device)

 optimizer = AdamW(bert_classifier.parameters(),

 lr=5e-5, eps=1e-8 )

 total_steps = len(train_dataloader) * epochs
```

```
    scheduler = get_linear_schedule_with_warmup(optimizer,
                                                num_warmup_steps=0,
                                                 num_training_steps=total_steps)
     return bert_classifier, optimizer, scheduler
device = 'cuda' if torch.cuda.is_available() else 'cpu' EPOCHS=2
```

BERT Training

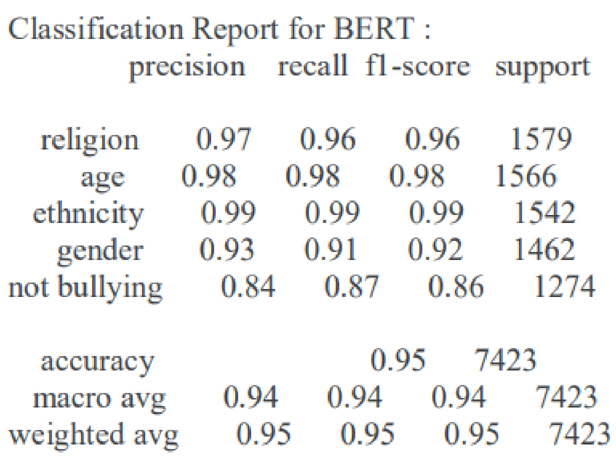
```
loss_fn = nn.CrossEntropyLoss()
def bert_train(model, train_dataloader, val_dataloader=None, epochs=4, evaluation=False):
    print("Start training...\n")
    for epoch_i in range(epochs):
          print("-"*10)
          print("Epoch :      {}".format(epoch_i+1))
          print("-"*10)
          print("-"*38)
           print(f"{'BATCH NO.':^7} | {'TRAIN LOSS':^12} | {'ELAPSED (s)':^9}")
           print("-"*38)
           t0_epoch, t0_batch = time.time(), time.time()
           total_loss, batch_loss, batch_counts = 0, 0, 0
           model.train() for step, batch in enumerate(train_dataloader):
           batch_counts +=1
           b_input_ids, b_attn_mask, b_labels = tuple(t.to(device) for t in batch)
          model.zero_grad()
          logits = model(b_input_ids, b_attn_mask)

          loss = loss_fn(logits, b_labels)

          batch_loss += loss.item()

          total_loss += loss.item()

           loss.backward()

          torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

          optimizer.step()

         scheduler.step()

if (step % 100 == 0 and step != 0) or (step == len(train_dataloader) - 1):

     time_elapsed = time.time() - t0_batch

     print(f"{step:^9} | {batch_loss / batch_counts:^12.6f}

                                   {time_elapsed:^9.2f}")

     batch_loss, batch_counts = 0, 0

     t0_batch = time.time()

     avg_train_loss = total_loss / len(train_dataloader)

    model.eval()

    val_accuracy = []

    val_loss = []

   for batch in val_dataloader:

         batch_input_ids, batch_attention_mask, batch_labels = tuple(t.to(device) for t in batch)

         with torch.no_grad():

          logits = model(batch_input_ids, batch_attention_mask)

   loss = loss_fn(logits, batch_labels)
   val_loss.append(loss.item())

   preds = torch.argmax(logits, dim=1).flatten()

  accuracy = (preds == batch_labels).cpu().numpy().mean() * 100

  val_accuracy.append(accuracy)

  val_loss = np.mean(val_loss)

  val_accuracy = np.mean(val_accuracy)

  time_elapsed = time.time() - t0_epoch

print("-"*61) print(f"{'AVG TRAIN LOSS':^12} | {'VAL LOSS':^10} | {'VAL ACCURACY (%)':^9}
| {'ELAPSED (s)':^9}")

print("-"*61) print(f"{avg_train_loss:^14.6f} | {val_loss:^10.6f} | {val_accuracy:^17.2f} |
{time_elapsed:^9.2f}")

print("-"*61)

print("\n")

print("Training complete!")

bert_train(bert_classifier, train_dataloader, val_dataloader, epochs=EPOCHS)
```



```
Epoch : 2
----------
----------------------------------------
BATCH NO. |   TRAIN LOSS   | ELAPSED (s)
----------------------------------------
   100    |    0.136883    |    39.02
   200    |    0.146909    |    38.61
   300    |    0.129318    |    38.65
   400    |    0.110697    |    38.64
   500    |    0.117687    |    38.66
   600    |    0.129523    |    38.59
   700    |    0.110534    |    38.64
   800    |    0.121064    |    38.62
   887    |    0.115063    |    33.63
-------------------------------------------------------------
AVG TRAIN LOSS |   VAL LOSS   | VAL ACCURACY (%) | ELAPSED (s)
-------------------------------------------------------------
   0.124334    |   0.179864   |       94.36       |  354.43
-------------------------------------------------------------


Training complete!
```

BERT Prediction

```
def bert_predict(model, test_dataloader):

    preds_list = []

    model.eval()

    for batch in test_dataloader:

    batch_input_ids, batch_attention_mask = tuple(t.to(device) for t in batch)[:2]

    with torch.no_grad():

    logit = model(batch_input_ids, batch_attention_mask)

    pred = torch.argmax(logit,dim=1).cpu().numpy()

    preds_list.extend(pred)

    return preds_list

    bert_preds = bert_predict(bert_classifier, test_dataloader)

    print('Classification Report for BERT :\n', classification_report(y_test, bert_preds,
target_names=sentiments))
```



```
Classification Report for BERT :
              precision    recall  f1-score   support

    religion       0.97      0.96      0.96      1579
         age       0.98      0.98      0.98      1566
   ethnicity       0.99      0.99      0.99      1542
      gender       0.93      0.91      0.92      1462
not bullying       0.84      0.87      0.86      1274

    accuracy                           0.95      7423
   macro avg       0.94      0.94      0.94      7423
weighted avg       0.95      0.95      0.95      7423
```

Confusion Matrix

```
def conf_matrix(y, y_pred, title, labels):

  fig, ax =plt.subplots(figsize=(7.5,7.5))

  ax=sns.heatmap(confusion_matrix(y, y_pred), annot=True, cmap="Purples",

                    fmt='g', cbar=False, annot_kws={"size":30})

  plt.title(title, fontsize=25)

  ax.xaxis.set_ticklabels(labels, fontsize=16)

  ax.yaxis.set_ticklabels(labels, fontsize=14.5)

  ax.set_ylabel('Test', fontsize=25)

  ax.set_xlabel('Predicted', fontsize=25)

  plt.show()

  conf_matrix(y_test, bert_preds,' BERT Sentiment Analysis\nConfusion Matrix',

                                                                  sentiments)
```

4.3 SYSTEM TESTING

4.3.1 OVERVIEW OF TESTING

Software Testing is evaluation of the software against requirements gathered from users and system specifications. Testing is conducted at the phase level in software development life cycle or at module level in program code. Software testing comprises of Validation and Verification.

4.3.2 TYPES OF TESTS

UNIT TESTING

Unit testing is a level of software testing where individual units/ components of a software are tested. The purpose is to validate that each unit of the software performs as designed. A unit is the smallest testable part of any software. It usually has one or a few inputs and usually a single output.

INTEGRATION TESTING

Integration testing is a level of software testing where individual units are combined and tested as a group. The purpose of this level of testing is to expose faults in the interaction between integrated units. Test drivers and test stubs are used to assist in Integration Test

4.4 RESULT

This classification report provides a detailed evaluation of the performance of a BERT model trained for sentiment analysis on a dataset with five different classes: "religion", "age", "ethnicity", "gender", and "not bullying". The report provides the values of four evaluation metrics for each of the classes:

	precision	recall	f1-score	support
Religion	0.97	0.96	0.96	1579
Age	0.98	0.98	0.98	1566
Ethnicity	0.99	0.99	0.99	1542
Gender	0.93	0.91	0.92	1462
Not bullying	0.84	0.87	0.86	1274
Accuracy	0.86	0.90	0.95	7423
Macro avg	0.94	0.94	0.94	7423
Weighted avg	0.95	0.95	0.95	7423

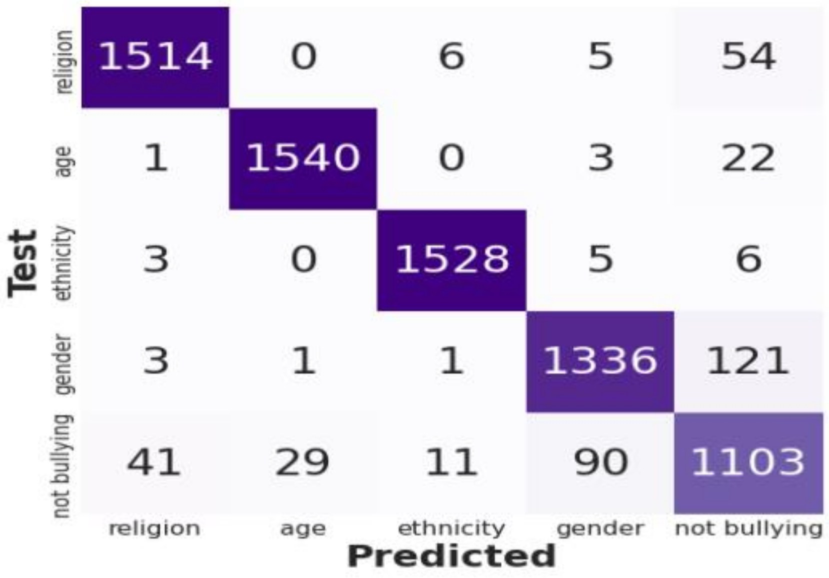


Fig No:4.4.1 Confusion Matrix

.

4.5 CONCLUSION

This paper proposed deep learning-based approach using the BERT model for detecting cyberbullying in online text messages has shown promising results. The BERT model's bidirectional nature and its pre-training and fine-tuning capabilities help it to perform well in detecting cyberbullying. The performance scores, with an overall accuracy of around 95% and F1 scores over 95%, demonstrate the effectiveness of the BERT model in detecting cyberbullying. These high scores, higher than those achieved using an LSTM model, indicate that the BERT model is capable of accurately identifying cyberbullying cases while minimizing false positive and false negative cases. This paper has shown positive results in identifying cyberbullying in online text messages. This paper highlights the potential of deep learning-based approaches, specifically the use of BERT, in addressing the growing concern of cyberbullying

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