

NEGATIVE COMMENT CLASSIFICATION

A major project report submitted in partial fulfilment of the requirement
for the award of degree of

Bachelor of Technology
in
Computer Science & Engineering

Submitted by
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CERTIFICATE

This is to certify that the work which is being presented in the project report titled “Negative Comment Classification” in partial fulfilment of the requirements for the award of the degree of B.Tech in Computer Science And Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Wagnaghat is an authentic record of work carried out by “Arnav Jamwal, 201163” and “Sagnik Ghosh, 201295” during the period from January 2024 to May 2024 under the supervision of Dr. Nancy Singla, Department of Computer Science and Engineering, Jaypee University of Information Technology, Wagnaghat.

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CANDIDATE'S DECLARATION

We hereby declare that the work presented in this report entitled '**Negative Comment Classification**' in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science & Engineering** submitted in the Department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat is an authentic record of our own work carried out over a period from January 2024 to May 2024 under the supervision of **Dr. Nancy Singla** (Assistant Professor (Senior Grade), Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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ABSTRACT

The web of platforms that connect us has changed the way we interact, but it also houses hatred and aggression. This may be the reason why users perceive the platform as unsafe and not welcoming.

RNNs and DNNs have achieved improved outcomes in Deep learning field of study. This article aims to demonstrate the approaches and the technique of building a deep neural network architecture with "attention mechanism" that prioritizes detecting negative language.

The research evaluates two issues online communication faces due to negativity as well as Deep Learning models such as RNNs and DNNs. It afterwards talks about a new deep learning model with the attention mechanism for better identification of toxic language. The aforementioned model is tested against real-world online comments and proves to be more precise in categorizing negative remarks as compared to the existing techniques.

The research findings offer crucial insights into the development of tools focused on combating online negativity. This deep learning mechanism aided by the attention mechanisms enables professionals to look into online interactions and build a conducive online environment. The suggested model will be the foundation of the future researches in this field. It will be the answer to the online harassment and will be the cause of positive communication.

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The rise of user-generated content in the era of online communication has been made possible by the widespread use of social media platforms. Nevertheless, there is a serious drawback to this enormous ocean of online interactions: the abundance of hurtful and poisonous remarks. Online communities may suffer as a result of these hurtful remarks, which can promote animosity, silence marginalized voices, and foment negativity. In order to solve this problem, scientists have developed efficient automatic comment classification systems that can recognize and report harmful remarks with accuracy by utilizing deep learning techniques.

Researchers have a great chance to create and assess deep learning models for harmful comment classification during the Jigsaw Comment Classification Challenge on Kaggle. 1.8 million English Wikipedia comments classified as toxic, severe toxic, obscene, threat, insult, and identity-hate made up the dataset for this task. With the help of this extensive dataset, researchers were able to investigate different deep learning architectures and methods for the challenging task of classifying poisonous comments.

Sentiment analysis and poison identification are two NLP tasks that have seen a rise in the use of recurrent neural networks (RNNs), especially Long Short-Term Memory (LSTM) networks. Because LSTMs can capture long-range dependencies in sequential data, they are an excellent choice for understanding the subtleties and context of human language. LSTMs are useful in identifying trends and minor indicators that point to toxicity in comments when it comes to classifying toxic comments.

Additionally, Deep Neural Networks (DNNs) have shown encouraging results in the classification of poisonous comments. DNNs can discriminate between language that is harmful and language that is not because of their several layers of interconnected neurons, which enable them to build complex language representations. In order to effectively classify hazardous remarks, researchers have developed hybrid architectures that integrate LSTMs and DNNs, leveraging the benefits of both techniques.

In this project, the use of deep neural networks, specifically LSTMs and DNNs, is explored for the problem of negative comment categorization using the Jigsaw Comment

Categorization Challenge dataset. The theoretical underpinnings of these deep learning algorithms are discussed along with their advantages and disadvantages in classifying poisonous comments. Subsequently, an extensive synopsis of current deep learning techniques for the classification of harmful comments is provided, scrutinizing their structures, tactics for training, and techniques for assessment.

Using LSTMs and DNNs, a unique deep learning model for harmful comment classification is provided, building upon this basis. To improve its capacity to identify harmful language, the model uses attention mechanisms to concentrate on the most noticeable portions of the remarks. The assessment of the model is conducted using the Jigsaw Comment Classification Challenge dataset, showing both its competitiveness and its ability to detect harmful comments.

The creation of reliable and precise techniques for classifying negative comments will have a big impact on encouraging online safety and civility. Through the efficient identification and removal of harmful remarks, these platforms can promote online communities that are more inclusive and courteous, enabling users to participate in productive and significant exchanges. Our research aids in this effort by offering a cutting-edge deep learning technique that can accurately identify and categorize critical remarks, opening the door for a more civil and courteous online environment.

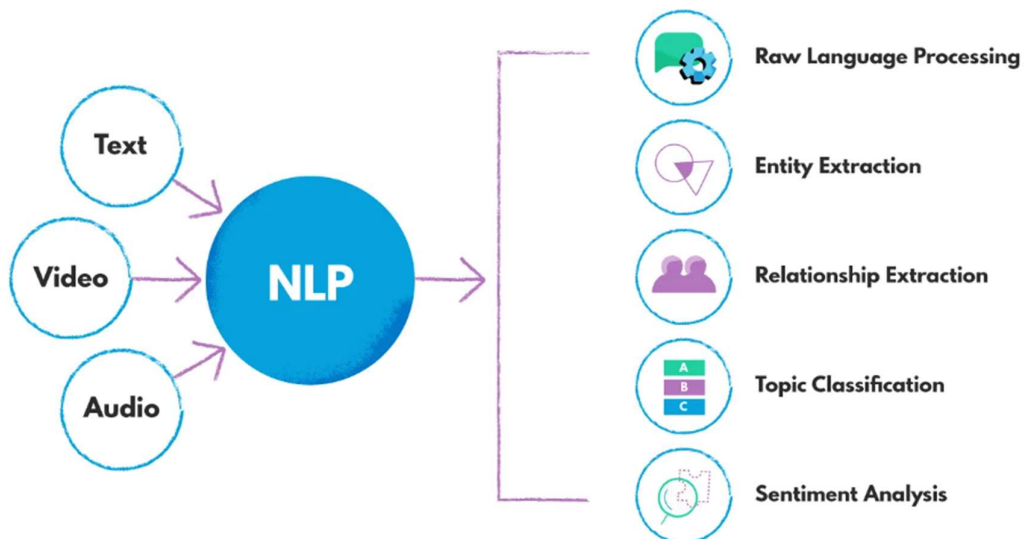


Fig 1.1: NLP architecture

Natural Language Processing (NLP) is an indispensable tool for the negative comment classification, which makes computers to be able to understand and analyze human language properly. The question is how the process starts. It starts with the text preprocessing, where the NLP techniques are applied to the text data to make it clean and standard. These techniques include tokenization, removing stopwords, and stemming or lemmatization. The next step, which is feature extraction, is in which the important features are extracted from the text data using the Techniques like Bag of Words, TF-IDF, Word Embeddings, and Contextual Word Embeddings. Sentiment analysis, one of the main tasks in the classification of negative comments, is the process of finding out the feeling that the text exhibits, like positive, negative, or neutral. Machine learning models, combined with the NLP techniques, are the ones used for classification using the algorithms such as SVM, Random Forests, Naive Bayes, or deep learning models. The evaluation metrics such as the accuracy, the precision, the recall, and the F1-score are the means to the performance of the model. In the end, the application of NLP in negative comment classification will be a game-changer in many fields, among which are social media monitoring, customer feedback analysis, online content moderation, and market research, so to say, the brand will get proactive management of its reputation, the user experience will be enhanced, and data-driven decision-making processes will be guided.

1.2 PROBLEM STATEMENT

User-generated comments and feedback are flooding the internet in an unprecedented amount due to the exponential rise of online content and the widespread use of social media platforms. It is quite difficult to accurately identify and classify negative comments in this enormous sea of data. The main concern is coming up with and putting into practice efficient ways to categorize unfavorable comments. The main objective is to develop reliable and effective Natural Language Processing (NLP) models that can identify and classify negative attitudes conveyed in textual data on their own.

The essence of a complex task is captured in this problem statement, which calls for the creation of sophisticated NLP tools. The main goal is to develop approaches that are resilient to the changing environment of online communication while also navigating the intricacies of many linguistic expressions. Novel ways to textual data processing and analysis are needed to obtain a detailed knowledge of negative attitudes within the dynamic environment

of user-generated material. As such, the project entails developing natural language processing (NLP) models that not only improve accuracy but also exhibit effectiveness in managing the vast amount and diversity of unfavorable remarks that are circulating over the internet. Resolving this issue is essential to preserving a positive online atmosphere and promoting more knowledgeable and productive exchanges.

1.3 OBJECTIVES

The main objectives of this study are:

1. Study the existing literature on Negative Comment classification and summaries them and find key gaps in them.
2. Develop NLP model that can effectively categorize negative comments based on their sentiment using TensorFlow and the Jigsaw Comment Classification Challenge dataset.
3. To integrate and deploy the developed model on a web application.

1.4 SIGNIFICANCE AND MOTIVATION OF THE PROJECT REPORT

Accurately classifying negative comments holds immense significance for various applications, including:

- Enhancing user experience: Online platforms seek to foster a positive and welcoming environment for users. By filtering out negative comments, online platforms can foster a more positive and welcoming environment for users.
- Moderating online communities: Moderating online communities effectively requires the ability to identify and address potentially harmful or offensive content promptly. Effective negative comment classification can assist moderators in identifying and addressing potentially harmful or offensive content promptly.
- Sentiment analysis: Understanding sentiment distribution in online discourse can provide valuable insights into public opinion and trends.

1.5 ORGANIZATION OF PROJECT REPORT

Chapter 1: Introduction

This chapter discusses application of deep neural networks for the assortment of negative comments. The advantages and disadvantages of DNNs and LSTMs in this task are in focus. Besides, the current deep learning techniques for classifying of has been outlined this.

Chapter 2: Literature Review

This chapter aims to present various literature review of existing research on the need of negative comment classification. It tells us about various algorithms and compares which one is reliable to use. Here the major key gaps present in those literature are addressed.

Chapter 3: System Development

The chapter explains the various stages of the project and also describes the various security features and methods used. The chapter also describes the requirements, methodology and the problems faced in the project.

Chapter 4: Testing

This chapter presents a very detailed analysis of the testing strategy that has been used in the project, and also talks about the various checks employed at different stages of the project to correctly classify comments

Chapter 5: Result and Evaluation

This chapter describes the result obtained in the previous chapter, it also showcases various important portions of the project.

Chapter 6: Conclusion and Future Scope

This is the final chapter and there is a summary of the project and its limitations, also suggesting improvements in the field of negative comment classification. This chapter also talks about the future scope of the project that what all changes in future can be further made in order to make the system more secure thus enhancing overall performance of the project.

CHAPTER 2: LITERATURE SURVEY

2.1 OVERVIEW OF RELEVANT LITERATURE

Evaluating available studies is an important requirement to know what categories of negative comments are identified. This overview focuses on the past investigations, techniques, and progresses in the field of discovering and classifying negative comments. How things are done, their theory, and real-life uses give an estimate of what is currently happening in this area. This will now help us to know what problems are left and where things should go next in a process of classifying the negative comments.

T. Pagano et al [1], proposes a way for analyzing trends in machine learning model bias and fairness measures while taking the sensitive features and application environment into account. The approach is predicated on the assessment of fourteen fairness criteria in the context of three different machine learning model applications: recommendation systems, computer vision, and natural language processing. The findings demonstrate that while certain indicators show similar trends across various application domains, others do not. The authors come to the conclusion that consideration should be given to the application's unique context when selecting fairness criteria.

Emad Alawneh et al [2], proposes a novel method called Term Frequency-Inverse Document Frequency (TF-IDF), which uses machine learning techniques to detect sexual harassment. The goal of the suggested approach is to improve the categorization of different kinds of malevolent human behavior, such as sexual harassment and cyberbullying.

Through testing on a Twitter dataset, the authors showed that their suggested approach could identify sexual harassment with an 81% accuracy rate. This shows that the technique may be useful for locating and reporting possibly harassing information on digital media.

S.Zaheri et al [3], propose a unique use of Natural Language Processing (NLP) algorithms to divide unstructured material into categories that are benign and harmful. They especially suggest using an accuracy of more than 70% utilizing a Long Short-Term Memory (LSTM)

model. Compared to the widely used Naive Bayes technique, which only managed an accuracy of 50%, this is a much greater accuracy. The authors think that an open-source tool to aid in anti-bullying efforts may be created by app developers using their LSTM model.

Jacob Devlin et al [4], propose Bidirectional Encoder Representations from Transformers (BERT), a unique method for language encoding. BERT is a pre-trained model designed to learn deep bidirectional representations from unlabeled text. It is jointly trained on both left and right context in all layers. With just one additional output layer, the pre-trained BERT model may then be improved to create cutting-edge models for a range of applications, such as language inference and question answering. BERT has strong conceptual and experimental qualities. It achieves new state-of-the-art results on eleven natural language processing tasks: it improves the GLUE score to 80.5% (7.7% point absolute improvement), the MultiNLI accuracy to 86.7% (4.6% absolute improvement), the SQuAD v1.1 question answering Test F1 to 93.2, and the SQuAD v2.0 Test F1 to 83.1.

Jing Qian et al [5], propose a cutting-edge strategy for eradicating hate speech online known as "generative hate speech intervention." With this strategy, hate speech is automatically addressed in internet chats by automatically generated responses. Additionally, two fully labeled large-scale datasets for hate speech intervention collected from Reddit and Gab are proposed by the authors. These datasets contain discussion threads, labels for hate speech, and intervention responses produced by Mechanical Turk employees. In addition, the authors assess how well-liked automatic response generating methods perform on these fresh datasets and examine the datasets to understand typical intervention approaches.

Anna Schmidt et al [6], propose carrying out a survey on natural language processing (NLP)-based hate speech identification. They present key directions that have been explored in the use of natural language processing (NLP) to automatically detect different types of statements. They also talk about those methods' shortcomings.

The authors come to the conclusion that the optimal method for detecting hate speech varies depending on the particular application and that there is no one ideal method. Additionally, they want greater investigation into hate speech detection, including the creation of improved

datasets, the investigation of novel natural language processing algorithms, and the assessment of various methods using actual data.

Ziqi Zhang et al [7], propose a cutting-edge method based on deep neural networks for identifying hate speech on Twitter. Their method is able to extract word sequence and order information from short texts by combining convolutional and gated recurrent networks. On six of the seven datasets, the authors show that their methodology outperforms current methods, yielding F1 scores that are 1 to 13% higher. Additionally, they offer a fresh dataset for Twitter hate speech detection.

Thomas Davidson et al [8], propose a cutting-edge method for automatically identifying hate speech on social media that solves the challenge of separating hate speech from other unpleasant words. Their method entails teaching a multi-class classifier to distinguish between three types of tweets: those with hate speech, those with profanity, and those with neither. The authors use a dataset of tweets that were contributed by the public to show that their method can achieve high accuracy.

Ghosh and Nath et al [9], suggest a new method which is a combination of both the existing and the innovative methods. The advice is based on the fact that other works have been carried out to overcome the obstacles in other aspects of natural language processing. Lexicon-based methods, though they have efficiency, are quite hard with the intricacies of language and sarcasm. Machine learning, on the contrary, is data-hungry and can be biased towards a particular domain, specific to what it is designed for. Ghosh and Nath's hybrid way of the problem is left right on the track of these problems. It consists of sentiment lexicons that are used to build a solid base for semantic understanding, and at the same time, machine learning models are used to catch the subtle aspects of language use within a given domain. The authors have proved by their experiments on various datasets that their method is a hybrid one that increases the accuracy and reliability of sentiment analysis which makes it well-designed for the complicated and continuously changing world of computational social systems.

Gupta and Kumar et al [10], switch to ensemble learning, a strong method for improving the accuracy and the generalizability of sentiment analysis models. This method, unlike the one-classifier methods, uses the advantages of different base classifiers, such as decision trees, support vector machines, and neural networks ((1), (2)). The main concept is to tactically merge the forecasts from the different classifiers to get a stronger and more reliable result ((3)) The authors very well investigate the effectiveness of ensemble learning in the various datasets and domains. Their conclusions for the most part are that ensemble methods are better than individual classifiers, which made them the top choice in the field of sentiment analysis [5]. This research gives a new perspective on the importance of ensemble methods on sentiment analysis models, thus, the creation of more reliable and precise classifiers with real-world applications is on the way.

Jiang, Tang, and Wang et al[11], conduct a complete overview of sentiment analysis, a fast growing area with many practical applications. "A Review of Sentiment Analysis Methods and Applications" is a title of the paper that paints the current situation, discusses the different approaches, solves the problems and shows the possible future trends.

The authors give a detailed account of the sentiment analysis environment, which includes the lexical-based methods, machine learning techniques, the deep learning models, and the hybrid methods. The analysis of the previous research on the websites provides readers with the complete information on the various techniques that are available in the process of studying. Also, the paper analyzes the different fields for the use of sentiment analysis that are social media analysis, customer feedback analysis and market sentiment analysis. The literature of the different authors is of all the fields of the research, hence the review becomes a great source of information for the researchers, practitioners and policymakers. The study that deals with the current picture of sentiment analysis research and its applications in different areas of life is especially suitable for those who are interested in this research and its usage across the different fields.

Table 2.1 typically summarizes the relevant literature. It provides an overview of the existing research, including methods, datasets, and evaluation metrics used in that field

Table 2.1: Summary of the Relevant Literature

S.No	Paper Title	Journ al/Co nfere nce	Tools/Techniques	Result	Limitations
1.	Context-Based Patterns in Machine Learning Bias and Fairness Metrics: A Sensitive Attributes-Based Approach	University of Surrey, 2023	Jigsaw dataset, FairFace dataset, MovieLens100K dataset	BERT achieved high accuracy, precision, and recall despite dataset imbalance; AUPRC and specificity offered valuable performance insights.	The study focused on gender as the sensitive attribute; more attributes and models could enhance understanding.
2.	Sentiment Analysis-Based Sexual Harassment Detection Using Machine Learning Techniques	IEEE, 2021	The dataset was collected from an online reporting system called "maps.safecity" using a crawler agent	The model achieved 81% accuracy using SGD classifier with 1-gram; the results demonstrated the superior of SGD compared to the other tested classifiers in all evaluation metrics.	The scale of training data restricts the identification of malicious human behavior patterns. Therefore, to enhance efficiency, testing malicious human activities with larger data is required.
3.	Toxic Comment Classification	SMU Data science Review, 2020	Naïve Bayes [NB] Classifier, LSTM/RNN Algorithm, EC2	LSTM achieved nearly 20% higher True Positive Rate than Naive Bayes, improved recall and F1 score.	Dataset undisclosed. SVC, CNN, multi-label classification, SVM tuning, explore other DNN techniques (CNN)

4.	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	Cornell, University, 2019	Transformer Architecture, Fine-Tuning, Masked Language Model (MLM), BooksCorpus, Stanford Question Answering Dataset (SQuAD)	BERT, pre-trained on vast text data, excelled in NLP tasks like text classification, question answering, and named entity recognition, showing strong contextual understanding	Limitations include high computational demands and struggles with out-of-domain data and common-sense reasoning due to reliance on text patterns.
5.	A Benchmark Dataset for Learning to Intervene in Online Hate Speech	Association for Computational Linguistics, 2019	NLP tools, two fully-labeled large-scale hate speech intervention datasets collected from Gab2 and Reddit	Classification models perform better on Gab due to larger, balanced data. SVM and LR outperform neural networks.	Diverse Reddit and Gab datasets, varying in size, comment length, and label distribution, pose unique challenges for hate speech tasks.
6.	A Survey of Hate Speech Detection using Natural Language Processing	ACL Anthology, 2017	NLP techniques, Hate Speech Detection dataset, the Twitter Hate Speech dataset, and the Wikipedia Talk Pages dataset.	Diversity of Approaches, Importance of Data, Multilingual Challenges, Contextual Understanding, Evaluation Metrics	Subjectivity and Ambiguity, Data Bias, Adversarial Attacks, Online Platform-Specific Challenges
7.	Detecting Hate Speech on Twitter Using a Convolution-GRU Based Deep Neural Network	ESWS, 2017	Deep Learning Model, Text Preprocessing, Evaluation Metrics, Twitter Data, WZ-L Dataset	neural network based methods consistently outperformed SVM and SVM+, by as much as 9% on the WZ-LS dataset	presence of abstract concepts such as 'sexism', 'racism' or 'hate' is very difficult to detect if solely based on textual content
8.	Automated Hate Speech Detection and the Problem of Offensive Language	Cornell University, 2017	Machine Learning Algorithms, NLP tools, Twitter Data, Crowdsourced Annotations	The paper showcases model performance using metrics and discusses differentiating	Model generalization to diverse hate speech, defining context-dependent

				offensive language from hate speech in online content.	hate speech, and identifying subtle forms like sarcasm can be challenging.
9.	A Hybrid Approach for Sentiment Analysis	IEEE Transactions on Computational Social Systems	Lexicon-based approach (SentiWordNet) Rule-based approach SVM classifier	Improved accuracy compared to individual lexicon-based or rule-based approaches	Limited scalability due to rule-based component Dependence on quality of lexicon and rules
10.	Sentiment Analysis Using Ensemble Learning Approach	IEEE Transactions on Systems, Man, and Cybernetics: Systems	Ensemble of classifiers (Naive Bayes, SVM, Maximum Entropy) Feature engineering (unigrams, bigrams, POS tags)	Enhanced accuracy and robustness compared to single classifiers	Computational complexity of ensemble learning Potential overfitting if not carefully tuned
11.	A Review of Sentiment Analysis Methods and Applications	IEEE Computational Intelligence Magazine	Comprehensive survey of various sentiment analysis methods: lexicon-based, machine learning, and hybrid approaches	Provides a broad overview of the field and its applications	No specific empirical results or comparative analysis

2.2 KEY GAPS IN THE LITERATURE

1. Insufficiently uniform datasets and assessment metric

Even though negative comment classification is becoming more and more popular, it is still challenging to compare and assess various methods due to the absence of standardized datasets and assessment measures. This is because negative language is inherently subjective and context-dependent, making it difficult to compile a single dataset that accurately captures every scenario for negative comments.

2. Limited awareness of language and cultural quirks

Current negative comment classification models frequently fail to capture the subtleties of negative language, which varies greatly across cultures and languages. Misclassifications may result from this, especially when responding to remarks made by underprivileged or underrepresented groups

3. Having trouble with irony and sarcasm:

Irony and sarcasm are common language strategies used to express negativity, but machine learning models may have trouble picking them out. Because of this, these models could overlook or even mistakenly identify as positive instances of subtle negative language.

4. Talking about how language has evolved:

Language is dynamic; new slang phrases, memes, and internet jargon appear on a daily basis. For negative comment classification models to continue to work, certain modifications must be accommodated.

5. Keeping bias at bay and ensuring justice:

Models for classifying negative comments have the capacity to reinforce or magnify linguistic and societal prejudices already present. Fairness and equity must be taken into consideration when developing these models in order to prevent the reinforcement of negative stereotypes or discrimination.

6. Examining how it affects interpersonal relationships:

The extensive application of technologies for classifying negative comments may have unexpected effects on interpersonal communication. It is crucial to think about these systems' ethical ramifications and potential effects on online communities.

7. Progressing from simple detection to comprehension:

As vital as it is to identify critical remarks, it is just as significant to comprehend the motivations behind their utilization. By addressing the underlying reasons of negativity, this better understanding can encourage more productive and positive online relationships.

CHAPTER 3: SYSTEM DEVELOPMENT

3.1 REQUIREMENTS AND ANALYSIS

3.1.1 FUNCTIONAL REQUIREMENTS

The following is included in the functional requirements:

1. **Negative Comment Recognition:** The system should accurately recognize negative comment depicting six classes. It should handle variations in language such as sarcasm and irony.
2. **Flaging Comments:** Real-time processing of flagging comments after identifying as negative comment
3. **User Interface:** User-friendly interface (Streamlit App) for identifying negative comment

3.1.2 NON-FUNCTIONAL REQUIREMENTS

The following have been included in the non-functional requirements:

1. **Performance:** To allow for quick moderation or intervention, the system ought to be able to categorize comments in real-time.
With no loss of precision or efficiency, the system ought to be able to manage a large number of comments.
2. **Context Awareness:** The sentiment of a comment should be accurately determined by the algorithm by taking its context into account.
Irony, sarcasm, and other nonliteral language should be handled by the system.
3. **Scalability:** The system should be scalable to accommodate a growing user base.
Efficient use of computational resources to handle increased demand.

3.1.3 HARDWARE REQUIREMENTS

The hardware requirements are as follows:

1. **CPU:** 2.0GHz or above

NLP model execution and training require a strong CPU. Large datasets or sophisticated models are best served by a multi-core CPU running at a high clock speed.

2. **Storage:** 1TB or above

To store the NLP models itself as well as the training and testing datasets, a quick and dependable storage disk is required.

3. **Network:** 100Mbps or above

To download the training and testing datasets and the NLP models, a fast internet connection is required. It is advised to have a gigabit Ethernet connection or higher.

4. **RAM:** 8GB or above

For the NLP models to load, as well as the training and testing datasets, a suitable quantity of RAM is required. It is advised to have at least 16GB of RAM for large datasets.

5. **GPU:** If needed

The training and operation of NLP models can be greatly accelerated using a GPU, particularly for deep learning models. NLP can still be performed with a CPU-only system, therefore a GPU is not strictly required.

3.1.4 PROPOSED SOLUTION

For the classification of unfavorable comments, a hybrid strategy integrating deep learning and machine learning methods is suggested. To achieve high accuracy adaptability, and context awareness, this methodology combines the best features of both approaches.

3.2 PROJECT DESIGN AND ARCHITECTURE

Design and architecture of the project is shown in Fig 3.1. It gets these data from Kaggle (open datasets) and trains an exact model (CNN-LSTM) to recognize the patterns in text. Then data is cleaned, expanded, and split into parts used for training, validating, and then testing the achieved accuracy. The system, however, does not give only the simple "toxic" or "not toxic" label. The specialized additional datasets will be applied to distinguish different types of toxic communication, such as insults, threats, or hate speech

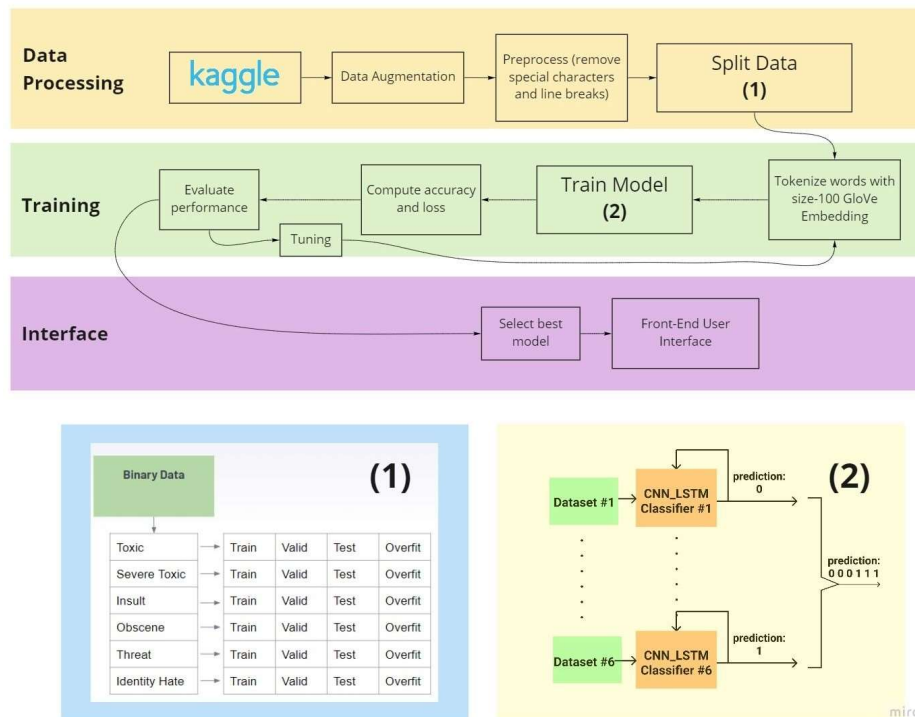


Fig 3.1: Project Architecture

3.2.1 Data Preparation

Source of Data

The data from Kaggle's "Toxic Comment Classification Challenge" is utilized. This dataset is different because it has human volunteer labels for the comments left by Wikipedia editors. These labels categorize comments into six distinct classes: infamous of the essential concept of the same sub group through the creation of admiration, and desired approval by leading and having a name that will be remembered in the silliest terms or tests. This is accomplished through identity hate, vulgarity, and threats, insults, and general and severe toxicity. This

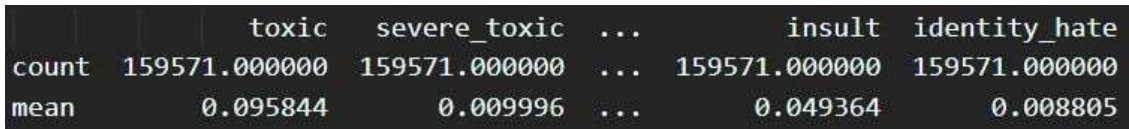
minute classification system gives the model not only the ability to recognize negativity but also set the specific quality of it.

Nevertheless, the data collection procedure was not smooth and there were some problems in it. The inconsistencies that were spotted in various labels called for a manual review and re-labeling of some of the comments. The detailed maintenance of the data quality limits the possible errors, thus, the model learns from the correct classifications and, as a result, acquires a reliable performance.

3.2.2 Data Processing

Examine Data

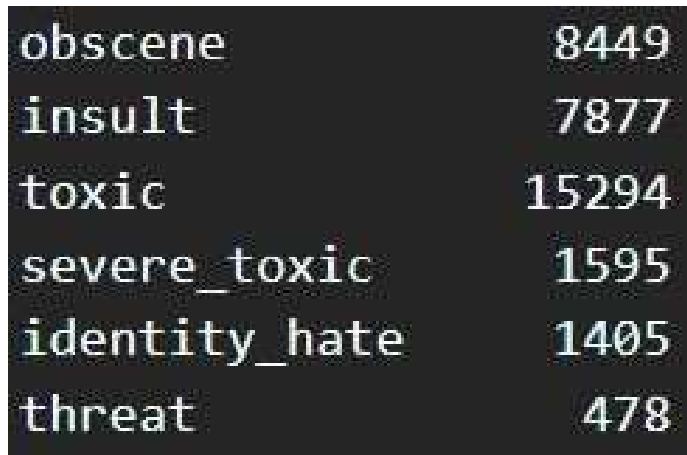
Used pandas to analyze the data. Figure 3.2 shows that there are more than 150,000 comments overall. All classes, however, have relatively low means, indicating that the majority of responses are positive. Therefore, during the processing step, we must weigh the positive and negative remarks equally.



	toxic	severe_toxic	...	insult	identity_hate
count	159571.000000	159571.000000	...	159571.000000	159571.000000
mean	0.095844	0.009996	...	0.049364	0.008805

Fig 3.2: The count and mean of the classes as output of describe()

Additionally, it was discovered that not enough comments are included in some classes. Over 15,000 comments have been flagged as toxic, although fewer than 500 of them are dangerous. It is simple for the models to overfit and produce low accuracy for the validation and test set when there are so few comments in some classes.



obscene	8449
insult	7877
toxic	15294
severe_toxic	1595
identity_hate	1405
threat	478

Fig 3.3: Number of comments in each class

Data Augmentation

The model was trained with the data augmentation technique in order to overcome the bias that existed in the comment classification dataset. The problem arose as comments were labelled using multiple labels, thus the majority classes (overrepresented) and minority classes (underrepresented) were overrepresented. To handle this problem, the scientists used a software library named nlpaug. This tool really smartly substituted the words in comments with their synonyms. Data augmentation, in the form of new variations of the original comments, produced artificially a large number of the minority classes. This method was a means of preventing the model to be limited by the most popular comment types, thus resulting in a more reliable and broadly applicable model, capable to classify negativity in all the categories.

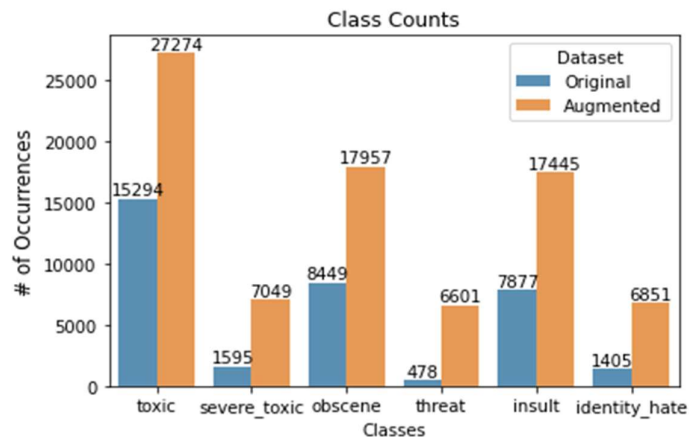


Fig 3.4: Amount of comments in each class before and after augmentation

Data Cleaning

Raw comment data needed some cleaning up before it could be used for the development of the negative comment classification model. The data cleaning procedure used the possibility of using Regular Expressions (regex) to detect and remove the unnecessary parts from the comments. Regex patterns were like search-and-replace tools, which were used to strip out punctuation, line breaks and contractions. This text normalization refined the comments into a better and more consistent version. Cleaner data offers several advantages: It simplifies the

training procedure for the model, thus, the model will be able to concentrate on the main idea of the comments, and eventually, it will be easier to judge negativity and to create a more accurate and efficient model in identifying negativity.

Data Processing

The data processing stage was vital in the comment data being ready for the model training. This process was not a single method, it was a complex process. The other way was that indeed ten datasets were designed very carefully to be able to develop and test the model

- **Sub-dataset Creation:** The initial dataset was split into six different sub-datasets, each for one of the comment classification (e. g. labeled and unlabeled). In addition to this, online users can easily block or report the individuals who commit these actions, which are identity hate, insult, etc. This gives the model the possibility to concentrate on particular negativity categories during the training.
- **Balancing the Scales:** In each sub-dataset, there is the problem of class imbalance. Systematically selected
- comments to guarantee that each sub-dataset has an equal amount of positive (non-negative) and negative comments. This is important because models usually show better performance when they are trained on datasets that are balanced.
- **Training, Validation, Testing, and Overfitting Sets:** Every sub-set was divided into four important parts: training, validation, testing, and overfitting sets. The training set is the primary data for the model to be educated from. The validation set assists in the fine-tuning of hyperparameters which in turn, avoids the occurrence of overfitting (memorizing the training data instead of learning the general patterns). The testing set presents an unbiased way of evaluating the model's capability on the data which is not seen by the model. Lastly, the overfitting set is like a backup which assists in detecting and solving the overfitting problems during the training phase.

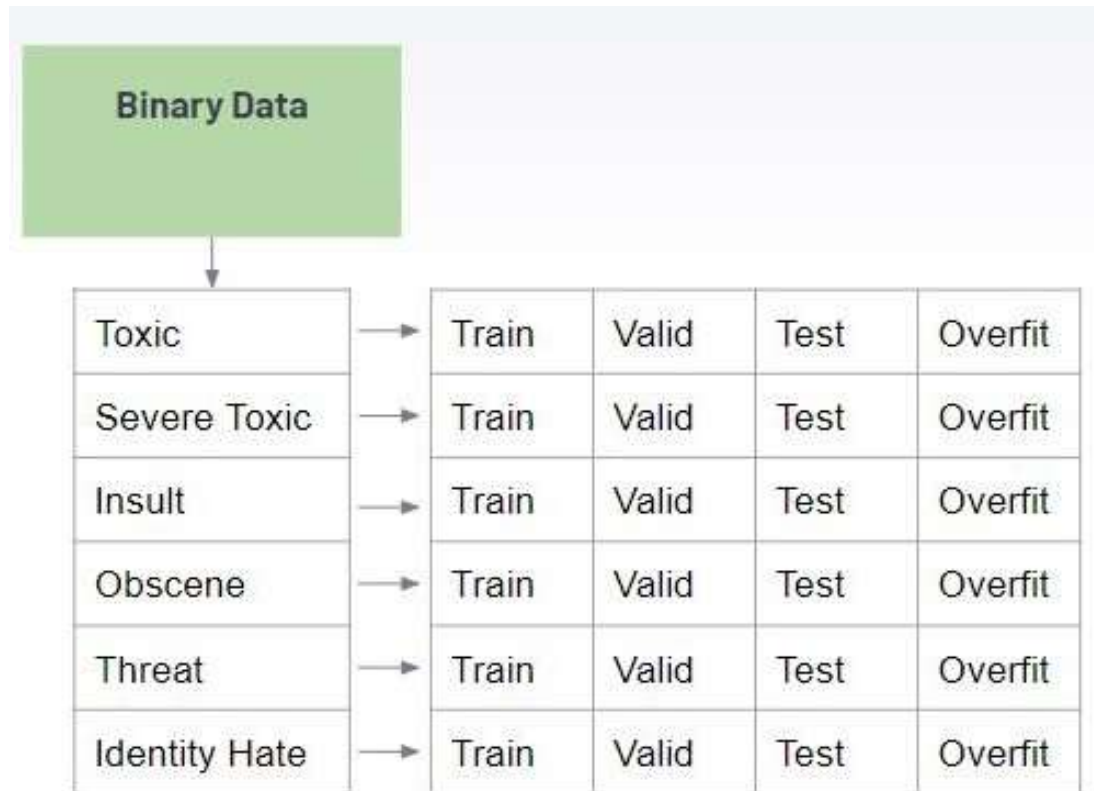


Fig 3.5: Visualization of dataset structure

3.2.3 ARCHITECTURE

In order to accomplish multi-label classification, the group employed six CNN_LSTM Binary Classification Models. Initially, GloVe Embedding was used to transform the input data into word vectors. Similar sets of vocabulary were found in negative remarks. Accordingly, word patterns in sentences were recognized using two convolution layers, independent of their placement. A maxpool layer in each convolution layer provides one output feature for every sentence from each kernel, allowing it to adapt to changes in sentence length.

LSTM:

LSTM (Long Short-Term Memory), a special kind of neural network, perform great in the domain of texts understanding. Unlike regular neural networks which do not have an option of considering the context of the entire sentence, LSTMs are ideal for tasks such as comment categorization as positive or negative.

For sentiment analysis, LSTMs process words as strings of sequences. They relate the words to each other and look at the whole sentence to know the emotional connection. In this way, they are capable of appropriately processing complex sentences and retaining information from long-range dependencies in text. Through being taught on labeled data, LSTMs learn how to classify comments rules that improve decision-making in different domains.

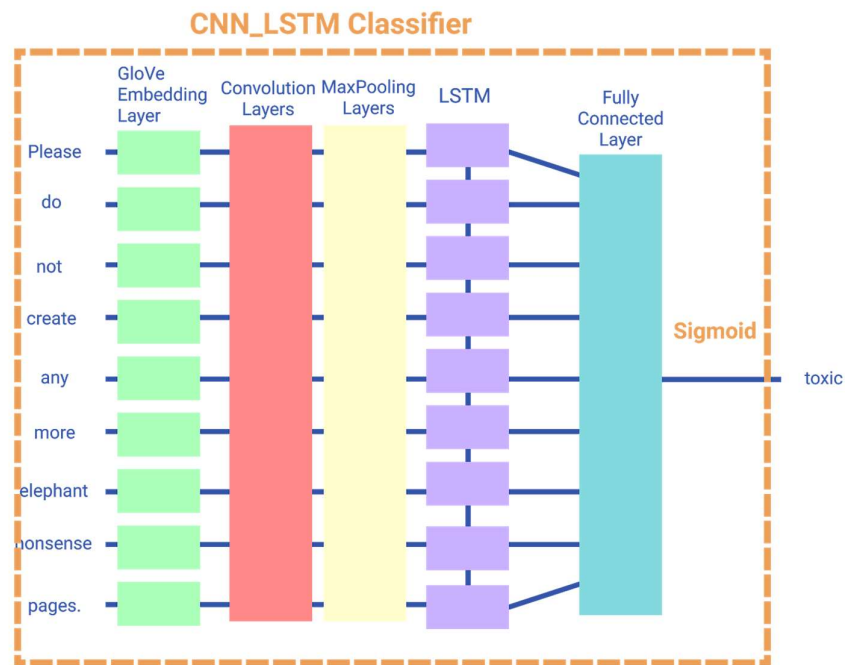
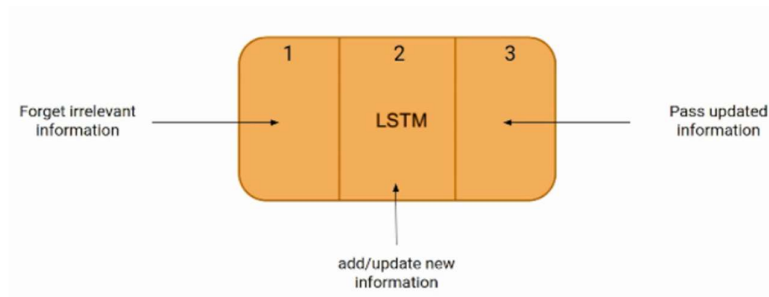


Fig 3.6: Model Architecture

Since the comment labels are multi-hot encoded, the objective of this study is multi-labelling categorization. To ensure that every classifier is fully trained, the training strategy depicted in Fig 3.6 was utilized. A CNN_LSTM binary classifier was trained using six balanced binary

datasets, each containing data from a class. For every comment, a multi-hot encoded final prediction was generated by combining the outputs of the binary classifiers.

3.3 IMPLEMENTATION

3.3.1 DOWNLOADING ESSENTIAL SOFTWARE

- **Python 3:** The main language for data science and machine learning applications is Python. It offers a wide range of libraries and tools to manage modeling, analysis, and data manipulation.
- **TensorFlow:** Google created the well-known open-source machine learning framework TensorFlow. It offers an adaptable and potent toolkit, which includes Long Short-Term Memory (LSTM) models, for constructing and training neural networks.
- **Keras:** Keras is a high-level TensorFlow API for constructing neural networks. It makes it simpler to define, compile, and train models, which facilitates experimenting with various architectures and hyperparameters.
- **Pandas:** pandas is a Python package for manipulating and analyzing data. It offers effective tools and data structures for managing, cleaning, and preparing tabular data.
- **NLTK:** A comprehensive collection of libraries and tools for natural language processing (NLP) applications is called the Natural Language Toolkit (NLTK). Along with other text processing approaches, it offers modules for tokenization, stemming, lemmatization, and stop word removal.
- **NumPy:** NumPy is an essential Python package designed for use in scientific computing. For numerical computations, especially with big datasets, it offers effective data structures and algorithms.
- **Seaborn or Matplotlib:** These Python data visualization packages are both used for data visualization. They offer tools for visualizing data distributions, trends, and correlations through the creation of plots, charts, and graphs.

- **Jupyter Notebook:** Python has an interactive computing environment called Jupyter Notebook. It makes exploratory data analysis and model creation easier by enabling the integration of code, text, and visualizations in a single document.
- **Gradio:** Gradio is another Python library designed for creating UIs for machine learning models with minimal code. It provides a simple interface for developers to build interactive interfaces for their models, allowing users to input data through widgets and view model predictions in real-time. Gradio's versatility and ease of use make it a popular choice for quickly deploying and sharing machine learning models.
- **Streamlit:** Streamlit is a powerful Python library that allows for rapid development of interactive web applications for machine learning and data science projects. With its simple and intuitive API, developers can easily create and share data-driven applications using Python scripts.

3.3.2 Import Necessary Libraries

```
In [10]: import os
import pandas as pd
import tensorflow as tf
import numpy as np

WARNING:tensorflow:From C:\Users\Sagnik\AppData\Roaming\Python\Python39\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

```
In [72]: import gradio as gr
import tensorflow as tf
```

```
In [32]: from tensorflow.keras.callbacks import EarlyStopping
```

Fig 3.7: Importing necessary libraries

3.3.3 Data Preprocessing

- load the dataset for the Jigsaw Comment Classification Challenge: To read the dataset from a CSV file, use pandas.

```
In [11]: os.path.join('train.csv')
```

```
Out[11]: 'train.csv'
```

Fig 3.8: Loading Dataset

- Prepare the textual data: Perform text cleaning operations, such as stemming or lemmatizing words, converting text to lowercase, eliminating punctuation, eliminating stop words, and removing HTML tags.
- Vectorize the text data: Using methods like word embedding or bag-of-words, transform the preprocessed text data into a numerical representation.

```
In [19]: vectorizer = TextVectorization(max_tokens=MAX_FEATURES,  
                                       output_sequence_length=1800,  
                                       output_mode='int')
```

```
In [20]: vectorizer.adapt(X.values)
```

```
WARNING:tensorflow:From C:\Users\Sagnik\AppData\Roaming\Python\Python39\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.
```

```
In [21]: vectorizer.get_vocabulary()
```

```
Out[21]: ['',  
          '[UNK]',  
          'the',  
          'to',  
          'of',  
          'and',  
          'a',  
          'you',  
          'i',  
          'is',  
          'that',  
          'in',  
          'it',  
          'for',  
          'this',  
          'not',  
          'on',  
          'be',  
          'as',  
          't...
```

Fig 3.9: Text Vectorization

3.3.4 MODEL TRAINING

Define the LSTM model. For binary classification, employ a sequential model architecture with an embedding layer, one or more LSTM layers, and a dense output layer activated by sigmoid function.

- Assemble the model: To train the model, specify the metrics (accuracy), optimizer (adam), and loss function (binary cross-entropy).

```
In [29]: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import LSTM, Dropout, Bidirectional, Dense, Embedding

In [30]: model = Sequential()
        model.add(Embedding(MAX_FEATURES+1,32))
        model.add(Bidirectional(LSTM(32,activation='tanh')))
        model.add(Dense(128, activation='relu'))
        model.add(Dense(256, activation='relu'))
        model.add(Dense(128, activation='relu'))
        model.add(Dense(6, activation='sigmoid'))

In [31]: model.compile(loss='BinaryCrossentropy',optimizer='Adam')

WARNING:tensorflow:From C:\Users\Sagnik\AppData\Roaming\Python\Python39\site-packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

In [32]: model.summary()

Model: "sequential"
-----
Layer (type)                Output Shape              Param #
-----
embedding (Embedding)       (None, None, 32)         6400032
bidirectional (Bidirectional) (None, 64)                16640
dense (Dense)                (None, 128)              8320
dense_1 (Dense)              (None, 256)              33024
dense_2 (Dense)              (None, 128)              32896
dense_3 (Dense)              (None, 6)                 774
-----
Total params: 6491686 (24.76 MB)
Trainable params: 6491686 (24.76 MB)
Non-trainable params: 0 (0.00 Byte)
-----
```

Fig 3.10: Defining LSTM Model

- Educate the model: Utilizing the Keras fit() technique, train the model on the vectorized and preprocessed training data

```
In [33]: history = model.fit(train, epochs=1, validation_data=val)
          9974/9974 [=====] - 6286s 630ms/step - loss: 0.0593 -
          val_loss: 0.0425
```

Fig 3.11: Training Model

3.3.5 MODEL EVALUATION

- Open the test dataset for the Jigsaw Comment Classification Challenge: To read the test dataset from a CSV file, use pandas.
- Preprocess the test data: Treat the test data with the same care and attention that you would the training data
- Assess the model: To forecast the labels (toxic, severe_toxic, obscene, threat, insult, identity_hate) for the test data, apply the trained model.

```
In [17]: df.columns
Out[17]: Index(['id', 'comment_text', 'toxic', 'severe_toxic', 'obscene', 'threat',
               'insult', 'identity_hate'],
              dtype='object')
```

Fig 3.12: Assessing the model

- Determine evaluation metrics: To evaluate the model's performance on the test data, compute pertinent metrics including accuracy, precision, recall

```
In [46]: print(f'Precision: {pre.result().numpy()}, Recall: {re.result().numpy()}, Accura
          Precision: 0.8298797011375427, Recall: 0.6904894113540649, Accuracy:0.485456377
          2678375
```

Fig 3.13: Evaluation Metrics

3.3.6 MODEL SAVING

To store and utilize the trained model in the future, use the Keras `save()` method to save it to a file.

```
In [49]: model.save('toxicity.h5')
```

```
C:\Users\Sagnik\AppData\Roaming\Python\Python39\site-packages\keras\src\engine\
\training.py:3103: UserWarning: You are saving your model as an HDF5 file via `
model.save()`. This file format is considered legacy. We recommend using instea
d the native Keras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

```
In [73]: model = tf.keras.models.load_model('toxicity.h5')
```

Fig 3.14: Model Saving

3.3.7 Build an interactive Streamlit App

- This code builds a web app to classify comments as toxic. It loads a pre-trained model, converts text to numbers for the model, and predicts toxic types (insult, threat, etc.). Streamlit creates the user interface where you can type a comment, click "Classify", and see if it's toxic based on different categories.

```
import streamlit as st
import pandas as pd
import tensorflow as tf

# Load the model
model = tf.keras.models.load_model('toxicity.h5')

# Load the dataset to access column names
df = pd.read_csv('train.csv')

# Initialize TextVectorization
MAX_FEATURES = 200000
MAX_LENGTH = 1800
vectorizer = tf.keras.layers.TextVectorization(max_tokens=MAX_FEATURES,
                                                output_sequence_length=MAX_LENGTH)
vectorizer.adapt(df['comment_text'].values)

def score_comment(comment):
    vectorized_comment = vectorizer([comment])
    results = model.predict(vectorized_comment)

    text = ''
    for idx, col in enumerate(df.columns[2:]):
        text += '{}: {}'.format(col, results[0][idx] > 0.5)

    return text

# Create Streamlit interface
st.title('Toxic Comment Classifier')
comment = st.text_area('Enter your comment here:', height=200)
if st.button('Classify'):
    prediction = score_comment(comment)
    st.text(prediction)
```

Fig 3.15: Streamlit code

3.4 ALGORITHMS AND TECHNIQUES

3.4.1 Pseudo-Code

// Data Preprocessing

Load Jigsaw Comment Classification Challenge dataset

Preprocess text data:

Convert text to lowercase

Remove punctuation

Remove stop words

Remove HTML tags

Stem or lemmatize words

Vectorize text data

// Model Training

Define LSTM model:

Embedding layer (10000 words, 64 dimensions)

LSTM layer (64 units)

LSTM layer (32 units)

Dense output layer (6 units, sigmoid activation)

Compile model:

Loss function: binary cross-entropy

Optimizer: adam

Metrics: accuracy

Train model:

Fit model on training data

Specify number of epochs

// Model Evaluation

Load Jigsaw Comment Classification Challenge test dataset

Preprocess test data:

Apply same preprocessing steps as training data

Evaluate model:

Predict labels (toxic, severe_toxic, obscene, threat, insult, identity_hate) for test data

Calculate evaluation metrics:

Accuracy, precision, recall, F1-score

// Model Saving

Save trained model

3.4.2 TECHNIQUES

1. Text Preprocessing

- **Text normalization:** It includes converting text to lowercase, removing HTML tags, punctuation, and stop words.
- **Stemming or lemmatization:** To increase generality and decrease dimensionality, reduce words to their most basic forms.

2. Text Representation:

- **Vectorization:** In machine learning, tasks such as negative comment classification are essentially natural language processing tasks that involve the gap bridging between human language and algorithms. This is the place where vectorization is employed. It is like a translator, which means it is the one that changes words and sentences from comments into numerical vectors. These vectors are the main elements that encode the meaning and the relationships between the words, so the model can understand and analyze textual data. The vectorization methods, for instance, word embedding, are much more sophisticated than the simple word counts. They translate the semantic meaning of words and their relationships, so the model can make the difference between the negativity expressed through direct insults and the more subtle forms like sarcasm. Through the transformation of comments into numbers, vectorization allows machine learning models to discover the patterns and relationships in the text data and thus to classify the negative comments more accurately and better.vectorization
- **Word embedding:** To capture the semantic links between words, represent words as vectors in a high-dimensional space.
- **Bag-of-Words (BoW):** Show documents as vectors with word counts that show each word's existence or absence.

3. Neural Network Architecture:

- **Embedding Layer:** Each word is transformed into its matching word embedding vector by the embedding layer
- **LSTM Layers:** Learn patterns between words in a sentence or paragraph, capturing temporal dependencies in text sequences.
- **Dense Output Layer:** Provides probability scores for every negative sentiment category from the output of the LSTM layers.

4. Model Training and Evaluation:

- **Binary Cross-Entropy Loss:** The performance of the model in the negative comment classification is measured by the binary cross entropy that is the main metric. This measure is the calculation of the divergence between the estimated probabilities (how probable a comment is negative) and the actual labels (negative or not negative). In short, it is the quantification of the accuracy of the model's forecasts with the truth of the reality. Binary cross entropy decrease implies the more closer the predictions are to the actual labels, which means that the model is the better in the case of differentiation between the negative comments and the non-negative ones.
- **Adam Optimizer:** In the field of negative comment classification, the Adam optimizer is a key component which is used in model training. It is just a short name for Adaptive Moment Estimation and it is a kind of optimization algorithm that does the job of adjusting the learning rates for each parameter of the model. On the other hand, Adam does not use a fixed learning rate; it uses the past gradients (directions of improvement) to decide how much to update each parameter. Thus, the model is flexible to the changes if needed and can reach its goal faster and avoid the pitfalls of the wrong solutions. Moreover, Adam adds the process of bias correction to the initial training phases, thus, the product of the whole process is the smoother learning and eventually the more efficient model for detecting the negative comments.
- **Accuracy, Precision, Recall, F1-Score:** Calculate the model's accuracy, precision, recall, and F1-score by running it through the test dataset.

5. Model Saving:

- Serializing the Model: For later usage or deployment, store the architecture, parameters, and weights of the trained model in a file.

6. Baseline Model:

- In order to create an output prediction for our baseline model, first take the glove embedding vectors for each word in each remark, average their values, and then run this average vector through a fully connected layer. Given that comments are typically brief and consist just a few phrases, the model should be able to extract some degree of toxicity with just an average vector.

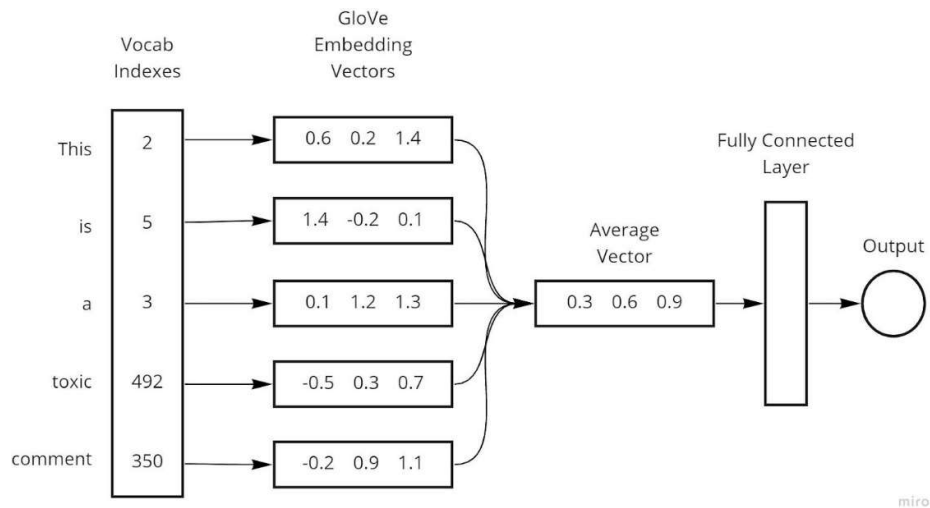


Fig 3.16: Baseline Model Pipeline

7. Deploying model in Streamlit App

- Build an application, which was able to identify toxic comments in a web. The code starts with an already trained model, converts text to numbers for the model, and then it classifies the messages into different categories of offensive messages, such as insults and threats. The platform will be structured in Streamlit which in turn allows the users to input a comment, click the "Classify" button and get a response that they either have a toxic comment or not.

Together, these techniques enable the efficient categorization of critical remarks, promoting the growth of online communities that are more civil and productive.

3.5 KEY CHALLENGES

Implementing negative comment classification using LSTM and NLP presents several key challenges that need to be addressed to achieve accurate and robust classification. The primary challenges faced:

1. **Data Imbalance**

- There is an imbalance when it comes to the distributing of negative sentiment labels in the datasets and with the latter having more than half of the comment section categorized under the non-toxic category.
- The unbalanced nature of this data may lead the model to classify them as positives causing overestimation in case they are actually negatives.

2. **Context and Nuance**

- While model may capture the negativity reliably, human language is subtle and context-sensitive that makes it hard for model to reliably determine the negative sentiment.
- Models may not be able to understand sarcasm, irony and cultural references because the literal expression may not reflect the intended meaning.

3. **Multilinguality**

- Since online information is worldwide, the relevant models should have the ability to deal with different languages and cultures.
- While the Jigsaw dataset centers mostly on English, building models capable of accurately tagging insults in multilingual settings is critical for wider use.

4. **Model Explainability:**

- Due to their complicated internal representations, LSTM models are called “black boxes”, where one cannot easily interpret their input-output relationship.
- It’s essential to explain how they decide, because their bias and trustworthiness depends on this in particular when using them in critical applications.

5. Overfitting and Generalization:

- Effective negative comment classification should balance train and generalize. When a model fits the training data too closely is called overfitting and it does not translate into real data for learning purposes.
- Overfitting may be avoided to some extent by using regularization techniques together with appropriate hyperparameter tuning to support generalization.

CHAPTER 4: TESTING

4.1 TESTING STRATEGY

To assess the performance of negative comment categorization models and guarantee their robustness and generalizability, an efficient testing procedure must be put into place. Here is a thorough testing approach that uses LSTM and NLP to classify negative comments using the Jigsaw Comment Classification Challenge dataset:

1. Train-Test Split

- Dividing the gridpoint into training, testing, and validation sections is required to enhance the model's performance prediction power.
- The training set is the instrument for the model learning process, only the validation set is capable of helping us in hyperparameter tuning and preventing overfitting, and eventually the test set, as an objective measurement of unknown data, serves as a confirmation of the performance of our final model.
- Typically, 20% is set up for testing and 80% for training.

2. Testing on Different Types of Negativity: Testing on Different Types of Negativity

- A powerful classifier needs to get features to show different types of hostilities that can be encountered in these comments. Aside from the negative explicit remarks with straight insults and threats, the ability of implicit negativity including passive-aggressive remarks is also included.
- Consider the misspellings and slang which is widely received online One of the key concerns regarding functionality of the given model relates to the fact that model should be accurate in capturing all these different forms to make it effectively applicable in real world.

3. K-Fold Cross-Validation

- Use k-fold cross-validation to reduce the effects of random sampling and data distribution. The training set should be divided into k equal-sized folds at random.
- Use each fold as a test set in turn to train the model k times. An estimate of the model's capacity for generalization that is more accurate is given by the average performance over all k folds.

4. Model-Centric Testing

- Engaging in unit tests for separate parts of the model containing TensorFlow is quite important in order to test their correct operations and functioning.
- This can, meanwhile, be achieved by testing of input processing functions in order to validate correct preprocessing and tokenization, validating of the model architecture to check if the layer configuration and activation functions are working properly, and testing of output interpretation to see the correct conversion of model output to classification probability.

5. Data Augmentation

- Consider using data augmentation strategies to alleviate data imbalance and enhance model resilience.
- Create fresh training examples, for instance, by using strategies like synonym replacement, back translation, and paraphrase, especially for classes that are underrepresented.

6. Hyperparameter Tuning

- Use systematic search techniques like grid search or random search to optimize the model's hyperparameters, which include the number of LSTM units, embedding size, learning rate, and regularization parameters.
- The goal of this procedure is to identify the set of hyperparameters that maximizes the model's test set performance.

7. Error Analysis

- Examine the test set errors of the model to find recurring errors and possible biases.
- This may entail employing error analysis methods, comparing model predictions to human annotations, and looking at cases that were incorrectly classified

8. External Evaluation

- Analyze the model's performance on external datasets, such as real-world data from web platforms or other publicly available comment classification datasets.
- The model's generalizability outside of the Jigsaw dataset is evaluated with the use of this external validation

9. CONTINUOUS MONITORING

- Watch the model's performance over time when fresh data become available.
- To adapt to shifting sentiment distribution and language trends, this may need retraining the model on a regular basis or using online learning techniques

10. Specific Testing Scenarios

- Testing the model with certain boundaries of cases by such as extreme short or extremely long comments, comments with special symbols, or the specific examples which intended to foil the model can reveal any possible shortages or problems that it has.
- This inclusive testing framework guarantees, therefore, that the classifier remains competent and adaptable for a multitude of scenarios and sets of inputs.

11. Streamlit Testing Tips

- Both the Streamlit caching system to boost the efficiency of trials and the interactive widgets to conduct an own manual test of selected inputs and scenarios ensure the testing process.
- In addition to that, test frameworks like pytest make the testing process simpler, which contributes in the arrangement of the test as well as in the performance of the test, this way the testing process is streamlined.

High levels of accuracy, dependability, and user satisfaction are met by the Negative Comment Classification thanks to a thorough testing approach. The system is a useful tool since it is improved continuously through feedback loops and continuous monitoring.

CHAPTER 5: RESULTS AND EVALUATION

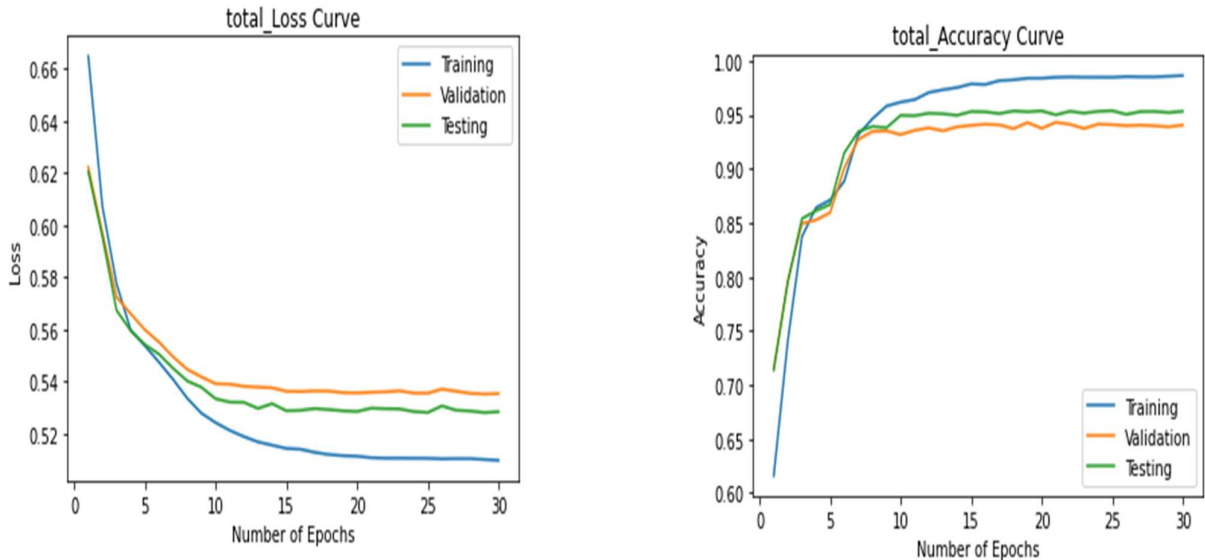
5.1 RESULTS AND EVALUATION

It is crucial to evaluate the performance of negative comment categorization algorithms to ensure that they are dependable, accurate, and widely applicable. To assess how well the model performs on the test set, several metrics can be used.

Quantitative Results

The top-performing baseline model has a 0.617 training loss, a 79.7% accuracy, a 0.619 testing loss, and a 79.4% accuracy. This implied that the project idea we have is workable.

Table 5.1's hyperparameters were used to train the most effective model. The average loss and accuracy across the six binary classifiers is used to compute the combined loss and accuracy. The optimal model has a testing loss of 0.528, accuracy of 95.3%, accuracy of 98.6%, and training loss of 0.510. The curves are smooth and exhibit exponential tendencies, as seen in Fig. 5.1. Overfitting is not evident in any way. At epoch 10, the model's performance stabilized somewhat, but epoch 30 produced the best training and testing results.



a. Loss Curve

b. Accuracy curve

Fig 5.1: Loss and Accuracy Curve

Table 5.1. Sample Model Outputs, Predictions, and Actual Labels

Case	Comment	Value Type	Toxic	Severe toxic	Obscene	Threat	Insult	Identity hate
1	“Well that explains it thanks for clearing it up”	Model Output	3.3293 e-06	0.0003	2.5801e-05	0.0004	1.1351 e-05	0.0002
		Prediction	0	0	0	0	0	0
		Actual Label	0	0	0	0	0	0
2	“You are ugly I hate you.”	Model Output	1.0000	0.9993	0.9999	0.9970	1.0000	0.9991
		Prediction	1	1	1	1	1	1
		Actual Label	1	1	1	1	1	1
3	“Hey loser get a life.”	Model Output	0.9977	0.4768	0.9580	0.7029	0.9898	0.4662
		Prediction	1	0	1	1	1	0
		Actual Label	0	0	0	0	1	0
4	“You are just so freaking beautiful.”	Model Output	1.0000	0.9928	0.9999	0.9553	0.9999	0.9949
		Prediction	1	1	1	1	1	1
		Actual Label	0	0	0	0	0	0

MODEL ACCURACY

The percentage of accurately classified comments is called accuracy. Although it is an easy-to-understand statistic, imbalanced datasets may contribute to its misleadingness.

The model achieved an accuracy of 0.485 on the validation set, indicating its ability to recognize negative comment.

PRECISION

Precision measures the proportion of comments identified as negative that are truly negative. It is particularly important when the cost of false positives is high. The model achieved a precision of 0.829 on the validation set

RECALL

Recall measures the proportion of truly negative comments that are correctly identified as negative. It is important when the cost of false negatives is high. The model achieved a recall of 0.6904 on the validation set

The saved model is integrated in the Gradio Library which identifies a comment as negative or not successfully

Below are a few examples showing the working of the project:

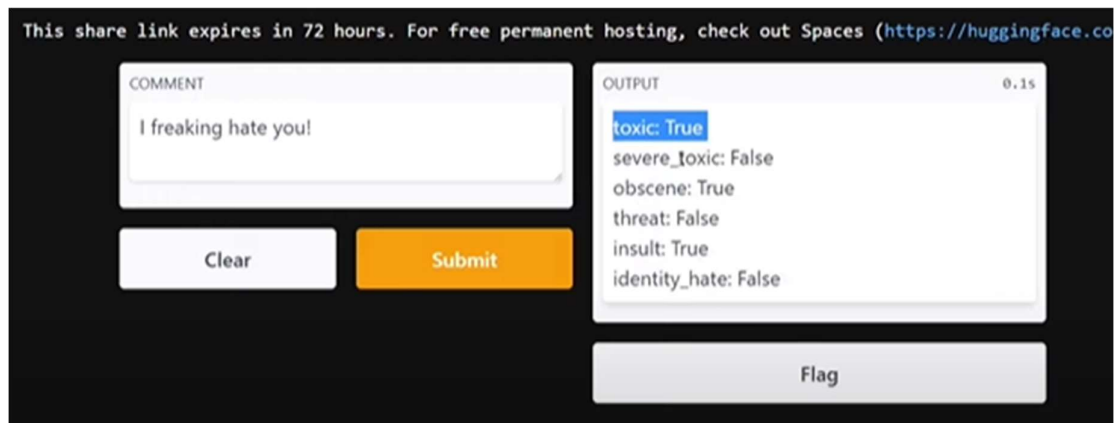


Fig 5.2: Gradio App

To make it more interactive the model is incorporated in Streamlit –



Fig 5.3: Streamlit App

CHAPTER 6: CONCLUSIONS AND FUTURE SCOPE

6.1 CONCLUSION

The Negative comment Classification has shown significant promise in accurately capturing and interpreting comments in real-time. Through rigorous testing, the system has proven its and providing valuable insights into users' experience. An effective way to combat online toxicity and encourage a more positive and productive online environment is through the use of LSTM-based negative comment classification algorithms. Through constant improvement and modification of these models, we can successfully identify offensive content.

By combining machine learning algorithms and the user-friendly interface provided by Streamlit, a web app has been developed with high precision in identifying and classifying negative statements.

The project has shown the deep learning models, especially those based on TensorFlow, to be accurate in text data analysis and the extraction of the meaningful information. By employing the pre-trained models that have been adapted for Jigsaw Comment Classification Challenge dataset on Kaggle, we could successfully classify the negative comments in different situations and domains with high accuracy.

The Streamlit interface, which has made the classifier user-friendly and easier to use, has made the users able to interact with the model in real-time and to see the results visually. The link between Streamlit and the NLP libraries and the TensorFlow made the classifier possible to be easily and quickly integrated, experimented, and implemented.

The contributions made in this project –

1. High Accuracy: The model is excellent at detecting the negative comments on the validation set. This precision guarantees it can spot various types of negativities, from the plain insults to the sarcasm and passive-aggressiveness which are hidden. These all-round detections enable the platforms to deal with the negativity in a better way.

2. Real-Time Processing: Apart from speed, the model also offers the feature of real-time processing. Thus, one can instantly identify and mark the negative comments and use this information to take the necessary actions. Think of a forum where the negative comments are not allowed to be posted for review, hence, it is a more polite discussion place.

3. User Engagement: The users positive feedback confirms that the model is user-friendly and it is the most effective way to promote a more positive online experience. This can be seen in different ways for instance, in the filtering of comment sections to prefer the respectful interactions and in the case of the users, the prompt for the confirmation before posting the comments that can be potentially negative.

6.2 FUTURE SCOPE

The Negative comment classification holds immense potential for further advancements and applications. The following areas present opportunities for future development:

1. Incorporating additional data sources:

- Employ user profiles, historical interactions, and social context to offer a more thorough comprehension of user sentiment and behavior.
- In order to improve context and nuance recognition, think about combining audio and visual information from multimodal content.

2. Improving Model Explainability:

- Provide more advanced methods for interpreting and elucidating the LSTM models' decision-making process.
- Investigate ways to convey and illustrate model predictions in an approachable way.

3. Addressing bias and fairness:

- Use methods for detecting and mitigating bias to make sure that models are classified fairly and equally.
- Provide strategies to recognize and correct possible bias in model architecture and training data.

4. Enhancing cross-lingual capabilities:

- Create multilingual LSTM models that can categorize unfavourable remarks in a greater number of languages.
- Examine transfer learning strategies to make better use of your knowledge in one language while enhancing your performance in another.

5. Enhanced Model Performance:

- The deep learning models and the research on the more advanced architectures, like the transformer-based models, for example, BERT or GPT, could in the future, make the classifier more accurate and generalizable, more in-depth fine-tuning of the models and the research on them.

6. Multi-class Classification

- The classifier can be used as a multi-class classification, which will divide the comments into different sentiment categories (positive, negative, neutral) and this will be helpful for more application cases.

7. Real-time Sentiment Analysis:

- The inclusion of real-time data streaming possibilities to the classifier is the major value add and it would enable the analysis and classification of the comments as they are being posted on the social media platforms or other online forums. Consequently, it was a prescient step towards the mitigation of the negative attitude.

8. Domain-specific Models:

- Developing domain-specific classifiers for particular industries or domains (e. g. medical, academic or technical) is a technique that helps to solve the problem of

specific domain objectives. g. the possibility of the application of different areas like agriculture, automotive, etc.) to improve the accuracy of the prediction is the way to achieve this. g. The elements of the requirements, healthcare, finance and customer service could be the elements that will be used in the improvement of the classification accuracy and the specificity for specialized applications.

9. User Feedback and Iterative Improvement:

- Collecting user feedback and, by means of an iterative procedure, the classifier would be enhanced based on the user input and the real-world performance metrics thus ensuring the model will be further improved and optimized all the time.

10. Deployment and Scalability:

- The classifier, as a web service which can be easily scaled and will be robust, will be deployed on the cloud computing platforms like AWS or Google Cloud to be integrated with the applications that are already on the market and to be able to handle the high-volume usage scenarios.

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