Hierarchical Sentiment Analysis Framework for Hate Speech Detection: Implementing Binary and Multiclass Classification Strategy

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ABSTRACT

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A significant challenge in automating hate speech detection on social media is distinguishing hate speech from regular and offensive language. These identify an essential category of content that web filters seek to remove. Only automated methods can manage this volume of daily data. To solve this problem, the community of Natural Language Processing is currently investigating different ways of hate speech detection. In addition to those, previous approaches (e.g., Convolutional Neural Networks, multi-channel BERT models, and lexical detection) have always achieved low precision without carefully treating other related tasks like sentiment analysis and emotion classification. They still like to group all messages with specific words in them as hate speech simply because those terms often appear alongside hateful rhetoric. In this research, our paper presented the hate speech text classification system model drawn upon deep learning and machine learning. In this paper, we propose a new multitask model integrated with shared emotional representations to detect hate speech across the English language. The Transformer-based model we used from Hugging Face and sentiment analysis helped us prevent false positives. Conclusion. We conclude that utilizing sentiment analysis and a Transformer-based trained model considerably improves hate speech detection across multiple datasets.

Keywords: Multi-class classification, *Binary Classification, RoBERTa-base, XLM- RoBERTa, Sentiment analysis,*

Chapter 1: Introduction

Background and Motivation

In recent decades, people have become more and more addicted to social media platforms where they unleash their thoughts/ opinions or even daily moods. However, the downside of this trend is some or most harmful and racist material that gets spread on a mass level to target one person or community. What constitutes hate speech? It has no formal definition, but it is generally agreed to be speech that seeks to harm or enforce sins against socially disadvantaged groups [1,2]. The European Commission's General Policy Recommendation No. 15 offers a comprehensive definition, characterizing it as "advocacy, promotion, or incitement, in any form, of the denigration, hatred, or vilification of a person or group of persons, as well as any harassment, insult, negative stereotyping, stigmatization, or threat in respect of such a person or group of persons." This includes justification based on various personal characteristics or status.

In today's digital landscape, the sheer volume of daily web content makes manual content monitoring impractical. To address and counter the spread of online hate speech, the European Commission, in May 2016, brokered an agreement with Facebook, Microsoft, Twitter, and YouTube to establish a "Code of Conduct on countering illegal hate speech online."[3] Over the years, Instagram, Snapchat, and other sites like Dailymotion or Jeuxvideo. com and TikTok joined this initiative. Nevertheless, maintaining compliance with the EU Code of Conduct is difficult for online platforms. A tool that comes to the rescue in this case is Natural Language Processing (NLP). The hate speech detection systems designed by the NLP community have utilized different techniques and approaches primarily based on traditional machine learning and deep learning. Nevertheless, they are proving to be performing decently. Hate speech, on the other hand, generates real-life violence, increases polarization in societies, and perpetuates injustices. Higher levels of divisive language may provoke mental health issues, creating fear for those being targeted and preventing freedom of speech. In fact, hate speech is also a driving force behind the erosion of trust and the rise in toxicity that exists today within online communities.

In conclusion, individuals found guilty of employing hate speech often face substantial fines and even imprisonment. Additionally, this injurious and demeaning content can detrimentally impact an individual's mental well-being [4].

Purpose and Goal of the Project

The majority of studies in sentimental analysis center on the foundational human emotions delineated by Ekman [3], encompassing anger, fear, sadness, joy, surprise, and disgust. Psychological research emphasizes that [5] negative sentiment messages frequently indicate emotions like anger, disgust, fear, or sadness, while positive textual content is associated with feelings of joy. Moreover, it is essential to acknowledge that abusive language and conduct are inherently intertwined with the emotional and psychological condition of the speaker [6]. Notably, messages characterized by hate speech have been consistently shown, in recent years,[7] to exhibit negative sentiments and emotions such as anger, disgust, fear, and sadness, as substantiated by multiple studies [8].

Considering the significant impact of emotions on hate speech messages within this study, we have explored some novel techniques to identify new hateful cases from the data collected. This required the inclusion of Sentiment Analysis (SA), polarity identification, emotion classification, and a transformer-based ensemble in text criticism as additional hate speech detection mechanisms gradually increased.

This study introduces an innovative technique for hate speech (HS) classification on social media platforms, specifically focusing on English texts. Our model evaluation is performed on Hugging Face datasets that come with hateful instances, and this dataset needs to be manually annotated as hate. Notably, our research highlights the effectiveness of Multi-Task Learning (MTL) based models, in particular MTLsent+emo that combines with a monolingual Transformer model-BETO has incorporated adopted polarity and emotion knowledge for better HS detection. For benchmarking, we evaluate the performance of MTLsent+emo against a monolingual Transformer-based baseline model (re-trained for Romanian) and previous state-of-the-art results in English hate speech detection. We empirically evaluate various benchmark suites and, within our analysis, prove to be significantly superior in performance over the baseline model, walking through multi-task learning leveraging sentiment from hate tweets for compelling predictions. Our error analysis further presents critical analyses of how the MTL model performs and describes the unique ways in which English-speaking users are expected to produce hate speech. The current study helped enhance the work done to check on the spread of hatred, like an epidemic worldwide, specifically through English as an internet language.

In the future, our model aims to enhance its ability to identify all offensive language instances. This is particularly challenging because people often employ highly offensive terms in various qualitative contexts. For instance, some African Americans commonly use the term "n*gga" as a colloquial expression online [9]. We aim to address such prevalent language on social media by introducing fine-grained labels that categorize data from Hugging Face into three distinct groups: hate speech, offensive language, or neither. We will then proceed to train a model capable of effectively distinguishing between these categories, subsequently analyzing the outcomes to gain a deeper understanding of this differentiation. This research contributes to the broader field of hate speech detection and emphasizes some of the primary challenges associated with accurate classification. In conclusion, future endeavors should emphasize considering contextual factors and the diverse ways hate speech is employed [10].

Chapter 2: Research Literature Review

Existing Research and Limitations

In recent years, the prevalence of hate speech in online content has brought attention to its importance in dealing with text data. This is especially true in the field of Natural Language Processing (NLP), where a wide range of machine learning approaches have been tried as part of different research efforts. A considerable part of these investigations is based on finding Hate Speech in different social media networks. Bag-of-words methodologies typically show improvements in recall rates. However, it may lead to increased false positive rates because as more hate vocabulary is included in a lexicon, tweets mentioning those words get mislabeled as instances of Hate Speech [11,12]. At the beginning of the research, traditional machine learning algorithms were used for trials, such as support vector machines, random forests, decision trees, and logistic regression. These features were combined with different types of syntactic, semantic, lexical sentiment, and lexicon-based diverse feature sets [13,14,15]. The difference between hate speech and other types of offensive language is often a question of subtle linguistic distinctions. Syntactic attributes have been utilized to enhance the identification of both the specific targets and the degree of intensity associated with hate speech.

Due to learning mechanisms employed by Convolutional Neural Networks (CNNs) as features embeddings, the authors in [16], proposed a technique to detect hate speech in Twitter texts. These embeddings were one-hot characters and word vectors. The authors suggested that integrating character n-grams had only a limited impact on the process of detection. In [17, 18], the authors considered a wide range of traditional and deep learning methods. According to their findings, the best results are obtained by using a combination of LSTM networks with Gradient Boosted Decision Trees. The authors evaluated a number of models based on Transformers to analyze hate speech detection in the Spanish language. (Sohn, H. & Lee H, 2019) presented a multi-channel BERT model that concatenates the representations of multiple child variant BERT models trained in various languages. Therefore, the model is also able to capture diverse meanings across languages. As an example of sentimental method [19] used a research about prediction of hatred speech on textual content. The method itself is the result of combining lexicon-based and machine-learning methods. The experiment results revealed that extracting affective cues from text helps mitigate hate speech prediction. In addition, the authors proposed a hybrid neural architecture and integrated this module into it by coupling its bidirectional LSTM with CNN components. This amalgamation enables the model to attend to a broad context of local and sequential information in natural language texts. Multiple hate speech detection models have also been used in a wide range of languages, such as Arabic and Spanish. Though the algorithms and steps may differ, it is still a hate speech detection task. These works follow the single-task learning paradigm. Single Task Learning (STL) is a process that modifies the weights of neural networks concerning an input sequence from only one classification task with data belonging to it.
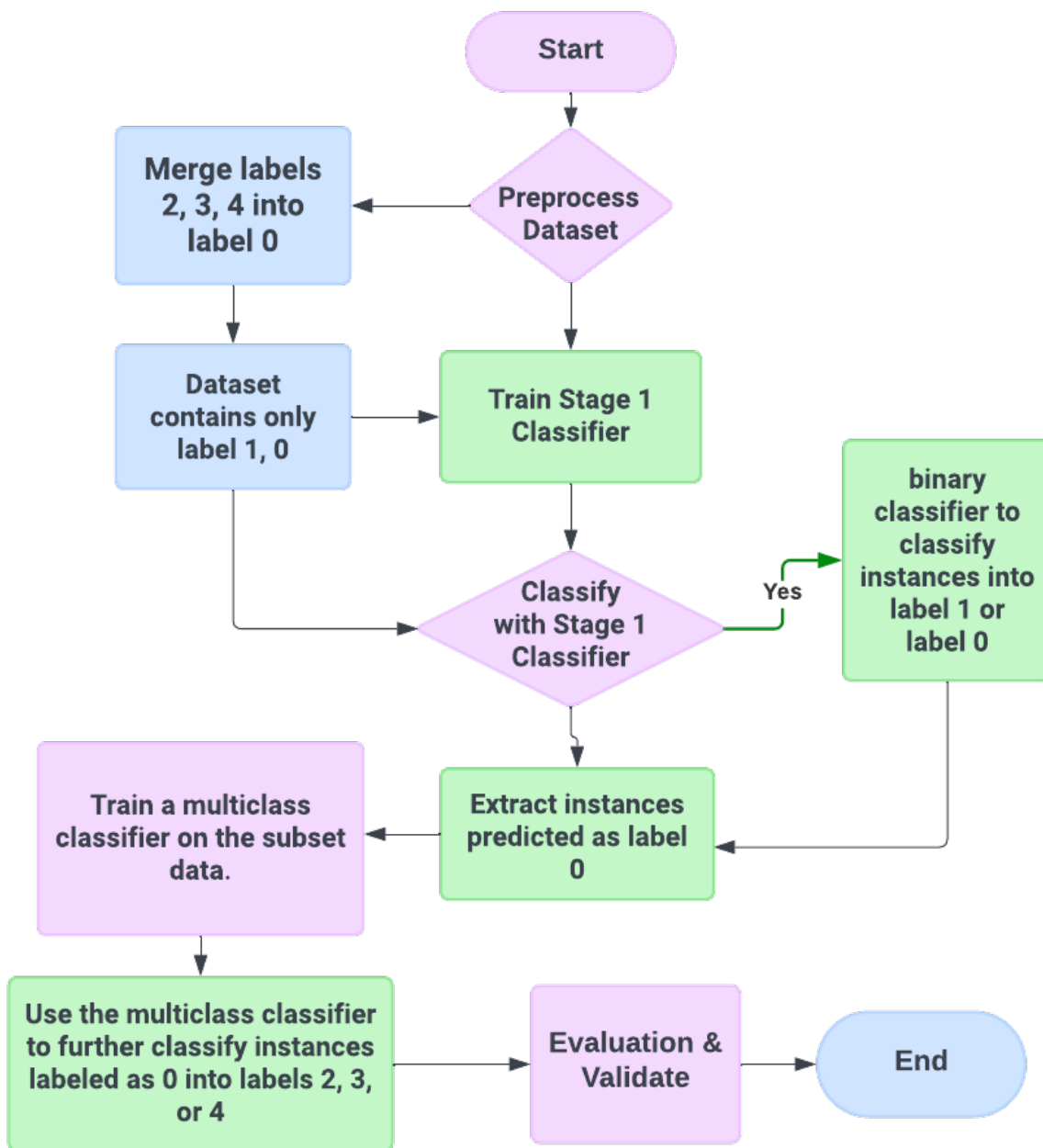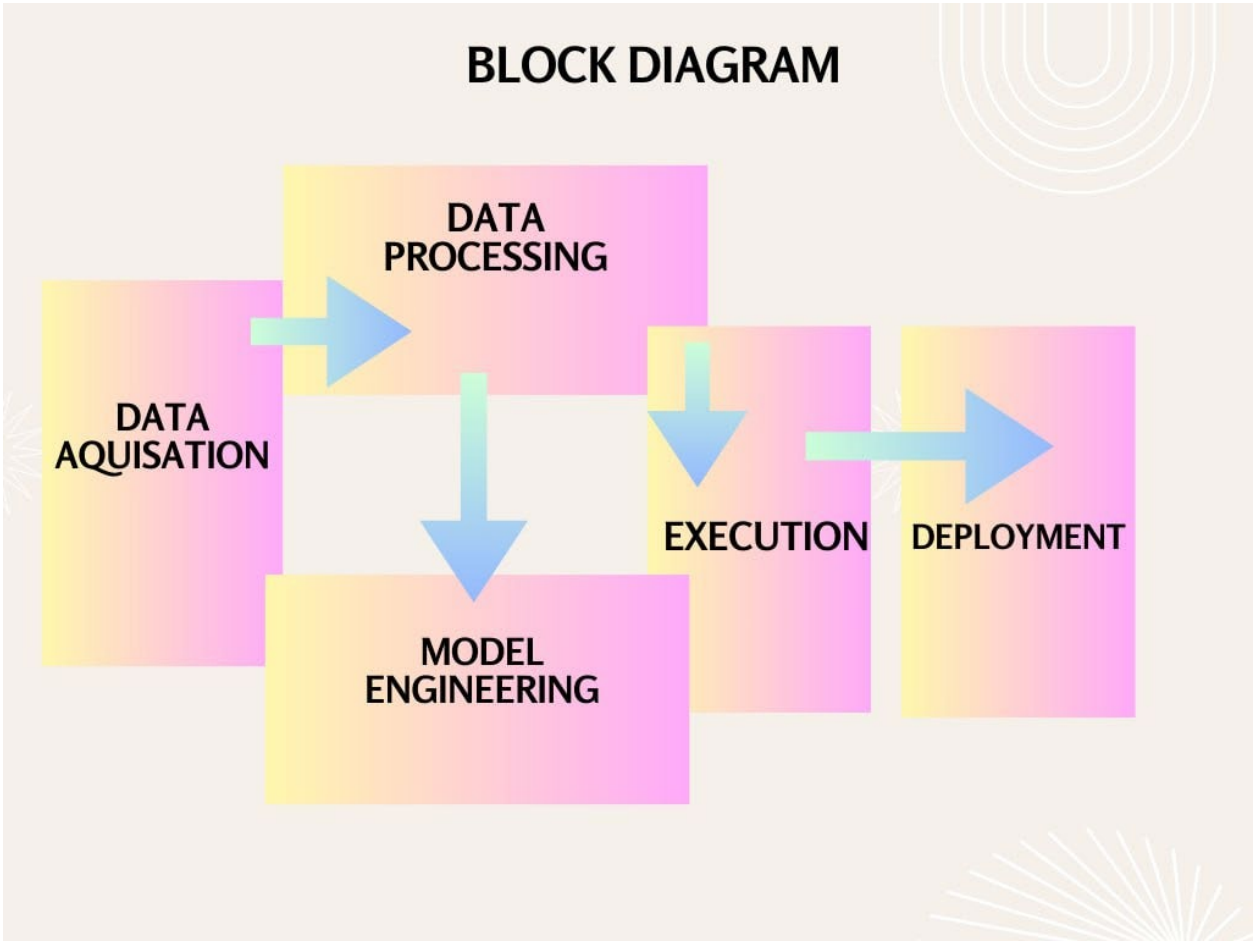
System Design

Figure 1: High Level Architecture

Figure 2: Block Diagram.

Hardware and/or Software Components

Tools	Functions	Other similar Tools (if any)	Why selected this tool
Hugging Face	Collecting datasets, and building, deploying, and training machine learning models.	Kaggle	Collecting datasets, and building, deploying, and training machine learning models.
Jupyter Notebook	An interactive environment for EDA and documentation	Pandas	A Python library for data manipulation and analysis.
Hugging Face Transformers	A library for state-of-the-art natural language processing models.	TensorFlow and PyTorch	Popular libraries for implementing deep learning models
RoBERTa-base	Text classification, sentiment analysis, named entity recognition, question answering.	BERT, DistilBERT, ALBERT, GPT-3, XLNet.	High performance, state-of-the-art accuracy, robust to various NLP tasks.
Scikit-Learn (sklearn)	A comprehensive ML library in Python that includes preprocessing functions.	TensorFlow Data Validation (TFDV)	A tool for data analysis and validation in the context of TensorFlow.
XLM-RoBERTa	Cross-lingual text classification, multilingual understanding, sentiment analysis, named entity recognition.	mBERT, M2M-100, T5, multilingual GPT-3, LASER	Superior multilingual capabilities, state-of-the-art performance, effective for cross-lingual tasks.

Table 1: List of Hardware and/or Software Components

Binary Classification: Binary classification of hate speech detection with base RoBERTa and XML-RoBERTa, in addition sentiment analysis to classify if the text contains a hateful content or not. It begins with tokenizing the input text into their respective Byte-Pair Encoding (BPE) tokens along with special [CLS] and [SEP]. These tokenized inputs get transformed into positional embeddings as well. These embeddings are fed into multiple Transformer encoder layers, producing contextualized token representation. The representation of the [CLS] token, which contains overall semantic information about an input sequence is grabbed. It can be applied to sentiment analysis by adding a few superimposed sentimental features with [CLS] representation, thus enabling the model more aware of the emotional tone in text. A single linear fully connected dense layer with a sigmoid activation function is applied on this concatenation to get the probability score indicating it being hate speech. The model is then fine-tuned using a binary cross-entropy loss function which update the Transformer layers, as well as the classification head to achieve higher performance. This is evident in both base RoBERTa (which was pretrained on English text) and XML-RoBERTa, with the latter proving especially useful for multilingual hate speech detection. Sentiment analysis has been incorporated to improve the efficiency of this model by determining how some language is used emotionally, in order to better distinguish offensive language from hate speech.

Multiclass Classification: Multiclass classification for hate speech detection, this is the task of classifying text into classes such as offensive language or benign content in addition to a specific category of hatred again using base RoBERTa and XML-RoBERTa which already embedded with sentiment analysis. The first step also includes tokenizing the input text with its 2 corresponding BPE Tokenizer and subsequently adding the special tokens [CLS](start) and [SEP][end] to them. Then, these tokenized inputs are reshaped into embeddings that consist of a token embedding along with positional embeddings. These embeddings go through a number of Transformer encoder layers, resulting in token level representations that are contextualized. The representation of the [CLS] token, which is a summary for entire sequence. This representation also includes sentiment analysis features to give an additional insight of the emotional context in text. The softmax function is used to generate a probability distribution over classes, i.e., at the final activation layer where an n x k (n = number of samples) matrix is output. It is performed using cross-entropy loss, updating the Transformer layers as well model classification head for higher accuracy. We show that our approach benefits base-roBERTa pretrained on English text, as well XML-RoBERTa version which is itself pretained over multilingual data has the ability to handle multiple written languages. By also integrating sentiment analysis, the model improves its accuracy still further because it brings along some added emotional context with which to more effectively identify where various types of potentially dangerous content contrasts against one another.

RoBERTa-Base: RoBERTa Base works with multiple key blocks mechanism. There is an input text of character, a Byte-Pair Encoding (BPE) tokenizer tokenizes the characters into subword tokens. And then convert these into tokens, and further get embeddings with the help of positional info as well. The embeddings are then passed to a stack of Transformer encoders composed of self-attention and feed-forward layers. RoBERTa is capable of modelling complex contextual relationships in the input text using these layers. The final-layer output will be a contextual representation for every token that encodes the meaning and context of each word within its sentence. RoBERTa takes this representation a step further with techniques like dynamic masking during training, where the model learns to predict masked tokens among in an input sequence. With the evacuation here, RoBERTa can crank out some of the most informative embeddings around and be an all-around great NLP AI model.

XML-RoBERTa: XML-RoBERTa or Cross-lingual RoBERTa, is a version of base RoBERTa that is designed around the idea cross-lingually. It starts with tokenizing inputs by using Byte-Pair Encoding tokenizer that works on texts coming from different languages. These tokens are then further mapped to embeddings which include information about the token as well as its position Then, the embeddings are passed through several layers of Transformer encoders (basically self-attention mechanisms followed by feed-forward neural networks). Because of this architecture, XML-RoBERTa can capture the fine-grained context dependencies in multilingual texts. Moreover, the XML-RoBERTa model also took benefit of a large-scale multilingual corpus for pretraining to capture universally valid language representations across different languages. These improvements in the knowledge of multilingual texts make XML-RoBERTa very suitable for multi-lingual cross-language text classification, machine translation or sentiment analysis tasks across different languages.

Chapter 4: Investigation/Experiment, Result, Analysis and Discussion

This section discusses the simulation results of the Binary Class Classification of the proposed hate speech recognition system. Fig. 3 demonstrates the training and testing accuracies vs. epochs of the applied XML-RoBERTa model.
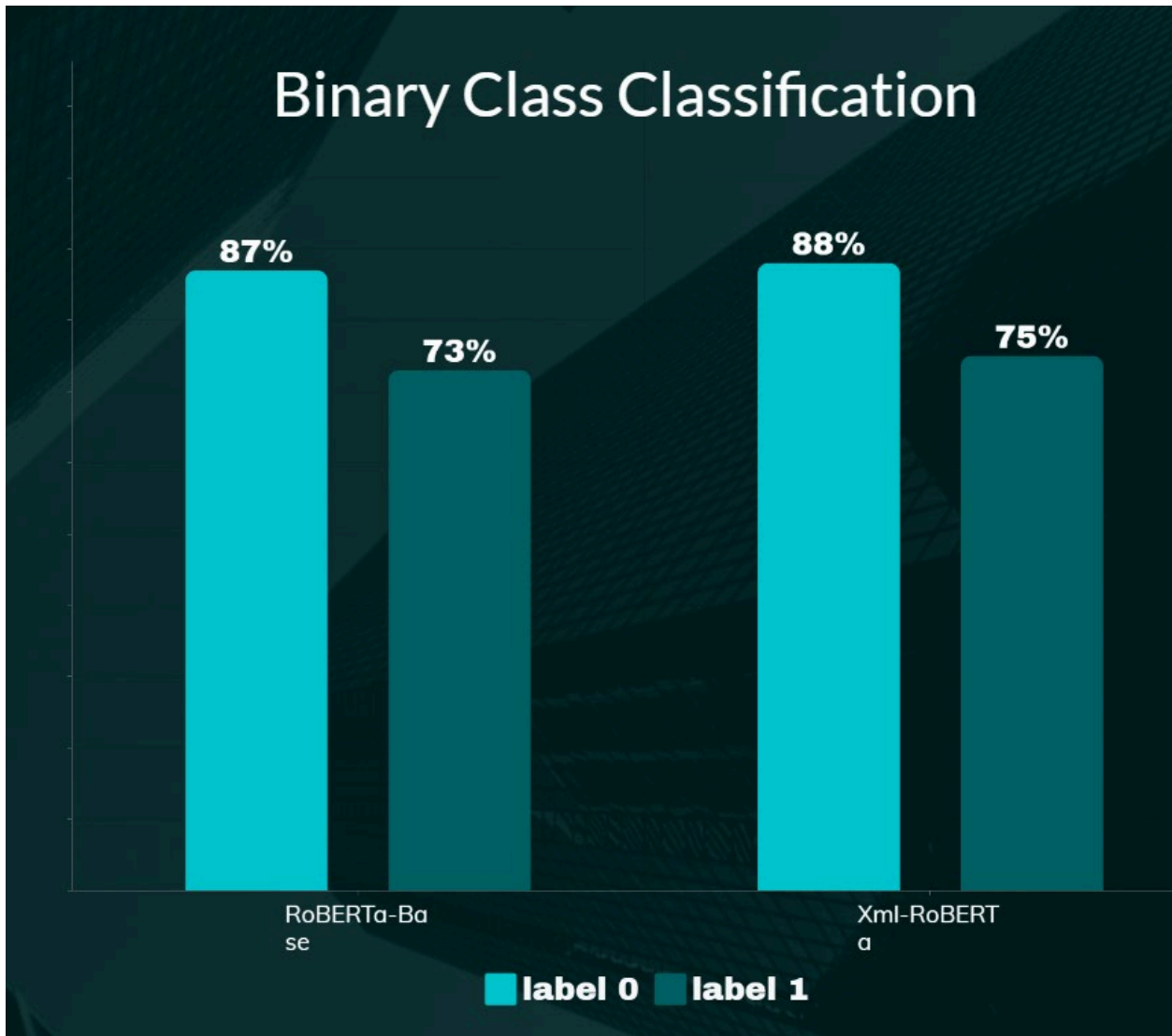

Figure 3: Accuracy for Binary Class Classification

Model	Class	Precision	Recall	Accuracy
RoBERTa -Base	0	0.67	0.45	87%
	1	0.89	0.95	73%
XML-RoBERTa	0	0.69	0.48	88%
	1	0.91	0.97	75%

Table 2: Various Performance Metrics for Binary Classification of The Applied Models

The table presents performance metrics for two models, RoBERTa-Base and XML-RoBERTa, on a binary classification task, including precision, recall, and accuracy for each class (0 and 1). For RoBERTa-Base, class 0 has a precision of 0.67, recall of 0.45, and accuracy of 87%, while class 1 has a precision of 0.89, recall of 0.95, and accuracy of 73%. For XML-RoBERTa, class 0 shows a precision of 0.69, recall of 0.48, and accuracy of 88%, whereas class 1 exhibits a precision of 0.91, recall of 0.97, and accuracy of 75%. Precision indicates the proportion of true positives among predicted positives, recall indicates the proportion of true positives among actual positives, and accuracy reflects overall model correctness. XML-RoBERTa demonstrates higher precision and recall for class 1 and better overall accuracy compared to RoBERTa-Base, despite slightly lower performance for class 0.

This section discusses the simulation results of the Multi Class Classification of the proposed hate speech recognition system. Fig. 3 demonstrates the training and testing accuracies vs. epochs of the applied XML-RoBERTa model.
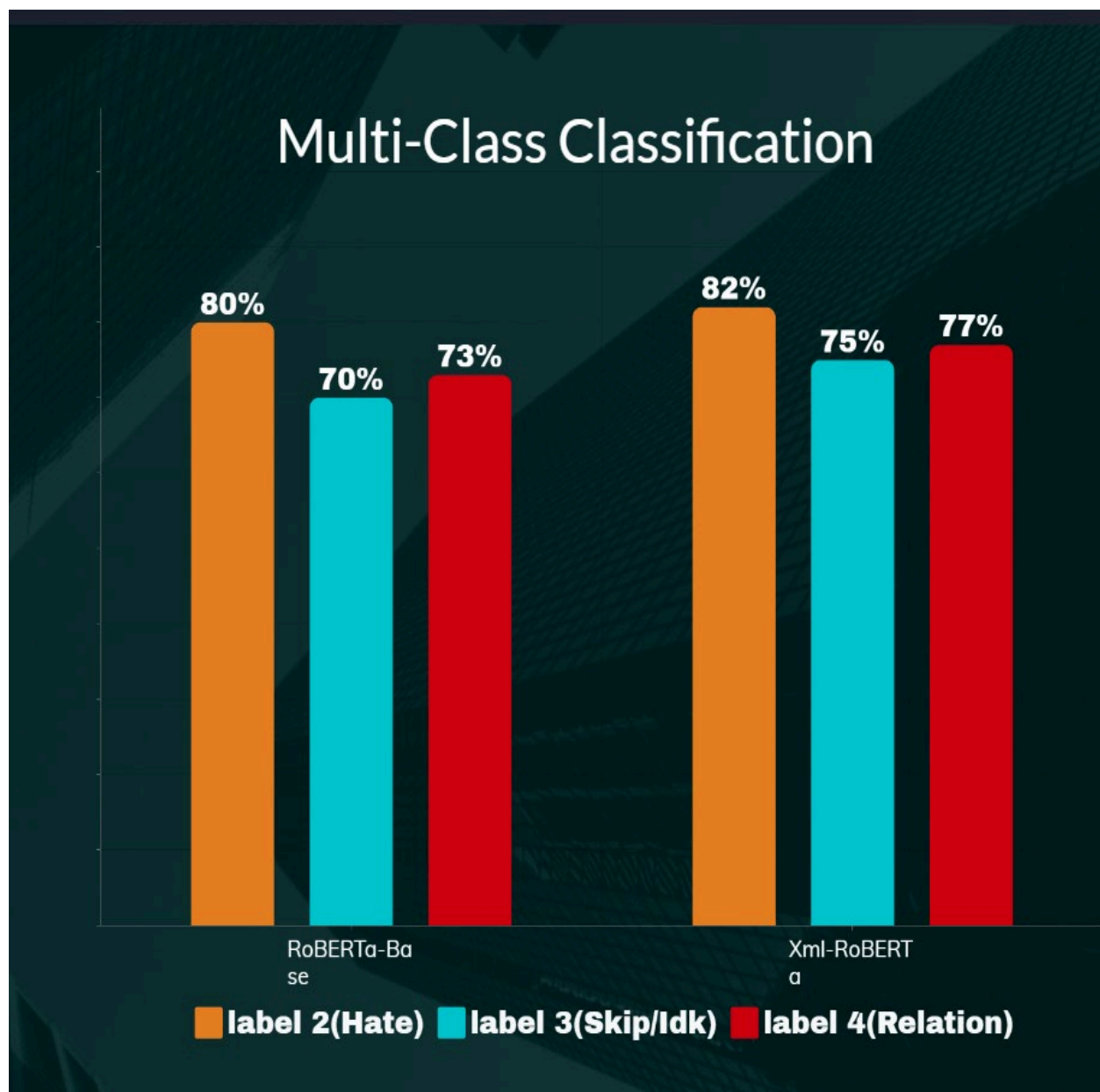

Figure 4: Accuracy for Multi Class Classification

Model	Class	Precision	Recall	Accuracy
RoBERTa -Base	2	62	52	80%
	3	49	35	70%
	4	47	38	73%
XML-RoBERTa	2	71	59	82%
	3	51	42	85%
	4	50	40	77%

Table 3: Various Performance Metrics for Multi Class Classification of The Applied Models

The table displays performance metrics for RoBERTa-Base and XML-RoBERTa models on a multi-class classification task, including precision, recall, and accuracy for classes 2, 3, and 4. RoBERTa-Base shows for class 2 a precision of 62, recall of 52, and accuracy of 80%; for class 3 a precision of 49, recall of 35, and accuracy of 70%; and for class 4 a precision of 47, recall of 38, and accuracy of 73%. XML-RoBERTa demonstrates higher metrics for class 2 with a precision of 71, recall of 59, and accuracy of 82%; for class 3 a precision of 51, recall of 42, and accuracy of 85%; and for class 4 a precision of 50, recall of 40, and accuracy of 77%. Overall, XML-RoBERTa outperforms RoBERTa-Base across most classes, especially with higher precision and recall for class 2, reflecting better performance and reliability in classification tasks.

Chapter 5: Impacts of the Project

Impact of this project on societal, health, safety, legal and cultural issues

Understanding the relationship between online hate speech and offline hate crimes allows policymakers, public safety agencies, and supportive services to react more effectively in order to protect communities from harm [20]. The more we learn to recognize and treat it, the better our online conversations will be.

By identifying and monitoring hate speech and radicalization activity online, we can identify people or groups at risk of perpetuating VE activities. In doing so, the identification of individuals early helps in being able to avail preemptive intervention and prevention strategies, thereby preventing or limiting radicalization into violence [21].

There is an argument that the suppression of hate speech diminishes free public discourse by silencing minority voices and narrowing diversity of opinion [22]. Hate speech laws that systematically target certain perspectives might also inadvertently nurture more intolerance [23]. The excessive carefulness that comes with identifying hate speech may well raise legitimate concern about infringements on the freedom of expression, a right which is one of the basic foundations in various democratic societies. Therefore, biased training data and algorithms in hate speech detection models can lead to targeting some groups unfairly and potentially ignoring others which cause fairness problems [24]. Given this, it is crucial to accurately recognize and reduce these biases when building and deploying hate speech detection systems in order to ensure fairness as well as accuracy.

The project "Hierarchical Sentiment Analysis Framework for Hate Speech Detection: Implementing Binary and Multiclass Classification Strategy" is one of the factors that determines public health safety. The AI takes the form of algorithms, and its job is to identify hate speech and harmful digital content – all essential for creating a safer cyberspace. It can go a long way in protecting the mental and emotional health of an individual against some negative psychological impacts that online harassment may have on him or her. This is also essential in avoiding even worse, real-world harm that can stem from hate speech driving up internet conflict. In addition, it improves mental health somewhat indirectly but effectively. This, though indirectly in nature, improves its citizens' security and psychological well-being. Reducing the spread of harmful content ensures that fewer people are affected by harm and creates a safer internet space.

Impact of this project on environment and sustainability

Specifically, exposure to hate speech has been shown create negative impacts on individuals in terms of self-esteem, reduced task performance and levels out anxiety or fear. In addition, it can result in a myriad of harmful effects such as radicalization, violence events and hate crimes, aggressiveness or incivility attitudes in society even mistrust [25]. The identification and reduction of hate speech can prevent many of those consequences, making the online atmosphere a healthier one.

Hate speech regularly focuses on marginalized communities, leading to a more hostile online space. Less hate speech means more people can contribute to the global conversation, and everyone can participate in newfound inclusive online spaces [26].

Algorithmic censorship could put unimaginable power in the hands of social platforms to control not just public but private conversations. This might lead to a decreased diversity of opinions and may also narrow the spectrum of perspectives available for constructive debates [28,29].

Even benign opinions could then be stifled as users sit back and think they might get incorrectly flagged by the detection systems. This can have a chilling effect, as this recent example highlights.

Hence, anyone using derogatory language to describe Native Americans as "merciless Indian savages," imputing them with inferiority is hate speech (to use simple common sense). Believe it or not, this is a particular quote from the Declaration of Independence. In the context of that user's history, it does not promote hate speech but may have been referring to a historical document (sorry, I cannot say what was shared) for some other purpose. This underscores the importance of considering user intent and context in detecting hate speech [30].

Another remaining challenge is that automatic hate speech detection is a closed-loop system; individuals are aware that it is happening, and actively try to evade detection. For instance, online platforms removed hateful posts from the suspect in the recent New Zealand terrorist attack (albeit manually), and implemented rules to automatically remove the content when re-posted by others. Users who desired to spread the hateful messages quickly found ways to circumvent these measures by, for instance, posting the content as images containing the text, rather than the text itself. Although optical character recognition can be employed to solve the particular problem, this further demonstrates the difficulty of hate speech detection going forward. It will be a constant battle between those trying to spread hateful content and those trying to block it [30].

Chapter 6: Conclusions

Summary

A novel way of classifying Hate Speech on social media, this project focuses on English language content. Based on datasets from 'Hugging Face,' the study deals with identifying and annotating hate speech. Its main reason is to make it even more accurate and efficient in recognizing hate speech with the help of sophisticated machine learning techniques.

RoBERTa-base and XLM-RoBERTa, two-strong transformer-based models, were used in this project. RoBERTa-base has been selected due to its high quality and performance in NLP tasks [8]. At the same time, XLM-RoBERTa is chosen because of its multi-lingual model, which could be helpful for cross-lingual scenarios. Notorious for its state-of-the-art performance in text classification, sentiment analysis, named entity recognition, and question answering.

The process begins with merging underrepresented labels into a new single class to balance classes. The classifying step is binary, where the dominant category is differentiated from the combined one. A multi-class classification is then carried out on the merged class to determine their original labels. Our two-step classification scheme also harnesses the power of a transformer-based model, which allows easier adaptation to imbalanced datasets and thus boosts robustness.

The steps of pre-processing data, training, and evaluation are done with the utmost care using the ktrain library, which makes transformers easy to use. The final model tuning includes training a binary classification model to separate between the original dominant class and combined one, then fine-tuning a classifier for multi-class task separating between initial labels inside combining classes.

This work makes a considerable contribution to dealing with hatred and, more specifically, hate speech, in the most used language by native speakers on an international level, which is English. In the next phase, we will improve its capacity to detect offensive language more fully because of how tricky these are with context usage by profanity words that occur very often. This study demonstrates the power of innovative machine learning algorithms in combating one of the most critical issues facing social media today.

Limitations

The project also has several limitations, mainly due to the lack of an internationally acknowledged definition of hate speech. One person's hate speech is another person's free words. It is the same fundamental subjectivity that makes it a difficult task to ascertain whether hate speech should be considered an instance of free speech. This also can be said for the datasets that are used for this as they all get affected by no firm, & or universal definition of them.

Moreover, one of the significant constraints behind hate speech detection is ambiguity. Many things can be interpreted in a million ways, making it hard to put together an exact and complete data set. Another factor that hinders the development of a viable hate speech detection system is the variety in language. These are the main constraints that one comes across in this field.

These considerations are pretty limited, and it is best to take them with a grain of salt while still acknowledging that combatting hate speech has become far more nuanced, but the effort may be as noble as before. Researchers and practitioners must overcome these limits, facing the fact that strategies for dealing with hate speech in digital spaces are under continuous development.

Future Improvement

This project is promising for future improvements. Initially developed for English, the methodologies may go beyond this scope and detect hate speech in other languages as well. Moreover, the principles of this project could be adjusted for voice messages so that its use is not limited to text. The main aim of the model in the upcoming years is to perform a better job at picking possibly abusive language in all the senses. However, it is a challenge to identify the most offensive terms because they are used in different qualitative contexts.

References

[1] Jacobs, J. B., and Potter, K. 2000. Hate crimes: Criminal Law and Identity Politics. Oxford University Press.

[2] Walker, S. 1994. Hate Speech: The History of an American Controversy. U of Nebraska Press.

[3] P. Ekman, "An argument for basic emotions", Cognit. Emotion, vol. 6, no. 3, pp. 169-200, 1992.

[4] . F. M. Plaza-Del-Arco, M. D. Molina-González, L. A. Ureña-López and M. T. Martín-Valdivia, "A Multi-Task Learning Approach to Hate Speech Detection Leveraging Sentiment Analysis," in IEEE Access, vol. 9, pp. 112478-112489, 2021, doi: 10.1109/ACCESS.2021.3103697.

[5] J. B. Nezlek and P. Kuppens, "Regulating positive and negative emotions in daily life", J. Personality, vol. 76, no. 3, pp. 561-580, Jun. 2008.

[6] G. T. Patrick, "The psychology of profanity", Psychol. Rev., vol. 8, no. 2, pp. 113, 1901.

[7] W. Alorainy, P. Burnap, H. Liu, A. Javed and M. L. Williams, "Suspended accounts: A source of tweets with disgust and anger emotions for augmenting hate speech data sample", Proc. Int. Conf. Mach. Learn. Cybern. (ICMLC), vol. 2, pp. 581-586, Jul. 2018.

[8] A. Rodriguez, C. Argueta and Y.-L. Chen, "Automatic detection of hate speech on Facebook using sentiment and emotion analysis", Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC), pp. 169-174, Feb. 2019.

[9] Warner, W., and Hirschberg, J. 2012. Detecting hate speech on the world wide web. In LSM, 19–26.

[10] Automated Hate Speech Detection and the Problem of Offensive Language, Thomas Davidson, Dana Warmsley, Michael Macy, Ingmar Weber

[11] Kwok, I., and Wang, Y. 2013. Locate the hate: Detecting tweets against blacks. In AAAI

[12] Burnap, P., and Williams, M. L. 2015. Cyber hate speech on Twitter: An application of machine classification and statistical modeling for policy and decision making. Policy & Internet. 7(2):223–242

[13] Fortuna, P., & Nunes, S. (2018). A survey on automatic detection of hate speech in text. ACM Computing Surveys (CSUR), 51(4), 1-30.

[14] Plaza-Del-Arco, F. M., Molina-González, M. D., Ureña-López, L. A., & Martín-Valdivia, M.T. (2020). Detecting misogyny and xenophobia in Spanish tweets using language technologies. ACM Transactions on Internet Technology (TOIT), 20(2), 1-19.

[15] Davidson, T., Warmsley, D., Macy, M., & Weber, I. (2017, May). Automated hate speech detection and the problem of offensive language. In Proceedings of the international AAAI conference on web and social media (Vol. 11, No. 1, pp. 512-515).

[16] Gambäck, B., & Sikdar, U. K. (2017, August). Using convolutional neural networks to classify hate speech. In Proceedings of the first workshop on abusive language online (pp. 85-90).

[17] Cañete, J., Chaperon, G., Fuentes, R., Ho, J. H., Kang, H., & Pérez, J. (2023). Spanish pre-trained Bert model and evaluation data. arXiv preprint arXiv:2308.02976.

[18] Samghabadi, N. S., Hatami, A., Shafaei, M., Kar, S., & Solorio, T. (2019). Attending the emotions to detect online abusive language. arXiv preprint arXiv:1909.03100.

[19] Sohn, H., & Lee, H. (2019, November). Mc-bert4hate: Hate speech detection using multi-channel bert for different languages and translations. In 2019 International Conference on Data Mining Workshops (ICDMW) (pp. 551-559). IEEE.

[20] Stechemesser, A., Levermann, A., & Wenz, L. (2022). Temperature impacts on hate speech online: evidence from 4 billion geolocated tweets from the USA. The Lancet Planetary Health, 6(9), e714-e725

[21] Araque, O., & Iglesias, C. A. (2022). An ensemble method for radicalization and hate speech detection online empowered by sentic computing. Cognitive Computation, 14(1), 48-61.

[22] THE PSYCHOLOGY OF CENSORSHIP, Jennifer M. Kinsley1

[23] Farrand, B. (2023). 'Is This a Hate Speech?' The Difficulty in Combating Radicalisation in Coded Communications on Social media Platforms. *European Journal on Criminal Policy and Research*, 1-17.

[24] Subramanian, M., Easwaramoorthy Sathiskumar, V., Deepalakshmi, G., Cho, J., & Manikandan, G. (2023). A survey on hate speech detection and sentiment analysis using machine learning and deep learning models. Alexandria Engineering Journal, 80, 110-121. https://doi.org/10.1016/j.aej.2023.08.038

[25] Ahmed, Z., Vidgen, B. & Hale, S.A. Tackling racial bias in automated online hate detection: Towards fair and accurate detection of hateful users with geometric deep learning. *EPJ Data Sci.* 11, 8 (2022). https://doi.org/10.1140/epjds/s13688-022-00319-9

[26] Subramanian, M., Sathiskumar, V. E., Deepalakshmi, G., Cho, J., & Manikandan, G. (2023). A survey on hate speech detection and sentiment analysis using machine learning and deep learning models. *Alexandria Engineering Journal*, *80*, 110-121.

[27] .Saha, K., Chandrasekharan, E., & De Choudhury, M. (2019). Prevalence and Psychological Effects of Hateful Speech in Online College Communities. *Proceedings of the ... ACM Web Science Conference. ACM Web Science Conference*, *2019*, 255–264. https://doi.org/10.1145/3292522.3326032

[28] .https://www.vox.com/recode/2019/8/15/20806384/social-media-hate-speech-bias-black-african -american-facebook-twitter

[29] Ahmed, Z., Vidgen, B. & Hale, S.A. Tackling racial bias in automated online hate detection:Towards fair and accurate detection of hateful users with geometric deep learning. EPJ Data Sci.11, 8 (2022). https://doi.org/10.1140/epjds/s13688-022-00319-9

[30] MacAvaney, S., Yao, H. R., Yang, E., Russell, K., Goharian, N., & Frieder, O. (2019). Hate speech detection: Challenges and solutions. PloS one, 14(8), e0221152.