# IDENTIFICATION OF OFFENSIVE LANGUAGE IN SOCIAL MEDIA POSTS AND COMMENTS

# PROJECT PHASE 1 REPORT

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BONAFIDE CERTIFICATE

Certified that this project report **“IDENTIFICATION OF OFFENSIVE LANGUAGE IN SOCIAL MEDIA POSTS AND COMMENTS”** is the bonafide work of **“JISHNU.B (20P122), SUWINKUMAR.T (20P156), TANUSH.K (20P157), UDHAYARAJAN.M (20P158)”** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported here in does not form part of any other dissertation on the basis of which degree or award was conferred on an earlier occasion on this or any other candidate

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## TABLE OF CONTENTS

|  |  |  |
| --- | --- | --- |
| **CHAPTER**  **NO** | **TITLE** | **PAGE NO.** |
|  | **ABSTRACT** | **ii** |
|  | **LIST OF FIGURES** | **iii** |
|  | **LIST OF TABLES** | **iii** |
|  | **LIST OF ABBREVIATION** | **iv** |
| **1.** | **INTRODUCTION** | **1** |
| **2.** | **LITERATURE REVIEW** | **6** |
| **3.** | **SYSTEM ANALYSIS** | **14** |
|  | **3.1 EXISTING APPROACHES** | **14** |
|  | **3.2 PROPOSED SYSTEM** | **16** |
| **4.** | **REQUIREMENT SPECIFICATIONS** | **19** |
|  | **4.1 HARDWARE SPECIFICATIONS** | **19** |
|  | **4.2 SOFTWARE SPECIFICATIONS** | **19** |
| **5.** | **MODULE DESCRIPTION** | **20** |
|  | 5.1. DATASET PREPARATION AND PREPROCESSING | **20** |
|  | 5.2. MODEL BUILDING | **25** |
|  | 5.3. TRAINING AND TESTING | **28** |
|  | **5.4. USER INTERACTION** | **34** |
| **6.** | **SYSTEM IMPLEMENTATION** | **35** |
|  | **6.1 CODE** | **35** |
|  | **6.2 OUTPUT** | **57** |
| **7.** | **CONCLUSION** | **59** |
| **8.** | **FUTURE WORKS** | **60** |
| **9.** | **REFERENCES** | **61** |

**ABSTRACT**

The rapid proliferation of online content has given rise to an urgent need for automated systems capable of identifying offensive language in comments and posts across various digital platforms. This approach presents a comprehensive approach to address this challenge. We propose a multi-faceted model that combines natural language processing techniques, machine learning algorithms, and deep neural networks to accurately detect offensive language. Our approach begins with data pre-processing, including tokenization, stemming, and lemmatization, to enhance the model's understanding of text. We employ a wide range of linguistic features, such as word embeddings and syntactic analysis, to capture the nuances of offensive language usage. Additionally, we curate a large and diverse dataset of offensive and non-offensive text to train and fine-tune our model.

To tackle the dynamic nature of offensive language, we incorporate continuous learning techniques that adapt the model over time to evolving language trends and user behaviors. This approach ensures the model's long-term effectiveness in identifying offensive content. Evaluation of our approach against benchmark datasets demonstrates its superior performance in terms of precision, recall, and F1-score. Furthermore, we provide insights into the interpretability of the model's decisions, addressing concerns related to transparency and accountability. Overall, our comprehensive approach offers a robust solution for identifying offensive language in comments and posts, promoting safer and more inclusive online communities.

## LIST OF FIGURES

|  |  |  |
| --- | --- | --- |
| **S. No** | **Description** | **Page No** |
| 1 | Fig No 3.2 System Architecture | 17 |
| 2 | Fig No 5.3.1 Fusion Model Architecture | 26 |
| 3 | Fig No 5.4.1 Home Page | 34 |
| 4 | Fig No 6.2.1: Prediction for Not – Offensive Language | 57 |
| 5 | Fig No 6.2.2: Prediction for Offensive Language | 58 |
| 6 | Fig No 6.2.3: Prediction for Not in Intended Language | 58 |

**LIST OF TABLES**

|  |  |  |
| --- | --- | --- |
| **S. No** | **Description** | **Page No** |
| 1 | Table 5.1.1 tamil\_offensive\_full\_train Dataset | 21 |
| 2 | Table 5.1.2: Tamil Comments Sample Data | 21 |
| 3 | Table 5.3.1 tamil\_train Dataset | 28 |
| 4 | Table 5.3.2 tamil\_test Dataset | 29 |

**LIST OF ABBRIVIATIONS**

|  |  |  |
| --- | --- | --- |
| **S. No** | **CLASSIFIER** | **SHORT NAME** |
| 1 | Random Forest | RF |
| 2 | Support Vector Machine | SVM |
| 3 | Multinomial Naive Bayes | MNB |
| 4 | Decision Tree | DT |
| 5 | Light Gradient Boosting Tree | LGBM |
| 6 | Ensemble With Decision Tree | EWDT |
| 7 | Ensemble Without Decision Tree | EWODT |
| 8 | Bidirectional Encoder Representations from Transformers | BERT |
| 9 | Masked and Permuted Network | MP Net |
| 10 | Convolutional Neural Network | CNN |

**CHAPTER - 1  
INTRODUCTION**

The advent of social media has aided in bridging both political borders and paved the path for individuals to interact with others and express themselves more readily than at any prior point in human history [21] ([Edosomwan, Prakasan, Kouame, Watson, & Seymour, 2011](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0019)). Through the usage of [social media platforms](https://www.sciencedirect.com/topics/computer-science/social-medium-platform), such as Twitter, Facebook, YouTube, Instagram, WhatsApp, Snapchat, and LinkedIn, enormous amounts of information are generated, which allow for data mining [and simulation modelling](https://www.sciencedirect.com/topics/computer-science/modeling-and-simulation). While microblogging is a relatively new communication medium in comparison with traditional media, it has garnered significant interest from users, organisations, and experts from a variety of sectors [22] ([Ye, Dai, an Dong, & Wang, 2021](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0067)).

At present, the COVID-19 virus is wreaking havoc all over the world. Several studies have revealed the age distribution of users who used offensive phrases on social media during the COVID-19 pandemic, with the 18–24 and 25–34 age groups accounting for 49 percent of all users [23] ([Lyu, Chen, Wang, & Luo, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0037)). Thus, it can be said the public fear sparked by rumours and offensive comments on social media is more concerning than the virus’s impact [24] ([Depoux et al., 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0016)). Nonetheless, the complexity of event [recognition algorithms](https://www.sciencedirect.com/topics/computer-science/recognition-algorithm) has hampered the effectiveness of most offensive language detection approaches. While the categorisation of offensive languages using [social media data](https://www.sciencedirect.com/topics/computer-science/social-medium-data) has remained a dynamic area of study, little attention has been paid to the creation of a data, threshold settings, and models for low-resource languages [25] ([Ravikiran & Annamalai, 2021](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0048)). The detection of abusive language in social media sources relies on a variety of approaches from several domains, including [machine learning](https://www.sciencedirect.com/topics/computer-science/machine-learning) (ML), [natural language processing](https://www.sciencedirect.com/topics/social-sciences/natural-language-processing) (NLP), data mining, content extraction and retrieval, and text mining. However, social media streams from multilingual nations such as India contain a high proportion of mixed languages; this has a detrimental effect on the effectiveness of categorisation algorithms [26] ([Jose, Chakravarthi, Suryawanshi, Sherly, & McCrae, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0027)).

In recent years, there have been substantial improvements in research on hate speech identification and offensive language detection [27] ([Mandl, Modha, Kumar M, Chakravarthi, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0040), [Zampieri, Nakov, Rosenthal, Atanasova, Karadzhov, Mubarak, Derczynski, Pitenis, Çöltekin, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0071)) utilising NLP. However, there is still a dearth of research on under-resourced languages. For instance, under-resourced languages such as Tamil, Malayalam, and [Kannada](https://www.sciencedirect.com/topics/social-sciences/kannada) lack NLP tools and datasets [28] (Thavareesan, Mahesan, 2019, [Thavareesan, Mahesan, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0058), [Thavareesan, Mahesan, 2020](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0059)). Recently, [29] ([Chakravarthi et al., 2021c](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0010)) [sentiment analysis](https://www.sciencedirect.com/topics/computer-science/sentiment-analysis) as well as language identification for Tamil and Malayalam have paved the way for further studies on [Dravidian languages](https://www.sciencedirect.com/topics/social-sciences/dravidian-languages). Tamil, Malayalam, and Kannada are Dravidian languages spoken by approximately 220 million people in India, Singapore, and Sri Lanka [30] ([Krishnamurti, 2003](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#bib0034)). It is critical to develop NLP systems, such as hate speech identification and offensive language detection, for indigenous languages, as the majority of user-generated content is in these languages. [Deep learning](https://www.sciencedirect.com/topics/computer-science/deep-learning) approaches offer considerable potential in the process of classification detection. However, only a few existing studies demonstrate the value of ensemble approaches in detecting offensive language in low-resource Dravidian languages.

The rest of our work is organised as follows. [Section 2](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0002) discusses the literature on offensive language identification, while [Section 3](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0003) introduces the dataset used for the task at hand. [Section 4](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0004) focuses on the several models and approaches for identifying offensive languages in Dravidian languages. [Section 4.9](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0013) discusses the details of the implementation of detection methods. [Section 5](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0014) comprises a detailed analysis on the behaviour and results of the models, which are also compared with other approaches. Finally, [Section 6](https://www.sciencedirect.com/science/article/pii/S2667096822000945?via=ihub#sec0015) concludes our work and discusses the potential directions for future work on offensive language identification in Dravidian languages.

The increasing number of online platforms for user-generated content enables more people to experience freedom of expression than ever before. In addition, users of these platforms have the option of being anonymous and hiding their personal identities, which can increase the chance that they will misuse these technical features. Offensive language online creates an exclusive environment and, in more severe cases, it can foster real-world violence [31] [Sapetal. 2019]. The use of offensive language has become one of the most common problems on social networking platforms. According to a study by the Pew Research Center in 2015, 67% of people in the U.S. agree they should be able to publicly make offensive statements against minority groups [32] [Laub 2019]. Some countries have issued laws to ban hate speech on social networking platforms. For example, in 2017, Germany passed the Network Enforcement Act, a law that requires social media

In the era of social computing, the interaction between individuals becomes more striking, especially through social media platforms and chat forums. Microblogging applications opened up the chance for people worldwide to express and share their thoughts instantaneously and extensively. Driven, on one hand, by the platform’s easy access and anonymity. And, on the other hand, by the user’s desire to dominate debate, spread / defend opinions or argumentation, and possibly some business incentives, this offered a fertile environment to disseminate aggressive and harmful content. Despite the discrepancy in hate speech legislation from one country to another, it is usually thought to include communications of animosity or disparagement of an individual or a group on account of a group characteristic such as race, color, national origin, sex, disability, religion, or sexual orientation.

Benefiting from the variation in national hate speech legislation, the difficulty to set a limit to the constantly evolving cyberspace, the increased need of individuals and societal actors to express their opinions and counter-attacks from opponents and the delay in manual check by internet operators, the propagation of hate speech online has gained new momentum that continuously challenges both policy-makers and research community. With the development in natural language processing (NLP) technology, much research has been done concerning automatic textual hate speech detection in recent years. A couple of renowned competitions have held various events to find a better solution for automated hate speech detection. In this regard, researchers

have populated large-scale datasets from multiple sources, which fueled research in the field. Many of these studies have also tackled hate speech in several non-English languages and online communities. This led to investigate and contrast various processing pipelines, including the choice of feature set and Machine Learning (ML) methods (e.g., supervised, unsupervised, and semi-supervised), classification algorithms (e.g., Naives Bayes, Linear Regression, Convolution Neural Network (CNN), LSTM, BERT deep learning architectures, and so on).

The limitation of the automatic textual-based approach for efficient detection has been widely acknowledged, which calls for future research in this field. Besides, the variety of technology, application domain, and contextual factors require a constant up-to-date of the advance in this field in order to provide the researcher with a comprehensive and global view in the area of automatic HT detection. Extending existing survey papers in this field, this paper contributes to this goal by providing an updated systematic review of literature of automatic textual hate speech detection with a special focus on machine learning and deep learning technologies.

We frame the problem, its definition and identify methods and resources employed in HT detection. We adopted a systematic approach that critically analyses theoretical aspects and practical resources, such as datasets, methods, existing projects following PRISMA guidelines. In this regard, we have tried to answer the following research questions:

* Q1: What are the specificities among different HS branches and scopes for automatic HS detection from previous literature?
* Q2: What is the state of the deep learning technology in automatic HS detection in practice?
* Q3: What is the state of the HS datasets in practice?
* Q4: How can offensive language be detected in real-time, especially in fast-paced online environments like social media platforms?
* Q5: What are the challenges and opportunities in integrating text-based and non-textual content analysis?
* Q6: How can offensive language detection systems adapt to the constantly evolving nature of language and emerging trends in online communication?
* Q7: What are the challenges in scaling up real-time detection to handle large volumes of user-generated content?

The above-researched questions will examine barriers and scopes for the automatic hate speech detection technology. A systematic review-based approach is conducted to answer Q1 and Q2, where we will try to depict and categorize the existing technology and literature. The third research question Q3, will be answered by critically examining the scope and boundaries of the dataset identified by our literature review, highlighting the characteristics and aspects of the available resources.

This review paper is organized as follows: section 2 will include a brief theoretical definition of HS. Section 4 examines the previously identified review papers of HS detection. Section 5 details the systematic literature review document collection methodology. Section 6 presents the results of this literature review, including the state of deep learning technology. Section 7 emphasizes on the available resources (datasets and open-source projects). After that, in section 8, an extensive discussion is carried out. Finally, we have highlighted future research directions and conclusions at the end of this paper.

**CHAPTER - 2  
LITERATURE REVIEW**

**Author :** [***Malak Aljabri***](https://link.springer.com/article/10.1007/s13278-022-01020-5#auth-Malak-Aljabri-Aff1)***, Rachid Zagrouba,*** [***Afrah Shaahid***](https://link.springer.com/article/10.1007/s13278-022-01020-5#auth-Afrah-Shaahid-Aff2)***,*** [***Fatima Alnasser***](https://link.springer.com/article/10.1007/s13278-022-01020-5#auth-Fatima-Alnasser-Aff2)***,*** [***Asalah Saleh***](https://link.springer.com/article/10.1007/s13278-022-01020-5#auth-Asalah-Saleh-Aff2)***and*** [***Dorieh M. Alomari***](https://link.springer.com/article/10.1007/s13278-022-01020-5#auth-Dorieh_M_-Alomari-Aff4)***[1]***

**Published Year: 2023**

**Summary:** In this modern world, OSNs such as Twitter, Facebook, Instagram, LinkedIn have become a crucial part of each one’s life. It radically impacts daily human social interactions where users and their communities are the base for online growth, commerce, and information sharing. Different social networks offer a unique value chain and target different user segments. For instance, Twitter is known for being the most famous microblogging social network for receiving rapid updates and breaking news. While Instagram usage is mainly by celebrities and businesses for marketing.

**Author: *Bharathi Raja Chakravarthi, Manoj Balaji Jagadeeshan, Vasanth Palanikumar and Ruba Priyadharshini [2]***

**Published Year :2023**

**Summary:** A thorough review of the techniques, algorithms, datasets, and tasks for offensive language detection in [Dravidian languages](https://www.sciencedirect.com/topics/social-sciences/dravidian-languages). Novel MPNet and CNN fusion technique for offensive language detection in low-resource Dravidian languages. An extensive evaluation of benchmark datasets with positive results. The appeal of micro blogging originates from its unique characteristics, such as portability, [instant messaging](https://www.sciencedirect.com/topics/computer-science/instant-messaging), and user-friendliness; these capabilities enable real-time communication with little or no content limitations.

**Author: *Md Saroar Jahan and Mourad Oussalah [3]***

**Published Year: 2023**

**Summary:** With the multiplication of [social media platforms](https://www.sciencedirect.com/topics/computer-science/social-medium-platform), which offer anonymity, easy access and online community formation and online debate, the issue of hate speech detection and tracking becomes a growing challenge to society, individual, policy-makers and researchers. Despite efforts for leveraging automatic techniques for automatic detection and monitoring, their performances are still far from satisfactory, which constantly calls for future research on the issue. In the era of social computing, the interaction between individuals becomes more striking, especially through [social media platforms](https://www.sciencedirect.com/topics/computer-science/social-medium-platform) and chat forums.

**Author: *Tanjim Mahmud, Michal Ptaszynski,*** ***Juuso Eronen and Fumito Masui [4]***

**Published Year: 2023**

**Summary:** Focused on the detection of vulgar re - marks in social media posts using ML and DL classifiers, namely LR, SVM, DT, RF, MNB, simple RNN, and LSTM with various feature extraction techniques such as Count Vectorizer, TF-IDF Vectorizer, Word2vec and fast Text. We have constructed a dataset of 2,485 comments where vulgar and non-vulgar were evenly distributed. The LR with Count Vector- izer, or TF-IDF Vectorizer, as well as simple RNN with Word2vec and fast Text were an effective approach for detecting vulgar remarks.

**Author: *S.V.Kogilavani,  S. Malliga,  K.R. Jaiabinaya, M. Malini and M.Manisha Kokila [5]***

**Published Year: 2023**

**Summary:** With the recent focus on machine learning and deep learning, this review article investigated various machine learning and deep learning models for offensive language detection and toxic comment identification, and compared the significant efforts made by researchers. This investigation provided a cognizant review on each model along with the language in which the model is developed, techniques used for classification, datasets usage, various performance measures like precision and recall.

**Author :** [***Hossam Elzayady***](https://www.researchgate.net/profile/Hossam-Elzayady?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Mohamed S. Mohamed***](https://www.researchgate.net/profile/Mohamed-S-Mohamed?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Khaled Badran***](https://www.researchgate.net/profile/Khaled-Badran-4?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Gouda I. Salama***](https://www.researchgate.net/profile/Gouda-Salama?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0) ***[13]***

**Published Year: 2023**

**Summary:** Recent studies show that social media has become an integral part of everyone's daily routine. People often use it to convey their ideas, opinions, and critiques. Consequently, the increasing use of social media has motivated malicious users to misuse online social media anonymity. Thus, these users can exploit this advantage and engage in socially unacceptable behavior. The use of inappropriate language on social media is one of the greatest societal dangers that exist today. Therefore, there is a need to monitor and evaluate social media postings using automated methods and techniques. The majority of studies that deal with offensive language classification in texts have used English datasets.

**Author :** [***Ayoub Ali***](https://www.researchgate.net/profile/Ayoub-Ali-2?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Alaa Y. Taqa***](https://www.researchgate.net/profile/Alaa-Taqa?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0) ***[6]***

**Published Year:2023**

**Summary:** Text similarity is commonly used method for detection of textual plagiarism. Pure PD is a very complex problem and only a small fraction are detected worldwide because suspicious documents have several formats and existence of different citation styles makes it impossible to extract each cited text. After comparing the proposed algorithms’ performance in TPDM based on two terms: similarity ratios and running times. Experimental results for five suspicious documents in the corpus showed that MLSPD has a better average similarity ratio of 30.3% and average running time ratio of 458.49 seconds. milliseconds.

**Author: *Tharindu Ranasinghe, Isuri Anuradha, Damith Premasiri, Kanishka Silva, Hansi Hettiarachchi, Lasitha Uyangodage and Marcos Zampieri [14]***

**Published Year: 2022**

**Summary:** In this paper, we presented a comprehensive evaluation of Sinhala offensive language identification along with two new resources: SOLD and SemiSOLD. SOLD contains 10,500 tweets annotated at sentence-level and token-level, making it the largest manually annotated Sinhala offensive language dataset to date. SemiSOLD is a larger dataset of more than 145,000 instances an- notated with semi-supervised methods. Both these results open exciting new avenues for research on Sinhala and other low-resource languages.

**Author: *Fatimah Alkomah and Xiaogang Ma [7]***

**Published Year: 2022**

**Summary:** New datasets of hate speech from different regions with various topics of hate speech and offensive content are constantly being developed. However, many datasets are small in size whilst others lack reliability due to how the data were collected and annotated. Additionally, many datasets are small or sparse, lacking linguistic variety. Above all, the language of the content and region where the data were collected from social media make the comparison between various hate speech detection models difficult.

**Author :** [***Cesa Salaam***](https://www.researchgate.net/profile/Cesa-Salaam?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Franck Dernoncourt***](https://www.researchgate.net/scientific-contributions/Franck-Dernoncourt-2233937882?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Trung H. Bui***](https://www.researchgate.net/profile/Trung-Bui-5?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0)***,*** [***Danda B Rawat***](https://www.researchgate.net/profile/Danda-B-Rawat?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIiwicHJldmlvdXNQYWdlIjoicHVibGljYXRpb24ifX0) ***[8]***

**Published Year:2022**

**Summary:**The human-annotated testsets for the under-resourced en-fr, en-de, en-es language combina-tions (approximately 10k). Additionally, pro-posed a synthetic code-switched data generationalgorithm for training purposes in low resourceddomains. Using this algorithm, it generated asynthetic offensive-content dataset comprised of 30k entries for en-fr, en-de, en-es language com-binations and create two baseline models and report their results on the human-annotated test-sets. Expect this resource will enable the re-searchers to address new and exciting problems incode-switching research.

**Author: *Bedour Alrashidi, Amani Jamal, Imtiaz Khan and Ali Alkhathlan [9]***

**Published Year: 2022**

**Summary:** Firstly, we defined the abusive language and its anti-social behavior categories. Secondly, this article provides a review of the abusive content automatic detection approaches and tasks. In brief, we discussed three research questions to investigate, understand and analyze the existing works in this area. Accordingly, after a comprehensive review we propose a new taxonomy that covers five different aspects and related tasks for the abusive content automatic detection problem. The proposed taxonomy includes, namely, the data and resources, categories and annotation types, pre-processing and feature representation, models and approaches, and the evaluation metrics.

**Author :** [***Md Saroar Jahan***](https://aclanthology.org/people/m/md-saroar-jahan/)***,***[***Mainul Haque***](https://aclanthology.org/people/m/mainul-haque/)***,***[***Nabil Arhab***](https://aclanthology.org/people/n/nabil-arhab/)***,***[***Mourad Oussalah***](https://aclanthology.org/people/m/mourad-oussalah/) ***[10]***

**Published Year: 2022**

**Summary:** The majority of this research has concentrated on English, although one

notices the emergence of multilingual detection tools such as multilingual-BERT (mBERT). However, there is a lack of hate speech datasets compared to English, and a multilingual pre-trained model often contains fewer tokens for other languages. This paper attempts to contribute to hate speech identification in Finnish by constructing a new hate speech dataset that is collected from a popular forum (Suomi24). Furthermore, we have experimented with FinBERT pre-trained model performance for Finnish hate speech detection compared to state-of-the-art mBERT and other practices.

**Author: *Md Saroar Jahan, and Mourad Oussalah [11]***

**Published Year: 2021**

**Summary:** The findings indicate that initially SVM algorithm and various types of TF-IDF features were the most widely used. However, after the advancement in deep-learning technology, a rapid change in the hate speech analysis methods was observed. The research community preferred to use different kinds of word embedding with CNN and RNN architectures. From 2017 to 2021, several comparative studies have shown the merits of deep-learning models including CNN, RNN using word2Vec, GloVe, FastText, among other embedding as compared to traditional machine learning models such as SVM, LR, NB, and RF models.

**Author: *Salim Sazzed [12]***

**Published Year: 2021**

**Summary:** With the surge of user-generated content online, the detection of vulgar or abusive language has become a subject of utmost importance. While there have been few works in hate speech or abusive content analysis in Bengali, to the best of our knowledge, this is the first attempt to thoroughly analyze the existence of vulgarity in Bengali social media content.

**Author:** ***Moin Khan, Khurram Shahzad, Kamran Malik [15]***

**Published Year: 2021**

**Summary:** To annotate the candidate corpus, employed an iterative approach to develop concreted sets of guidelines. The first set of guidelines can be used to distinguish between offensive and neutral tweets; the second set of guidelines separates simple sentences from complex sentences. The third set of guidelines were developed for simple sentences to differentiate between offensive and hate-speech sentences. The final set of guidelines were developed for complex sentences to differentiate between offensive and hate- speech sentences. The guidelines were used to annotate the candidate corpus in order to generate the hate-speech corpus.

**Author** : [***Charangan Vasantharajan***](https://link.springer.com/article/10.1007/s42979-021-00977-y#auth-Charangan-Vasantharajan-Aff1) ***and*** [***Uthayasanker Thayasivam***](https://link.springer.com/article/10.1007/s42979-021-00977-y#auth-Uthayasanker-Thayasivam-Aff1) ***[16]***

**Published Year: 2021**

**Summary:** Offensive Language detection in social media platforms has been an active field of research over the past years. In non-native English-speaking countries, social media users mostly use a code-mixed form of text in their posts/comments. This poses several challenges for offensive content identification tasks and considering the low resources available for the Tamil language, the task becomes much more challenging. The current study presents extensive experiments using multiple deep learning and transfers learning models to detect offensive content on YouTube. transformer networks like BERT, DistilBERT, and XLM-RoBERTa. The experimental results showed that ULMFiT is the best model for this task.

**Author :** [***Dorothee Beermann***](https://aclanthology.org/people/d/dorothee-beermann/)***,***[***Laurent Besacier***](https://aclanthology.org/people/l/laurent-besacier/)***,***[***Sakriani Sakti***](https://aclanthology.org/people/s/sakriani-sakti/) ***and*** [***Claudia Soria***](https://aclanthology.org/people/c/claudia-soria/) ***[17]***

**Published Year: 2020**

**Summary:** Understanding the sentiment of a comment from a video or an image is an essential task in many applications. Sentiment analysis of a text can be useful for various decision-making processes. One such application is to analyse the popular sentiments of videos on social media based on viewer comments. However, comments from social media do not follow strict rules of grammar, and they contain mixing of more than one language, often written in non-native scripts.

**Author: Hossam Elzayady, Mohamed S. Mohamed, Khaled M. Badran, Gouda I. Salama *[18]***

**Published Year: 2022**

**Summary:** Posting offensive or abusive content on social media have been a serious concern in recent years. This has created a lot of problems because of the huge popularity and usage of social media sites like Facebook and Twitter. The main motivation lies in the fact that our model will automate and accelerate the detection of the posted offensive content so as to facilitate the relevant actions and moderation of these offensive posts. The final comparative analysis concluded that the best model came out to be Bidirectional Encoder Representation from Transformer (BERT).

**Author :** [***Fabio Poletto***](https://link.springer.com/article/10.1007/s10579-020-09502-8#auth-Fabio-Poletto-Aff1)***,***[***Valerio Basile***](https://link.springer.com/article/10.1007/s10579-020-09502-8#auth-Valerio-Basile-Aff1)***,*** [***Manuela Sanguinetti***](https://link.springer.com/article/10.1007/s10579-020-09502-8#auth-Manuela-Sanguinetti-Aff1)***,***[***Cristina Bosco***](https://link.springer.com/article/10.1007/s10579-020-09502-8#auth-Cristina-Bosco-Aff1)***&***[***Viviana Patti***](https://link.springer.com/article/10.1007/s10579-020-09502-8#auth-Viviana-Patti-Aff1) ***[19]***

**Published Year: 2020**

**Summary:** The high number of resources and benchmark corpora for many different languages developed in a very narrow time span, from 2016 onward, confirms the growing interest of the community around abusive language in social media and HS detection in particular. Being the subject in a yet recent stage, it suffers from several weaknesses, related to both the specific targets and nuances of HS and the nature of the classification task at large, that represent an obstacle toward reaching optimal results.

**Author :** [***Rahul Pradhan***](https://www.researchgate.net/profile/Rahul-Pradhan?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19)***,*** [***Ankur Chaturvedi***](https://www.researchgate.net/scientific-contributions/Ankur-Chaturvedi-2237103329?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19)***,*** [***Aprna Tripathi***](https://www.researchgate.net/profile/Aprna-Tripathi?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19)***,*** [***Dilip Kumar Sharma***](https://www.researchgate.net/profile/Dilip-Sharma-7?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19) ***[20]***

**Published Year: 2020**

**Summary :** The work done recently in this field of automatic detection of offensive language and the research goes from using tf-idf to popular classifiers such as Naïve Bayes, Support vector machine (SVM), Logistic Regression, then research work goes to variant of these classifiers such as Linear SVM, Logistic Regression with L2, from here researchers further explore ensemble classifiers using the combination of these classifier by decomposing the task into sub tasks, then lastly usage of deep learning and we found many researcher using approaches such as LSTM, CNN and RNN.

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# CHAPTER 3

# SYSTEM ANALYSIS

## 3.1 EXISTING APPROACHES:

## 1. Keyword-Based Filtering: This is one of the simplest methods, where a predefined list of offensive words and phrases is used to filter out or flag comments or posts containing these keywords. This method is often combined with more sophisticated techniques for better accuracy.

## 2. Machine Learning Models: Many platforms employ machine learning models, such as natural language processing (NLP) models, to automatically detect offensive language. These models are trained on large datasets of offensive and non-offensive text to learn patterns and identify new forms of offensive language.

## 3. Sentiment Analysis: Sentiment analysis techniques are used to determine the emotional tone of a comment or post. Offensive language is often associated with negative sentiment, so sentiment analysis can be used as a component of a system for identifying offensive content.

## 4. Contextual Analysis: Understanding the context in which words or phrases are used is crucial for accurate detection. Words that might be offensive in one context could be harmless in another. Systems often consider the surrounding words and the overall context to make more accurate judgments.

## 5. User Reporting: Most platforms rely on users to report offensive content. When a user flags a comment or post as offensive, it can trigger a review process. User reporting is a valuable tool in combination with automated methods.

## 6. Human Moderation: Some platforms employ human moderators to review reported content. Human moderators can provide nuanced judgment, especially when dealing with complex or context-dependent cases.

## 7. Whitelists and Blacklists: Platforms maintain lists of known offensive and acceptable terms to aid in content filtering. Content containing blacklisted terms can be automatically flagged, while whitelisted terms are allowed.

## 8. Customization: Many platforms allow users to customize their content filters to a certain extent. Users can define which types of content they want to filter or allow, giving them control over their online experience.

## 9. Legal and Ethical Considerations: Systems need to take into account legal and ethical considerations, such as freedom of speech and avoiding censorship of legitimate content. Striking a balance between removing offensive content and respecting user rights is an ongoing challenge.

## 3.2 Limitations of Existing Approaches:

## Existing models for the above approaches have made significant advancements, but they still have several limitations:

## 1. Contextual Understanding: Models often struggle to understand the nuances of language and context. Offensive content can be highly context-dependent, and a model may misinterpret a benign statement as offensive or fail to detect offensive language when it's used in a subtle or disguised manner.

## 2. Multimodal Content: Many social media posts contain not only text but also images, videos, and audio. Existing models primarily focus on text-based analysis, which means they might miss offensive content presented in other media formats.

## 3. Evolving Language and Trends: Offensive language and trends on social media are constantly evolving. Models trained on historical data may not be up-to-date with the latest terminology and forms of online harassment or offensive content.

## 4. False Positives and Negatives: Models often generate false positives and false negatives. Achieving the right balance between these two is a challenging task.

## 5. Language Variability: Offensive content can vary significantly across languages and cultures. Models trained on one language or cultural context may not perform well in others.

## 6. Adversarial Attacks: Malicious users may intentionally try to fool offensive content detection systems, and models can be vulnerable to adversarial attacks, where slight modifications to the text can bypass the system's filters.

## 7. Privacy Concerns: Offensive content detection raises concerns about user privacy. To detect such content, models need access to users' posts and comments, which can be a privacy risk. Striking a balance between user privacy and content monitoring is an ongoing challenge.

## 8. Scalability: The sheer volume of social media content makes it challenging to scale up the process of identifying and moderating offensive content. Manual review is often required, which can be time-consuming and costly.

## 3.2 PROPOSED SYSTEM:

The proposed model is a BERT-CNN fusion classifier that combines the embeddings from different BERT and CNN models to detect offensive language in code-mixed Dravidian languages. The BERT models are fine-tuned on multilingual or language-specific transformer models, and the CNN models are trained on FastText word vectors. The fusion classifier is a feed-forward neural network with batch normalization and dropout. The model is trained and evaluated on a dataset of Youtube comments in Tamil. The model achieves the best results in Tamil.

**PROPOSED SOLUTION ARCHITECTURE:**

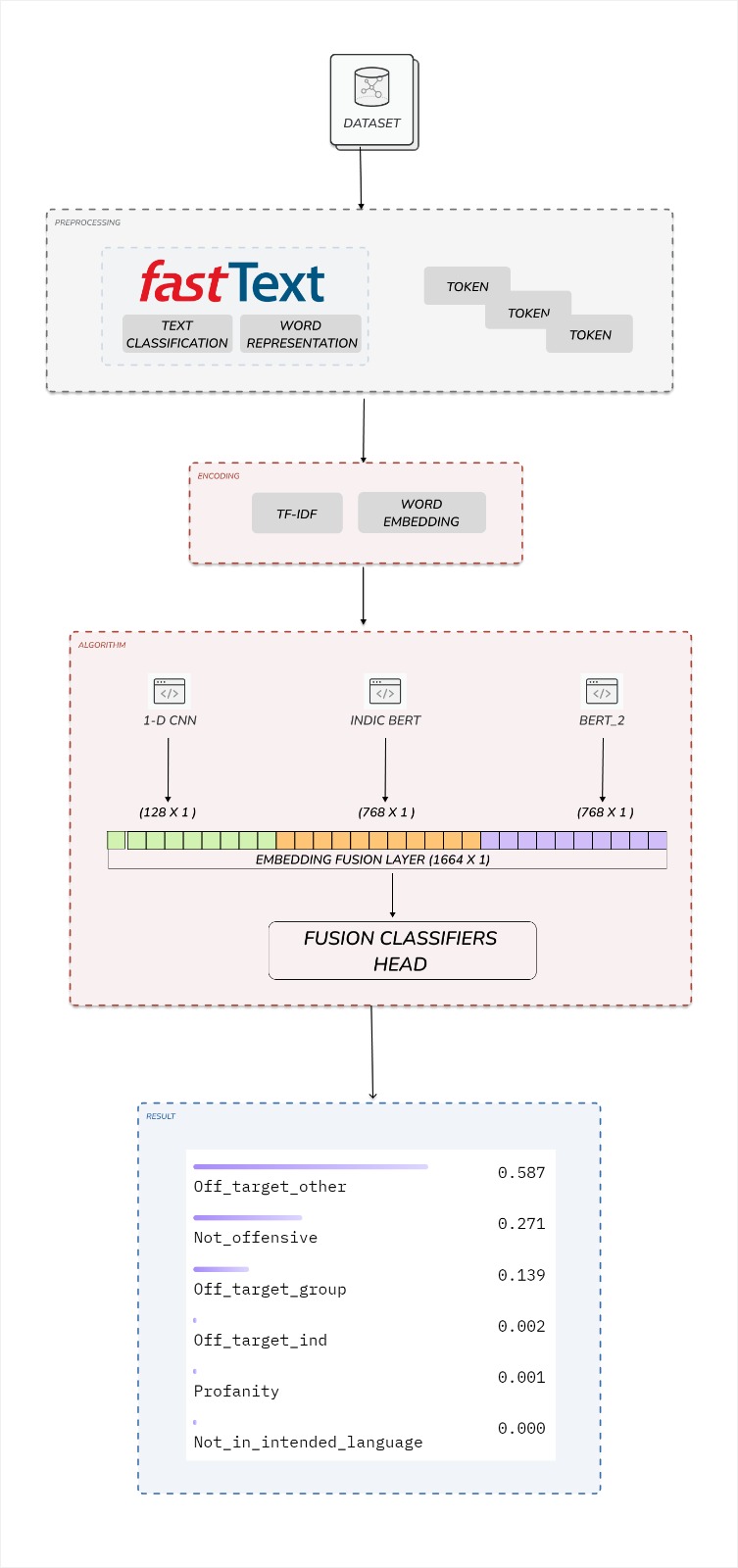


Fig 3.2: System Architecture

**Advantages of Our Approach:**

1. **Multilingual and Code-Mixed Competence**: Our approach excels in handling the multilingual and code-mixed nature of social media content, ensuring effectiveness in real-world scenarios where languages blend seamlessly.

2. **Customization through Fine-Tuning**: We fine-tune state-of-the-art transformer models on the specific dataset, enhancing the model's adaptability to the linguistic nuances of Dravidian languages, resulting in improved performance.

3. **Ensemble Fusion Model**: By combining BERT and CNN models, we leverage the strengths of each, capturing both semantic and neighborhood information, leading to more robust and accurate offensive language detection.

4. **Class Imbalance Handling**: Our approach acknowledges and addresses class imbalance problems, reflecting real-world scenarios, thus improving the model's effectiveness across different classes.

5. **Domain-Specific Pretraining**: We pretrain our model on the target dataset using Masked Language Modeling, enabling it to understand the semantics and context of the code-mixed corpus, enhancing its context-awareness.

6. **Transparent Architecture**: Our methodology is transparently defined, making it easily comprehensible and reproducible for research and further development.

7. **Scalability**: The flexibility in the number of BERT models in the fusion classifier ensures scalability, accommodating different resource constraints and needs.

8. **Utilization of State-of-the-Art Models**: We leverage cutting-edge models and techniques, benefiting from the latest advancements in natural language processing and machine learning, potentially outperforming older models.

These advantages collectively position our approach as a robust and adaptable solution for offensive language detection in Dravidian languages, ensuring that it is well-equipped to handle the complexities of real-world social media content.

# CHAPTER 4

## REQUIREMENTS

##### 4.1 HARDWARE SPECIFICATIONS

Processor - CPU 11th Gen Intel(R) Core(TM) i7-11800H @ 2.30GHz

RAM - 8 GB DDR4@3200MHz

Storage - 128 GB M.2 NvMe SSD

##### 4.2 SOFTWARE SPECIFICATIONS

OS - Windows 8, 10 or 11

Python – 3.11.5

* absl-py-2.0.0
* anyio-4.0.0
* argon2-cffi-23.1.0
* argon2-cffi-bindings 21.2.0
* arrow-1.3.0
* asgiref-3.7.2
* asttokens-2.4.0
* astunparse-1.6.3
* async-lru-2.0.4
* attrs-23.1.0
* Babel-2.13.0
* backcall-0.2.0
* beautifulsoup4-4.12.2
* bleach-6.1.0
* cachetools-5.3.1
* certifi-2023.7.22
* cffi-1.16.0
* charset-normalizer-3.3.0
* colorama-0.4.6
* comm-0.1.4
* debugpy-1.8.0
* decorator-5.1.1
* defusedxml-0.7.1
* Django-4.2.6
* django-emoji-2.2.2
* emoji-2.8.0
* exceptiongroup-1.1.3
* executing-2.0.0
* fastjsonschema-2.18.1
* fasttext-0.9.2
* flatbuffers-23.5.26
* fqdn-1.5.1
* gast-0.5.4
* google-auth-2.23.3
* google-auth-oauthlib-1.0.0
* google-pasta-0.2.0
* grpcio-1.59.0

Chrome - Version 118.0.6045.106 (Official Build) (64-bit)

# CHAPTER 5

## MODULE DESCRIPTION

## 5.1. DATASET PREPARATION AND PREPROCESSING

## DATASET:

Online media, for example, Twitter, Facebook or YouTube, contain quickly changing data produced by millions of users that can drastically alter the reputation of an individual or an association. This raises the significance of programmed extraction of sentiments and offensive language used in online social media. YouTube is one of the popular social media platforms in the Indian subcontinent because of the wide range of content available from the platform such as songs, tutorials, product reviews, trailers and so on. YouTube allows users to create content and other users to comment on the content. It allows for more user-generated content in under-resourced languages. Hence, we chose YouTube to extract comments to create our dataset. We chose movie trailers as the topic to collect data because movies are quite popular among the Tamil speaking populace. This increases the chance of getting varied views on one topic. Figure 1 shows the overview of the steps involved in creating our dataset.

We compiled the comments from different film trailers of Tamil, Kannada, and Malayalam languages from YouTube in the year 2019. The comments were gathered using YouTube Comment Scraper tool. We utilized these comments to make the datasets for sentiment analysis and offensive language identification with manual annotations. We intended to collect comments that contain code-mixing at various levels of the text, with enough representation for each sentiment and offensive language classes in all three languages. It was a challenging task to extract the necessary text that suited our intent from the comment section, which was further complicated by the presence of remarks in other non-target languages.

|  |  |
| --- | --- |
| **DATASET** | **NUMBER OF COMMENTS** |
| Data Collected | 39,531 |
| Non - Offensive Comments | 28,615 |
| Not in Intended Language Comments | 1,614 |
| Offensive Untargeted Comments | 3,274 |
| Offensive Targeted Insult Individual Comments | 2,658 |
| Offensive Targeted Insult Group Comments | 2,845 |
| Offensive Targeted Insult Other Comments | 525 |

Table 5.1.1 tamil\_offensive\_full\_train Dataset

|  |  |  |
| --- | --- | --- |
| **Code - Switching Type** | **Example** | **Translation** |
| No Code - Mixing Only Tamil (Written in Tamil Script) | இது மாதிரி ஒரு படதஂதை தானஂ இதஂதனை வருஷமா எதிாஂபாாஂதஂது கொணஂடிருநஂதேனஂ டிரெயஂலாஂ பாாஂகஂகுமஂபோதே மனசுகஂகு அவஂவளவு சநஂதோசமா இருகஂகு | How long I have been Waiting for this kind of Movie! Feels joyful just Watching this Trailer |
| Inter - Sentential Code - Mixing Mix of English and Tamil (Tamil Written only in Tamil Script) | ரெடஂடியாாஂ சமுகமஂ சாாஂபாக படமஂ வெறஂறி பெற வாழஂதஂதுகஂகளஂ… Mohan G All the Very Best we all behind you. | On behalf of Reddiyar Community, I am Wishing the Best for this Movie. Mohan G All the Very Best. We all behind you. |
| Only Tamil (Written in Latin Script) | Inga niraya perukku illatha kedda palakkam enkidda irukku. vassol mannan VIJAY anna. | ‘I have a bad habit which is not found here in others’. Brother Vijay is the king of blockbusters. |
| Code - Switching at morphological level (Written in both Tamil and Latin Script) | ஓ விஜயஂ படதஂதுகஂகு இபஂபடிதானஂ viewers sekkurangala | Oh. So this is how you gather more viewers for Vijay’s movie ? |
| Intra - Sentential mix of English and Tamil (Written in Latin Script Only) | Patti thotti engum pattaya kelaputha ne va thalaiva I am waiting | Rocking Performance that will be a hit among every type of audience. Come on, my star. I am Waiting |
| Inter - Sentential and Intra - Sentential Mix (Tamil Written in Both Tamil Script and Latin Script) | இநஂத படதஂத வர விட கூடாது... இநஂத படதஂத திரையரஙஂகிலஂ ஓட விட கூடாதுனு எவனாது தடை பனஂனா.. . Theatre la vera endha padam odunaalum screen கிழியுமஂ | If anybody imposes a ban that this movie should not be released, that it should not be allowed to run on theaters, then the screens will be torn if any other movie is released. |

Table 5.1.2: Tamil Comments Sample Data

**DATA PREPROCESSING:**

The process begins with the definition of a custom Python function named read\_csv\_from\_link(url). This function is designed to read CSV files from Google Drive links. It takes a URL as its input, extracts the file ID from the URL, and constructs a new URL that triggers the download of the CSV data.

The pandas library is then utilized to read this downloaded data into a DataFrame, making it readily available for manipulation and analysis. After this, the code proceeds to load specific datasets from their respective Google Drive URLs. In this case, three datasets, namely tamil\_train, tamil\_dev, and tamil\_test, are fetched using the read\_csv\_from\_link() function.

Subsequently, the preprocessing phase involves refining the structure of the data. Specifically, the tamil\_train and tamil\_dev datasets are subjected to a series of transformations. These transformations entail selecting only the first two columns from each dataset, which are conventionally used for text and labels. Furthermore, the column names are adjusted to "text" and "label" for consistency and clarity in data analysis.

One notable step in this preprocessing stage is the conversion of label data within the tamil\_train and tamil\_dev datasets to categorical data types. This categorical encoding is crucial, especially in classification tasks, as it simplifies the handling of label-based data. Lastly, the code provides insight into the distribution of labels in the tamil\_train dataset by printing the value counts. This serves as a useful summary, offering a quick overview of how the different categories are distributed within the training data.

Overall, the data import and preprocessing steps presented in this code snippet are a fundamental starting point in the workflow of data analysis and machine learning, ensuring that the data is structured and prepared for further exploration or model training. This is a common preprocessing step in Natural Language Processing tasks, where preparing your data for further analysis or model training.

**Pseudo Code:**

function read\_csv\_from\_link(url):

# Extract the file id from the url

file\_id = extract the part after the last '/' from url

# Construct the download path

path = concatenate 'https://drive.google.com/uc?export=download&id=' and file\_id

# Read the CSV file from the path

df = read CSV file from path with delimiter "\t" and no header

# Return the dataframe

return df

# Load all data

tamil\_train = call read\_csv\_from\_link with url 'https://drive.google.com/file/d/15auwrFAlq52JJ61u7eSfnhT9rZtI5sjk/view?usp=sharing'

tamil\_dev = call read\_csv\_from\_link with url 'https://drive.google.com/file/d/1Jme-Oftjm7OgfMNLKQs1mO\_cnsQmznRI/view?usp=sharing'

tamil\_test = call read\_csv\_from\_link with url 'https://drive.google.com/file/d/10RHrqXvIKMdnvN\_tVJa\_FAm41zaeC8WN/view?usp=sharing'

# Preprocess Tamil data

# Keep only the first two columns of tamil\_train and tamil\_dev

tamil\_train = keep only the first two columns of tamil\_train

tamil\_dev = keep only the first two columns of tamil\_dev

# Rename the columns of tamil\_train and tamil\_dev

tamil\_train = rename the columns of tamil\_train to "text" and "label"

tamil\_dev = rename the columns of tamil\_dev to "text" and "label"

# Convert the 'label' column of tamil\_train and tamil\_dev to categorical

tamil\_train['label'] = convert tamil\_train['label'] to categorical

tamil\_dev['label'] = convert tamil\_dev['label'] to categorical

# Print the count of each label in tamil\_train

print the count of each label in tamil\_train['label']

**5.2. MODEL BUILDING**

The process entails feeding the algorithm with training data. An algorithm will process data and output a model that is able to find a target value in new data. The purpose of model training is to develop a model. Supervised learning allows

for processing data with target attributes or labeled data. The goal of model training is to predict the most accurate abusive content.

In our project, we employed three types of models:

**ML Model**: We used random forests and logistic regression, trained on TF-IDF vectors. The best results were achieved with the ExtraTrees Classifier, yielding weighted F1-scores of 0.70, 0.63, and 0.95.

**Transformer Model**: We fine-tuned various multilingual BERT models, including XLMRo BERTa, multilingual-BERT, Indic BERT, and MuRIL. Additionally, we

pre-trained XLM-Roberta-Base on the target dataset using Masked Language Modeling for 20 epochs. All models were fine-tuned with both unweighted and weighted cross-entropy loss functions.

**Fusion Model:** To capture neighborhood information effectively, we introduced a BERT-CNN fusion classifier. This model utilizes embeddings from different BERT and CNN models, with the BERT models initialized with fine-tuned weights. We used FastText word vectors for the CNN part and implemented a feed-forward neural network with four layers for the fusion classifier.

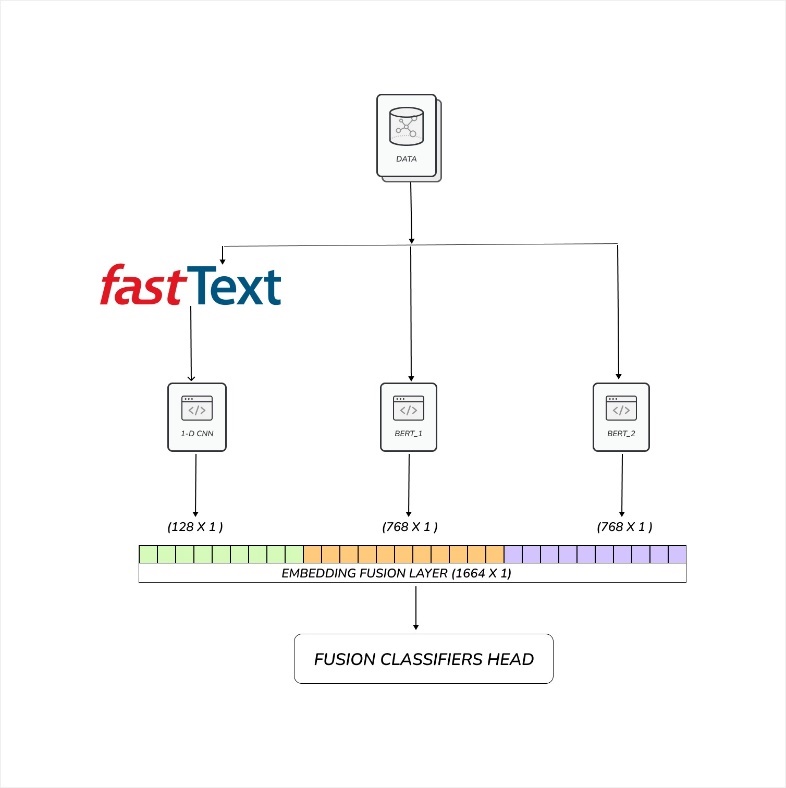


Figure 5.3.1: Fusion Model Architecture

**Pseudo Code:**

# Import necessary libraries

import MaxPooling2D from keras.layers.pooling

import other necessary libraries

# Define the input shape

inputs = define input shape (15, 300, 1)

# Define the CNN layers

conv\_0 = define a 2D convolutional layer with 64 filters, kernel size of 5, 'relu' activation, and 'valid' padding

conv\_1 = define a 2D convolutional layer with 32 filters, kernel size of 3, 'relu' activation, and 'valid' padding

conv\_2 = define a 2D convolutional layer with 32 filters, kernel size of 3, 'relu' activation, and 'valid' padding

drop = apply dropout with rate 0.6

conv\_3 = define a 2D convolutional layer with 16 filters, kernel size of 3, 'relu' activation

pool0 = apply 2D max pooling with pool size (2, 2) and 'valid' padding

conv\_4 = define a 2D convolutional layer with 16 filters, kernel size of 3, 'relu' activation

pool1 = apply 2D max pooling with pool size (2, 2) and 'valid' padding

# Flatten the tensor and define the dense layers

flatten = flatten the tensor

hidden1 = define a dense layer with 128 units and 'relu' activation

output = define a dense layer with 6 units and 'softmax' activation

# Define the models

model1 = define a model with inputs and output

model2 = define a model with inputs and hidden1

# Compile the models

compile model1 with 'adam' optimizer, 'categorical\_crossentropy' loss, and 'accuracy' metrics

compile model2 with 'adam' optimizer, 'categorical\_crossentropy' loss, and 'accuracy' metrics

# Train the model

for each epoch in range(50):

fit model1 on x\_train and y\_train, validate on x\_dev and y\_dev

predict on x\_train and x\_dev using model1

calculate and print the f1 score for train and validation predictions

if validation f1 score is greater than best f1 score:

update best f1 score

predict on x\_train, x\_dev, and x\_test using model2

save the predictions to numpy files

else:

increment counter

if counter is greater than or equal to 7:

  break the loop

**5.3. TRAINING AND TESTING**

A data set used for machine learning should be partitioned into two subsets —

training and test sets.

**Training set** – It is used to train a model and define its optimal parameters

it has to learn from data.

|  |  |
| --- | --- |
| **DATASET** | **NUMBER OF COMMENTS** |
| Trained Dataset | 35,139 |
| Not offensive Comments | 25,425 |
| Not in Intended Language Comments | 1,454 |
| Offensive Untargeted Comments | 2,906 |
| Offensive Targeted Insult Individual Comments | 2,343 |
| Offensive Targeted Insult Group Comments | 2,557 |
| Offensive Targeted Insult Other Comments | 454 |

Table 5.3.1: tamil\_train Dataset

**Test set** – It is needed for an evaluation of the trained model and its capability for

generalization. It means a model’s ability to identify patterns in new unseen data

after having been trained over a training data. It’s crucial to use different subsets

for training and testing to avoid model over-fitting.

|  |  |
| --- | --- |
| **DATASET** | **NUMBER OF COMMENTS** |
| Tested Dataset | 4,392 |
| Not offensive Comments | 3,190 |
| Not in Intended Language Comments | 160 |
| Offensive Untargeted Comments | 368 |
| Offensive Targeted Insult Individual Comments | 315 |
| Offensive Targeted Insult Group Comments | 288 |
| Offensive Targeted Insult Other Comments | 71 |

Table 5.3.2: tamil\_test Dataset

**Pseudo Code :**

# Define a function to build a vocabulary from a list of sentences

function build\_vocab(sentences):

# Create an empty dictionary to store word counts

word\_counts = {}

# Loop through each sentence in the list

for each sentence in sentences:

# Split the sentence into words

words = split sentence by spaces

# Loop through each word in the sentence

for each word in words:

# If the word is already in the dictionary, increment its count by one

if word is in word\_counts:

word\_counts[word] = word\_counts[word] + 1

# Otherwise, add the word to the dictionary with a count of one

else:

word\_counts[word] = 1

# Sort the dictionary by word counts in descending order

word\_counts = sort word\_counts by values in reverse order

# Create an empty list to store the vocabulary

vocabulary = []

# Loop through each word and count pair in the dictionary

for each word, count in word\_counts:

# Append the word to the vocabulary list

append word to vocabulary

# Return the vocabulary list

return vocabulary

# Define a function to map sentences and labels to vectors based on a vocabulary

function build\_input\_data(sentences, labels):

# Create an empty list to store the input vectors

x = []

# Create an empty list to store the label vectors

y = []

# Loop through each sentence and label pair in the list

for each sentence, label in zip(sentences, labels):

# Create an empty list to store the word vectors

word\_vectors = []

# Split the sentence into words

words = split sentence by spaces

# Loop through each word in the sentence

for each word in words:

# Get the fasttext vector for the word

word\_vector = get\_word\_vector(word)

# Append the word vector to the word vectors list

append word\_vector to word\_vectors

# Convert the word vectors list to a numpy array

word\_vectors = numpy array of word\_vectors

# Append the word vectors array to the input vectors list

append word\_vectors to x

# Append the label to the label vectors list

append label to y

# Convert the input vectors list to a numpy array

x = numpy array of x

# Convert the label vectors list to a numpy array

y = numpy array of y

# Return the input vectors and label vectors

return x, y

# Define a function to pad sentences to the same length

function pad\_sentences(sentences, padding\_word):

# Set the sequence length to 15

sequence\_length = 15

# Create an empty list to store the padded sentences

padded\_sentences = []

# Loop through each sentence in the list

for each sentence in sentences:

# Strip the sentence of any leading or trailing whitespace

sentence = strip sentence of whitespace

# Split the sentence into words

words = split sentence by spaces

# If the number of words is greater than the sequence length

if length of words is greater than sequence\_length:

# Truncate the words to the first 15 elements

words = first 15 elements of words

# Append the words to the padded sentences list

append words to padded\_sentences

# Otherwise

else:

# Calculate the number of padding words needed

num\_padding = sequence\_length - length of words

# Create a new list of words with the padding word appended to the end

new\_words = words + [padding\_word] \* num\_padding

# Append the new words to the padded sentences list

append new\_words to padded\_sentences

# Return the padded sentences list

return padded\_sentences

# Define a function to load and preprocess data for the dataset

function load\_data(train\_text, label):

# Pad the train text sentences to the same length

sentences\_padded = pad\_sentences(train\_text, "<PAD/>")

# Build the input vectors and label vectors for the train text and label

x, y = build\_input\_data(sentences\_padded, label)

# Print the type of x

print type of x

# Return the input vectors and label vectors

return x, y

# Load the train set

x\_train, y\_train = load\_data(tamil\_train["text"], tamil\_train["label"])

# Encode the labels using a dictionary

coded = {"Not\_offensive": 0, "Offensive\_Targeted\_Insult\_Group": 1, "Offensive\_Targeted\_Insult\_Individual": 2, "Offensive\_Untargetede": 3, "not-Tamil": 4, "Offensive\_Targeted\_Insult\_Other": 5}

# Loop through each label in the train set

for each i, j in enumerate(y\_train):

# Replace the label with the corresponding code

y\_train[i] = coded[j]

# Reshape the train input vectors to have four dimensions

x\_train = reshape x\_train to (length of x\_train, 15, 300, 1)

# Convert the train label vectors to categorical format

y\_train = to\_categorical(y\_train)

# Load the dev set

x\_dev, y\_dev = load\_data(tamil\_dev["text"], tamil\_dev["label"])

# Loop through each label in the dev set

for each i, j in enumerate(y\_dev):

# Replace the label with the corresponding code

y\_dev[i] = coded[j]

# Reshape the dev input vectors to have four dimensions

x\_dev = reshape x\_dev to (length of x\_dev, 15, 300, 1)

# Convert the dev label vectors to categorical format

y\_dev = to\_categorical(y\_dev)

# Load the test set

x\_test, y\_test = load\_data(tamil\_test[0], tamil\_test[1])

# Reshape the test input vectors to have four dimensions

x\_test = reshape x\_test to (length of x\_test, 15, 300, 1)

# Loop through each label in the test set

for each i, j in enumerate(y\_test):

# Replace the label with the corresponding code

y\_test[i] = coded[j]

# Convert the test label vectors to categorical format

y\_test = to\_categorical(y\_test)

**5.4. USER INTERACTION**

This is the module where the user can able to interact with our model. The values for the prediction are collected from the user and the output will be displayed.

**USER PAGE**:

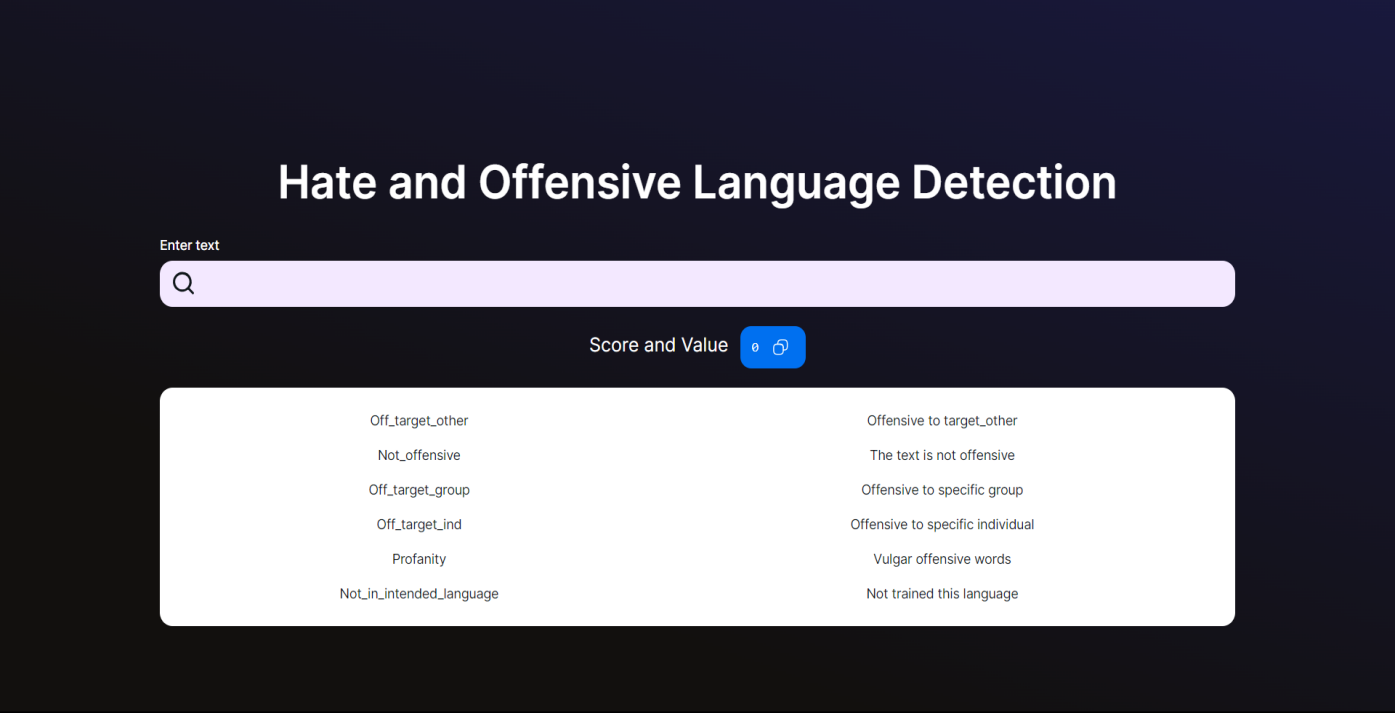


Fig No 5.4.1: Home Page

**CHAPTER 6**

**SYSTEM IMPLEMENTATION**

* 1. **6.1 CODES:**
  2. **Front End: Next js**
  3. **Landing Page:**
  4. import styles from "./LandingPage.module.scss";
  5. import {
  6. Button,
  7. Input,
  8. Snippet,
  9. Table,
  10. TableBody,
  11. TableCell,
  12. TableColumn,
  13. TableHeader,
  14. TableRow,
  15. } from "@nextui-org/react";
  16. import cx from "classnames";
  17. import { Icon } from "@iconify/react";
  18. import { ChangeEvent, useEffect, useState } from "react";
  19. import axios from "axios";
  20. interface DataResponse {
  21. label: string;
  22. score: number;
  23. }
  24. const initialState: DataResponse[] = [
  25. {
  26. label: "",
  27. score: 0,
  28. },
  29. ];
  30. export const LandingPage = () => {
  31. const [inputText, setInputText] = useState("");
  32. const [data, setData] = useState(initialState);
  33. const handleChange = (event: ChangeEvent<HTMLInputElement>) => {
  34. setInputText(event.target.value);
  35. };
  36. // api call function
  37. const fetchData = async (value: string) => {
  38. try {
  39. const response = await axios.get("http://127.0.0.1:5000/find/" + value);
  40. return response.data;
  41. } catch (error) {
  42. throw error;
  43. }
  44. };
  45. const handleSearch = () => {
  46. fetchData(inputText)
  47. .then((result) => setData(result))
  48. .catch((error) => console.error("API call error", error));
  49. };
  50. return (
  51. <div>
  52. <div className={styles.TitleText}>
  53. Hate and Offensive Language Detection
  54. </div>
  55. <div className="flex items-center mt-5">
  56. <div className="container mx-auto px-44">
  57. <Input
  58. classNames={{
  59. label: "active:text-black text-white",
  60. inputWrapper: "bg-purple-100 ",
  61. clearButton: "text-black",
  62. }}
  63. isClearable
  64. className={cx("")}
  65. type="email"
  66. labelPlacement="outside"
  67. label="Enter text"
  68. size="lg"
  69. onChange={handleChange}
  71. startContent={<Icon icon="mingcute:search-line" height="30" />}

endContent={

* 1. <Button color="primary" onClick={handleSearch}>
  2. Search
  3. </Button>
  4. }
  5. />
  6. </div>
  7. </div>
  8. <div className="flex items-center mt-5">
  9. <div className="container mx-auto px-44 text-center">
  10. {data.map((item, index) => (
  11. <div key={index}>
  12. <span className="text-white text-xl mr-2">Score and Value </span>
  13. <Snippet hideSymbol={true} color="primary" variant="solid">
  14. {item.label + " " + item.score}
  15. </Snippet>
  16. </div>
  17. ))}
  18. </div>
  19. </div>
  20. <div className="flex items-center mt-5">
  21. <div className="container mx-auto px-44 text-center">
  22. <Table hideHeader aria-label="Example static collection table">
  24. <TableHeader>
  25. <TableColumn>NAME</TableColumn>
  26. <TableColumn>ROLE</TableColumn>
  27. </TableHeader>
  28. <TableBody>
  29. <TableRow key="1">
  30. <TableCell>Off\_target\_other</TableCell>
  31. <TableCell>Offensive to target\_other</TableCell>
  32. </TableRow>
  33. <TableRow key="2">
  34. <TableCell>Not\_offensive</TableCell>
  35. <TableCell>The text is not offensive</TableCell>
  36. </TableRow>
  37. <TableRow key="3">
  38. <TableCell>Off\_target\_group</TableCell>
  39. <TableCell>Offensive to specific group</TableCell>
  40. </TableRow>
  41. <TableRow key="4">
  42. <TableCell>Off\_target\_ind</TableCell>
  43. <TableCell>Offensive to specific individual</TableCell>
  44. </TableRow>
  45. <TableRow key="5">
  46. <TableCell>Profanity</TableCell>
  47. <TableCell>Vulgar offensive words</TableCell>
  48. </TableRow>
  49. <TableRow key="6">
  50. <TableCell>Not\_in\_intended\_language</TableCell>
  51. <TableCell>Not trained this language</TableCell>
  52. </TableRow>
  53. </TableBody>
  54. </Table>
  55. </div>
  56. </div>
  57. </div>
  58. );
  59. };
  60. **layout.tsx :**
  61. import "./globals.css";
  62. import type { Metadata } from "next";
  63. import { Inter } from "next/font/google";
  64. import cx from "classnames";
  65. const inter = Inter({ subsets: ["latin"] });
  66. export const metadata: Metadata = {
  67. title: "Hate and Offensive Language Detection",
  68. description: "Generated by create next app",
  69. };
  70. export default function RootLayout({
  71. children,
  72. }: {
  73. children: React.ReactNode;
  74. }) {
  75. return (
  76. <html lang="en">
  77. <body className={cx(inter.className, "h-screen backgroundBody")}>
  78. {children}
  79. </body>
  80. </html>
  81. );
  82. }
  83. **page.tsx :**
  84. "use client";
  85. import { Button, NextUIProvider } from "@nextui-org/react";
  86. import { LandingPage } from "@/Modules/LandingPage";
  87. export default function Home() {
  88. return (
  89. <NextUIProvider>
  90. <LandingPage />
  91. </NextUIProvider>
  92. );
  93. }

**Back End : Python**

import pandas as pd  
import numpy as np  
  
  
# Reading CSV from link  
def read\_csv\_from\_link(url):  
 path = 'https://drive.google.com/uc?export=download&id=' + url.split('/')[-2]  
 df = pd.read\_csv(path, delimiter="\t", error\_bad\_lines=False, header=None)  
 return df  
  
# Loading All Data  
tamil\_train = read\_csv\_from\_link('https://drive.google.com/file/d/15auwrFAlq52JJ61u7eSfnhT9rZtI5sjk/view?usp=sharing')  
tamil\_dev = read\_csv\_from\_link('https://drive.google.com/file/d/1Jme-Oftjm7OgfMNLKQs1mO\_cnsQmznRI/view?usp=sharing')  
tamil\_test = read\_csv\_from\_link('https://drive.google.com/file/d/10RHrqXvIKMdnvN\_tVJa\_FAm41zaeC8WN/view?usp=sharing')

# Tamil Preprocess  
tamil\_train = tamil\_train.iloc[:, 0:2]  
tamil\_train = tamil\_train.rename(columns={0: "text", 1: "label"})  
tamil\_dev = tamil\_dev.iloc[:, 0:2]  
tamil\_dev = tamil\_dev.rename(columns={0: "text", 1: "label"})  
  
# Stats  
tamil\_train['label'] = pd.Categorical(tamil\_train.label)  
tamil\_dev['label'] = pd.Categorical(tamil\_dev.label)  
print(tamil\_train['label'].value\_counts())  
# Change Device - CPU/GPU-0/GPU-1  
torch.cuda.set\_device(0)  
device = 'cuda'  
device = device if torch.cuda.is\_available() else 'cpu'  
  
import torch.nn as nn  
import torch.nn.functional as F  
from torch.utils.data import DataLoader  
from tqdm import tqdm  
import os  
from sklearn.metrics import classification\_report, f1\_score  
from torch.utils.data import Dataset  
  
# Dataset  
class tamil\_Offensive\_Dataset(Dataset):  
 def \_\_init\_\_(self, encodings, labels, bpe=False):  
 self.encodings = encodings  
 self.labels = labels  
 self.is\_bpe\_tokenized = bpe  
  
 def \_\_getitem\_\_(self, idx):  
 if not self.is\_bpe\_tokenized:  
 item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}  
 else:  
 item = {  
 'input\_ids': torch.LongTensor(self.encodings[idx].ids),  
 'attention\_mask': torch.LongTensor(self.encodings[idx].attention\_mask)  
 }  
 item['labels'] = torch.tensor(self.labels[idx])  
 return item  
  
 def \_\_len\_\_(self):  
 return len(self.labels)  
  
# list of random seeds to try  
r\_seeds = [5, 10, 15, 23, 45, 52, 100, 150, 210, 500]  
from transformers import BertTokenizer, BertForSequenceClassification  
  
tokenizer = BertTokenizer.from\_pretrained('bert-base-multilingual-cased')  
model = BertForSequenceClassification.from\_pretrained('bert-base-multilingual-cased', num\_labels=6)  
model\_name = 'Mbert\_base\_cased\_tamil'  
  
from transformers import AdamW  
  
optimizer = AdamW(model.parameters(), lr=1e-5)  
  
label\_mapping = {  
 'Not\_offensive': 0,  
 'not-lTami': 1,  
 'Offensive\_Targeted\_Insult\_Other': 2,  
 'Offensive\_Targeted\_Insult\_Group': 3,  
 'Offensive\_Untargetede': 4,  
 'Offensive\_Targeted\_Insult\_Individual': 5  
}  
  
# Collecting Text and Labels  
train\_batch\_sentences = list(tamil\_train['text'])  
train\_batch\_labels = [label\_mapping[x] for x in tamil\_train['label']]  
dev\_batch\_sentences = list(tamil\_dev['text'])  
dev\_batch\_labels = [label\_mapping[x] for x in tamil\_dev['label']]  
  
# Defining Datasets  
train\_dataset = tamil\_Offensive\_Dataset(train\_encodings, train\_labels, bpe=False)  
dev\_dataset = tamil\_Offensive\_Dataset(dev\_encodings, dev\_labels, bpe=False)  
  
device = torch.device('cuda') if torch.cuda.is\_available() else torch.device('cpu')  
model.to(device)  
best\_val\_f1 = 0  
count = 0  
  
# Dataloaders  
train\_loader = DataLoader(train\_dataset, batch\_size=16, shuffle=True)  
dev\_loader = DataLoader(dev\_dataset, batch\_size=16, shuffle=False)  
for i in r\_seeds:  
 random.seed(i)  
 np.random.seed(i)  
 torch.manual\_seed(i)  
  
 for epoch in range(100):  
 train\_preds = []  
 train\_labels = []  
 total\_train\_loss = 0  
 model.train()  
 print("==========================================================")  
 print("Epoch {}".format(epoch))  
 print("Train")  
 for batch in tqdm(train\_loader):  
 optimizer.zero\_grad()  
 input\_ids = batch['input\_ids'].to(device)  
 attention\_mask = batch['attention\_mask'].to(device)  
 labels = batch['labels'].to(device)  
 outputs = model(input\_ids, attention\_mask=attention\_mask, labels=labels)  
 if loss\_weighted:  
 loss = loss\_function(outputs[1], labels)  
 else:  
 loss = outputs[0]  
 loss.backward()  
 optimizer.step()  
  
 for logits in outputs[1].detach().cpu().numpy():  
 train\_preds.append(np.argmax(logits))  
 for logits in labels.cpu().numpy():  
 train\_labels.append(logits)  
 total\_train\_loss += loss.item() / len(train\_loader)  
  
 print("Dev")  
 dev\_preds = []  
 model.eval()  
 total\_val\_loss = 0  
 with torch.set\_grad\_enabled(False):  
 for batch in tqdm(dev\_loader):  
 input\_ids = batch['input\_ids'].to(device)  
 attention\_mask = batch['attention\_mask'].to(device)  
 labels = batch['labels'].to(device)  
 outputs = model(input\_ids, attention\_mask=attention\_mask, labels=labels)  
 if loss\_weighted:  
 loss = loss\_function(outputs[1], labels)  
 else:  
 loss = outputs[0]  
 total\_val\_loss += loss.item() / len(dev\_loader)  
  
 for logits in outputs[1].cpu().numpy():  
 dev\_preds.append(np.argmax(logits))  
  
 y\_true = dev\_batch\_labels  
 y\_pred = dev\_preds  
 target\_names = label\_mapping.keys()  
 train\_report = classification\_report(train\_labels, train\_preds, target\_names=target\_names)  
 report = classification\_report(y\_true, y\_pred, target\_names=target\_names)  
 val\_f1 = f1\_score(y\_true, y\_pred, average='macro')  
  
 # Save Best Model  
 if val\_f1 > best\_val\_f1:  
 PATH = '../../finetuned\_models/' + model\_name + '\_seed\_' + i + '.pth'  
 torch.save(model.state\_dict(), PATH)  
 model.save\_pretrained(os.path.join('../../finetuned\_berts/', (model\_name + '\_seed\_' + i)))  
 best\_val\_f1 = val\_f1  
 count = 0  
 else:  
 count += 1

print(train\_report)  
 print(report)  
 print("Epoch {}, Train Loss = {}, Val Loss = {}, Val F1 = {}, Best Val f1 = {}, stagnant = {}".format(epoch, total\_train\_loss, total\_val\_loss, val\_f1, best\_val\_f1, count))  
 if count == 5:  
 print("No increase for 5 epochs, Stopping ...")  
 break

import Library  
import pandas as pd  
import numpy as np  
import fasttext  
import fasttext.util  
from keras.layers import Input, Dense, Embedding, Conv2D, MaxPool2D  
from keras.layers import Reshape, Flatten, Dropout, Concatenate  
from keras.callbacks import ModelCheckpoint  
from keras.optimizers import Adam  
from keras.models import Model  
from sklearn.model\_selection import train\_test\_split  
from keras import layers  
from keras.models import Sequential  
from keras.layers import Dense, Activation  
from keras.preprocessing.text import Tokenizer, one\_hot  
from keras.preprocessing.sequence import pad\_sequences  
from sklearn.metrics import classification\_report, f1\_score  
from keras.layers.pooling import MaxPooling2D  
  
Data Import and Preprocess

# Reading CSV from link  
def read\_csv\_from\_link(url):  
 path = 'https://drive.google.com/uc?export=download&id=' + url.split('/')[-2]  
 df = pd.read\_csv(path, delimiter="\t", error\_bad\_lines=False, header=None)  
 return df

# Loading All Data  
tamil\_train = read\_csv\_from\_link('https://drive.google.com/file/d/15auwrFAlq52JJ61u7eSfnhT9rZtI5sjk/view?usp=sharing')  
tamil\_dev = read\_csv\_from\_link('https://drive.google.com/file/d/1Jme-Oftjm7OgfMNLKQs1mO\_cnsQmznRI/view?usp=sharing')  
tamil\_test = read\_csv\_from\_link('https://drive.google.com/file/d/10RHrqXvIKMdnvN\_tVJa\_FAm41zaeC8WN/view?usp=sharing')  
  
# Tamil Preprocess  
tamil\_train = tamil\_train.iloc[:, 0:2]  
tamil\_train = tamil\_train.rename(columns={0: "text", 1: "label"})  
tamil\_dev = tamil\_dev.iloc[:, 0:2]  
tamil\_dev = tamil\_dev.rename(columns={0: "text", 1: "label"})  
  
# Stats  
tamil\_train['label'] = pd.Categorical(tamil\_train.label)  
tamil\_dev['label'] = pd.Categorical(tamil\_dev.label)  
print(tamil\_train['label'].value\_counts())  
Training  
Fasttext  
import emoji  
characters = ['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 't', 'u', 'v',  
 'w', 'x', 'y', 'z']  
def convert\_emoticons(text):  
 for emot in EMOTICONS:  
 text = re.sub(u'(' + emot + ')', "\_".join(EMOTICONS[emot].replace(",", "").split()), text)  
 return text

def preprocess(text):  
 text = emoji.demojize(text, delimiters=("", ""))  
 # text = convert\_emoticons(text)  
 res = text.lower()  
 res = res.replace('\_', ' ')  
 res = res.replace('.', ' ')  
 res = res.replace(',', ' ')  
 res = res.strip()  
 words = res.split()  
 for i, word in enumerate(words):  
 if (word[0] in characters):  
 if (len(word) < 3): continue  
 while words[i][-1] == words[i][-2]:  
 if (len(words[i]) < 2): break  
 words[i] = words[i][:-1]  
 if (len(words[i]) < 2): break  
 sen = " ".join(words)  
 return sen  
  
train\_text = []  
for key, value in tamil\_train['text'].iteritems():  
 train\_text.append(preprocess(value))  
  
dev\_text = []  
for key, value in tamil\_dev['text'].iteritems():  
 dev\_text.append(preprocess(value))  
tamil\_train['text'] = pd.DataFrame(train\_text)  
tamil\_dev['text'] = pd.DataFrame(dev\_text)  
  
corpus = []  
for i, sen in enumerate(tamil\_train['text']):  
 if (tamil\_train[label][i] == 'not-Tamil '):  
 continue  
 if i == 0: continue  
 corpus.append(preprocess(tamil\_train['text'][i]))  
for i, sen in enumerate(tamil\_dev['text']):  
 if (tamil\_train[label][i] == 'not-Tamil '):  
 continue  
 if i == 0: continue  
 corpus.append(preprocess(tamil\_dev['text'][i]))  
  
with open("corpus.txt", "w") as output:  
 output.write(str(corpus))  
  
# Train unsupervised skipgram model  
unsuper\_model = fasttext.train\_unsupervised('/home/punyajoy/corpus.txt', "skipgram", dim=300)  
Train and Test  
set  
# function to build vocabulary and inverse vocabulary dictionary  
def build\_vocab(sentences):  
# Build vocabulary  
 word\_counts = Counter(itertools.chain(\*sentences))  
 # Mapping from index to word  
 vocabulary\_inv = [x[0] for x in word\_counts.most\_common()]  
 vocabulary\_inv = list(sorted(vocabulary\_inv))  
 # Mapping from word to index  
 vocabulary = {x: i for i, x in enumerate(vocabulary\_inv)}  
 return [vocabulary, vocabulary\_inv]  
  
# Prepare X\_train by replacing text with fasttext embeddings  
def build\_input\_data(sentences, labels):  
 x = np.array([np.array([unsuper\_model.get\_word\_vector(word) for word in sentence]) for sentence in sentences])  
 y = np.array(labels)  
 return [x, y]  
  
# padding sentence for uniform input size  
def pad\_sentences(sentences, padding\_word="<PAD/>"):  
 sequence\_length = 15  
 padded\_sentences = []  
 for i in range(len(sentences)):  
 sentence = sentences[i].strip()  
 sentence = sentence.split(" ")  
 if (len(sentence) > sequence\_length):  
 sentence = sentence[0:15]  
 padded\_sentences.append(sentence)  
 else:  
 num\_padding = sequence\_length - len(sentence)  
 new\_sentence = sentence + [padding\_word] \* num\_padding  
 padded\_sentences.append(new\_sentence)  
 return padded\_sentences  
def load\_data(train\_text, label):  
 # Load and preprocess data  
 sentences\_padded = pad\_sentences(train\_text)  
 # vocabulary, vocabulary\_inv = build\_vocab(sentences\_padded)  
 x, y = build\_input\_data(sentences\_padded, label)  
 print(type(x))  
 return [x, y]  
  
# Loading train set  
x\_train, y\_train = load\_data(tamil\_train["text"], tamil\_train["label"])  
# Encoding labels  
x\_train = np.asarray(x\_train)  
coded = dict({'Not\_offensive': 0, 'Offensive\_Targeted\_Insult\_Group': 1,  
 'Offensive\_Targeted\_Insult\_Individual': 2,  
 'Offensive\_Untargetede': 3,  
 'not-Tamil': 4,  
 'Offensive\_Targeted\_Insult\_Other': 5})  
for i, j in enumerate(y\_train):  
 y\_train[i] = coded[j]  
  
x\_train = x\_train.reshape(x\_train.shape[0], 15, 300, 1)  
from keras.utils import to\_categorical  
  
y\_train = to\_categorical(y\_train)  
  
# Loading dev set  
x\_dev, y\_dev = load\_data(tamil\_dev["text"], tamil\_dev["label"])  
for i, j in enumerate(y\_dev):  
 y\_dev[i] = coded[j]  
  
x\_dev = x\_dev.reshape(x\_dev.shape[0], 15, 300, 1)  
y\_dev = to\_categorical(y\_dev)  
  
# Loading test set  
  
x\_test, y\_test = load\_data(tamil\_test[0], tamil\_test[1])  
x\_test = x\_test.reshape(x\_test.shape[0], 15, 300, 1)  
for i, j in enumerate(y\_test):  
 y\_test[i] = coded[j]  
y\_test = to\_categorical(y\_test)

CNN Model  
from keras.layers.pooling import MaxPooling2D  
  
inputs = Input(shape=(15, 300, 1))  
# embedding = Embedding(input\_dim=vocabulary\_size, output\_dim=embedding\_dim, input\_length=sequence\_length)(inputs)  
  
conv\_0 = Conv2D(64, kernel\_size=5, activation='relu', padding='valid')(inputs)  
conv\_1 = Conv2D(32, kernel\_size=3, activation='relu', padding='valid')(conv\_0)  
conv\_2 = Conv2D(32, kernel\_size=3, activation='relu', padding='valid')(conv\_1)  
drop = Dropout(0.6)(conv\_2)  
conv\_3 = Conv2D(16, kernel\_size=3, activation='relu')(drop)  
pool0 = MaxPooling2D(pool\_size=(2, 2), padding='valid')(conv\_1)  
conv\_4 = Conv2D(16, kernel\_size=3, activation='relu')(pool0)  
pool1 = MaxPooling2D(pool\_size=(2, 2), padding='valid')(conv\_2)  
# pool2 = MaxPooling2D(pool\_size=(2, 2), padding='valid')(conv\_3)  
# maxpool\_0 = MaxPool2D(pool\_size=(sequence\_length - filter\_sizes[0] + 1, 1), strides=(1,1), padding='valid')(conv\_0)  
# maxpool\_1 = MaxPool2D(pool\_size=(sequence\_length - filter\_sizes[1] + 1, 1), strides=(1,1), padding='valid')(conv\_1)  
# maxpool\_2 = MaxPool2D(pool\_size=(sequence\_length - filter\_sizes[2] + 1, 1), strides=(1,1), padding='valid')(conv\_2)  
  
# concatenated\_tensor = Concatenate(axis=1)([pool0, pool1, pool2])  
flatten = Flatten()(pool1)  
hidden1 = Dense(128, activation='relu')(flatten)  
output = Dense(6, activation='softmax')(hidden1)  
  
# this creates a model that includes  
model1 = Sequential() # To train the model on dataset  
model2 = Sequential() # To extract embeddings from cnn layer  
model1 = Model(inputs=inputs, outputs=output)  
model2 = Model(inputs=inputs, outputs=hidden1)  
adam = Adam(lr=1e-4, beta\_1=0.9, beta\_2=0.999, epsilon=1e-08, decay=0.0)  
  
model1.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'])  
model2.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'])  
# Training the model  
epoch = 50  
cnt = 0  
best\_f1 = 0  
for i in range(epoch):  
 model1.fit(x\_train, y\_train, epochs=1, validation\_data=(x\_dev, y\_dev))  
 pred = model1.predict(x\_train)  
 prediction = []  
 for i, j in enumerate(pred):  
 a = np.argmax(j)  
 prediction.append(a)  
 y\_true = []  
 for i, j in enumerate(y\_train):  
 a = np.argmax(j)  
 y\_true.append(a)  
 train\_f1 = f1\_score(y\_true, prediction, average='weighted')  
 print("train f1 - ", train\_f1)  
 pred = model1.predict(x\_dev)  
 prediction = []  
 for i, j in enumerate(pred):  
 a = np.argmax(j)  
 prediction.append(a)  
  
 y\_true = []  
 for i, j in enumerate(y\_dev):  
 a = np.argmax(j)  
 y\_true.append(a)  
  
 val\_f1 = f1\_score(y\_true, prediction, average='weighted')  
 # Updating best F1 socre and saving corresponding embeddings  
 if (val\_f1 > best\_f1):  
 cnt = 0  
 best\_f1 = val\_f1  
 x\_train\_dense\_cnn = model2.predict(x\_train)  
 x\_dev\_dense\_cnn = model2.predict(x\_dev)  
 x\_test\_dense\_cnn = model2.predict(x\_test)  
 np.save('/home/punyajoy/Dravidian\_Offensive\_Classification/sentence\_embeddings/cnn\_emb\_dev\_128\_tamil.npy',  
 x\_dev\_dense\_cnn)  
 np.save('/home/punyajoy/Dravidian\_Offensive\_Classification/sentence\_embeddings/cnn\_emb\_train\_128\_tamil.npy',  
 x\_train\_dense\_cnn)  
 np.save('/home/punyajoy/Dravidian\_Offensive\_Classification/sentence\_embeddings/cnn\_emb\_test\_128\_tamil.npy',  
 x\_test\_dense\_cnn)  
  
 else:  
 cnt += 1  
 # loop break condition  
 if (cnt >= 7):  
 print("NO increase for 5 itr, breaking....")

break

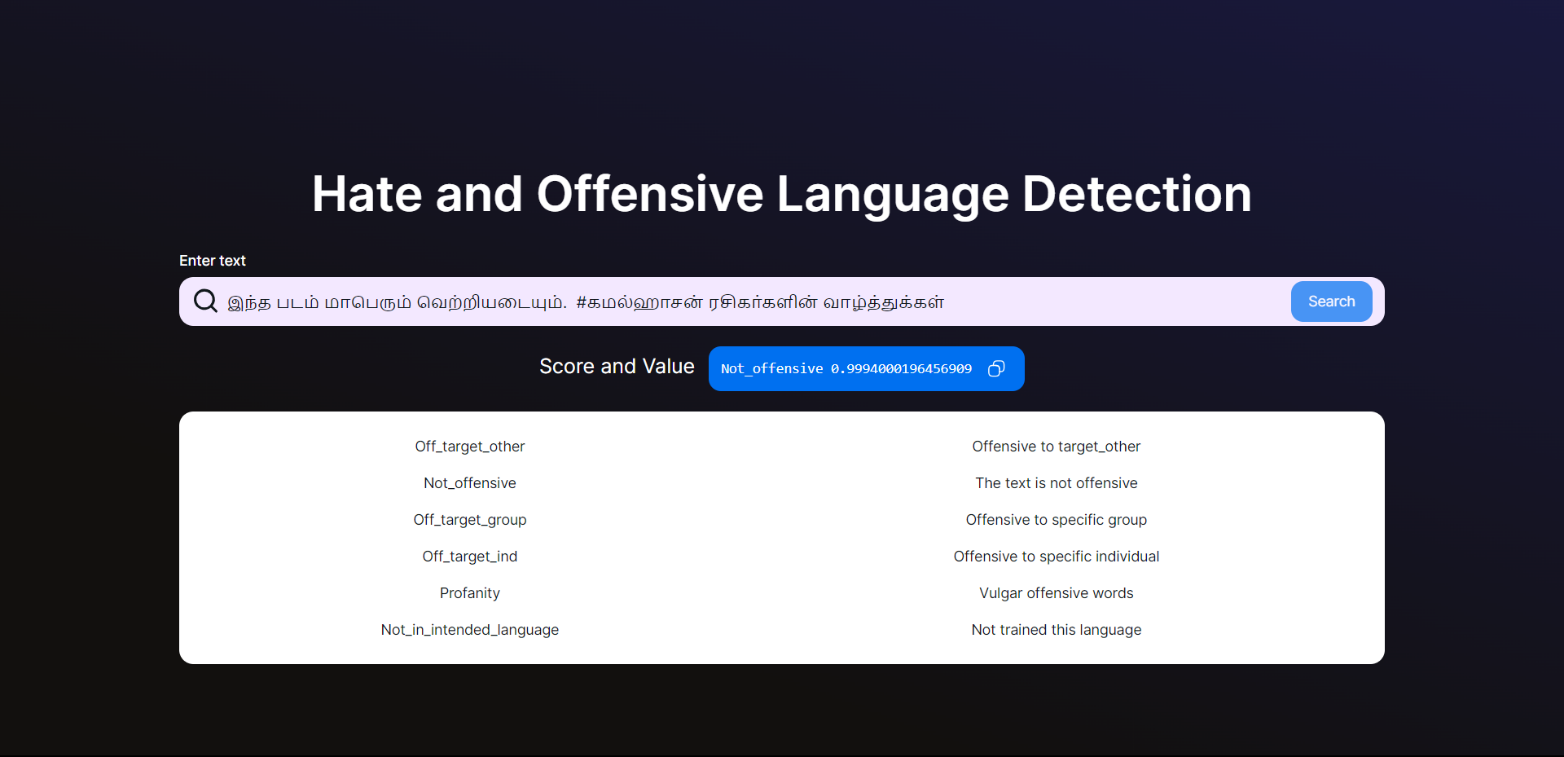
**6.2 OUTPUT**

Fig No 6.2.1: Prediction for Not – Offensive Language

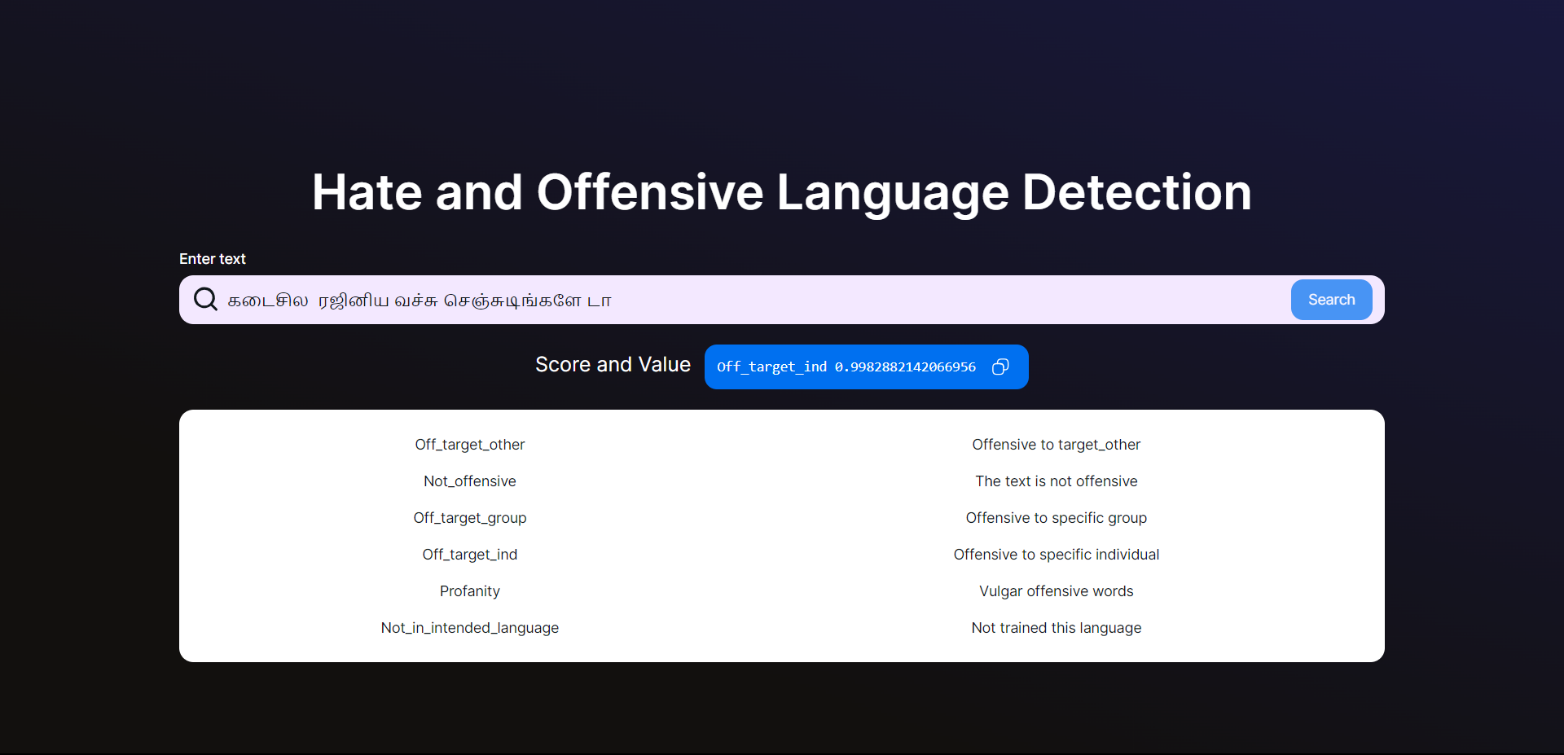


Fig No 6.2.2: Prediction for Offensive Language

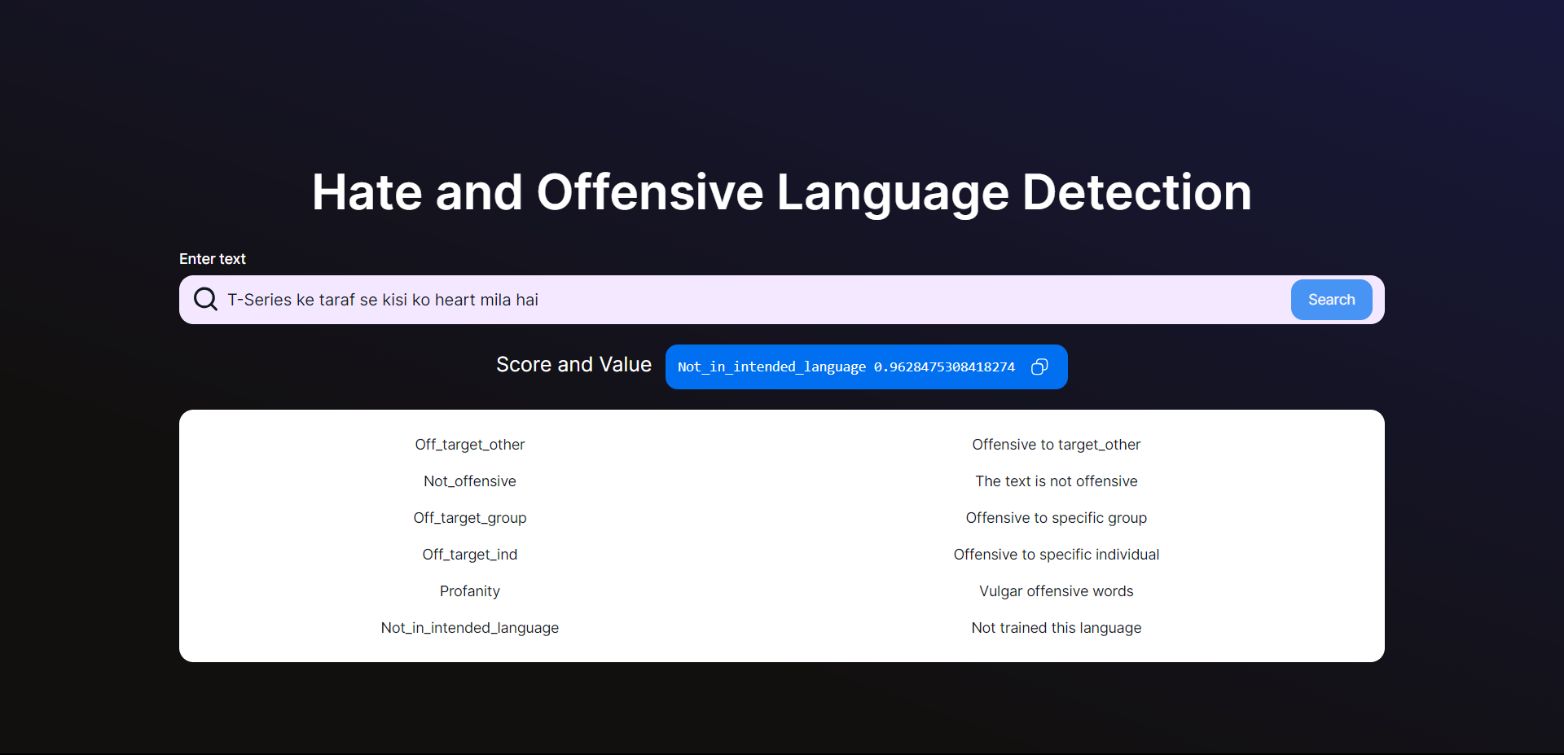


Fig No 6.2.3: Prediction for Not in Intended Language

# CHAPTER 7

## CONCLUSION

While several studies have been published on offensive language identification, there is considerable room for experimentation. New insights into low-resource Dravidian languages may result in more efficient and accurate models. Furthermore, to the best of our knowledge, this is the first study to propose an exhaustive examination of models, and newly proposed fusion of BERT and CNN model used for offensive language identification in three Dravidian languages. As demonstrated in this paper, such models perform admirably on a particular language but do not generalise effectively. It can be deduced that the application of deep neural networks to identify offensive language in Dravidian languages is promising. In the future, we will examine better neural network architectures apart from CNN and pre-trained embedding.

**CHAPTER 8**

**FUTURE WORKS**

In our ongoing project, we have successfully implemented an offensive language detection system for the Tamil language using a combination of Convolutional Neural Networks (CNN) and BERT Multilingual models, based on a research paper dataset. As we move forward, we intend to channel our efforts towards further research and development within the Dravidian language family.

Our upcoming goals primarily revolve around extending our offensive language detection capabilities to encompass additional Dravidian languages, specifically Malayalam, Telugu, and Kannada. This strategic expansion is aimed at enhancing the effectiveness and inclusivity of our system, ensuring that it can adequately address the unique linguistic characteristics and nuances present in these languages.

By concentrating on the Dravidian language family, we aim to contribute to a broader and more culturally diverse range of natural language processing solutions. Our commitment to this project remains resolute, as we seek to create a robust and reliable offensive language detection system that serves a significant portion of the linguistic diversity within the Dravidian language family.

# CHAPTER 9

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