**UNMASKING BOT-DRIVEN CYBERBULLYING WITH HYBRID CNN AND FEATURE-ENRICHED TEXT PROCESSING**

**ABSTRACT**

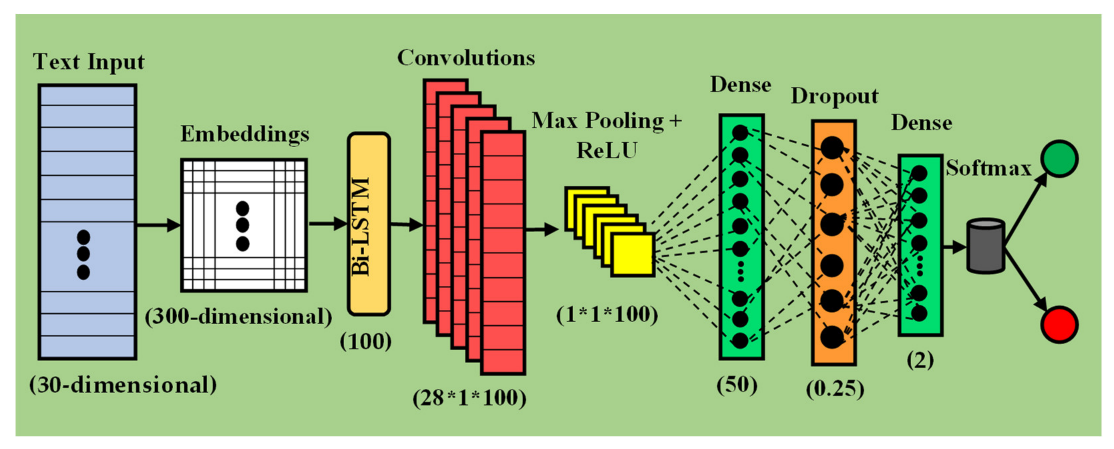
Bot cyberbullying has emerged as a critical issue in digital communication, with over 59% of teens reporting experiences of online harassment and more than 70% of cases occurring on social media platforms. Recent studies reveal that multi-class bot cyberbullying datasets often contain up to 25,000 labeled instances spanning categories like insult, threat, racism, and sexism, with severe class imbalance and linguistic variation. Manual detection methods suffer from subjectivity, inconsistent labeling, and the inability to scale with the rapid influx of user-generated content. Conventional machine learning approaches are limited by shallow feature representation, low recall on minority classes, and failure to detect implicit or masked abuse. Moreover, existing surveys often neglect to incorporate deep ensemble learning methods with optimized preprocessing and contextual analysis. To address these limitations, this study proposes a hybrid Multiclass Unmasking Bot Classification system that integrates a novel combination of feature-rich N-gram extraction with dual deep learning classifiers—Deep Neural Network (DNN) and Convolutional Neural Network (CNN). The process begins with dataset ingestion and detailed Exploratory Data Analysis (EDA) to identify distribution and imbalance. Text preprocessing follows, involving tokenization, lemmatization, and noise removal. The cleaned data is vectorized using TF-IDF with bi-gram support to capture both isolated and contextual word associations. The DNN captures deep semantic hierarchies, while CNN identifies local linguistic patterns. This parallel dual-stream architecture ensures robust learning across diverse bot cyberbullying types. Finally, the trained models are evaluated for prediction accuracy and class-wise performance, significantly outperforming baseline classifiers in terms of precision, recall, and F1-score.

**CHAPTER 1**

**INTRODUCTION**

**1.1 Introduction**

The Internet has become an integral part of everyday life, with social media evolving from basic web pages (Web 1.0) to intelligent Web 4.0 services. Technological advancements have transformed how information is accessed and how connections between different entities are made to obtain services over the network. Social media, commonly referred to as social media platforms (SMPs), includes tools for social interactions such as Facebook, Twitter, Instagram, LinkedIn, Pinterest, Telegram, and YouTube. These platforms empower users, enabling thousands to connect globally, creating a widespread social and expressive phenomenon [1]. As of January 2024, 5.35 billion people globally were internet users, comprising 66.2 percent of the population. Among them, 5.04 billion, or 62.3 percent of the world population, were active on social media platforms, emphasizing the widespread adoption and impact of digital connectivity today [2].



Professional networking supports career growth, while communities based on shared interests bloom, fostering a sense of belonging. Different businesses leverage SMPs for marketing and engagement, while educational institutions use them to broaden learning opportunities [3], [4]. However, the comprehensive exchange of personal information raises data security issues and the risk of misuse. On SMPs, individuals can face humiliation, insults, cyber threats, and cyberbullying from anonymous users [5], exacerbated by the constant accessibility and the ability for some users to remain unidentified [6]. Bullying through the use of digital technology is known as cyberbullying. Social media, messaging apps, gaming platforms, and mobile devices can be used for this purpose [7], [8]. It involves consistent behaviour intended to frighten or embarrass the targeted individuals. Examples include spreading false information about someone or sharing embarrassing pictures or videos of them on social media [9]. Some other examples include using fake accounts or sending unpleasant, abusive, or threatening texts, images, or videos through messaging apps [10]. While significant research has been conducted on Bot cyberbullying detection in English, there is a growing need to address this issue in non-English contexts, such as the Bangla language. The Bangla-speaking community faces unique challenges related to cyberbullying, with linguistic nuances and cultural factors influencing the nature and

manifestation of harmful online behaviours. Detecting and addressing cyberbullying in Bangla is essential for promoting a safe and inclusive digital environment for individuals communicating in this language.

**1.2 Research Motivation**

In today’s workplace environments, online communication platforms like Slack, Microsoft Teams, and company social forums have become vital for collaboration. However, these platforms are not immune to cyberbullying, which can undermine team cohesion, reduce productivity, and increase employee turnover. Real-time data analysis in such contexts enables organizations to maintain a healthy, respectful digital environment, ensuring employees feel safe and valued. Detecting harmful behavior quickly helps HR and management intervene before conflicts escalate, fostering a positive workplace culture.

Social media companies face immense pressure to provide safe online spaces while managing billions of daily user interactions. Platforms must balance freedom of expression with the prevention of harassment and abuse. Automated data analysis tools become indispensable to scan and classify millions of messages and posts instantly. This capability supports content moderation teams by highlighting potentially harmful content and prioritizing cases that need urgent human review. It also assists in complying with regulations around user safety and digital well-being.

Furthermore, educational institutions increasingly integrate social networks into student engagement and learning processes. However, cyberbullying incidents on these platforms can severely impact student mental health and academic performance. Real-time analysis tools help schools identify problematic interactions, enabling timely counseling and support interventions. The ability to process multilingual and culturally nuanced data is particularly important in diverse student populations. Thus, data-driven insights not only help protect individuals but also guide policy decisions in various sectors reliant on digital communication.

**1.3 Problem Definition**

Bot cyberbullying detection presents a complex challenge due to the dynamic and diverse nature of online communication. The problem involves identifying instances of harmful behavior within vast and varied datasets that include text, images, and multimedia across multiple languages and contexts. Online posts and messages often contain slang, abbreviations, sarcasm, and coded expressions, which complicates straightforward identification. The need arises to develop techniques that can accurately recognize harmful intent while minimizing false positives that could censor legitimate speech.

In addition, the high velocity and volume of data generated on social media platforms require scalable and efficient detection systems. These systems must operate in near real-time to provide timely alerts and prevent further harm. Moreover, cyberbullying may occur in private or encrypted groups, posing additional challenges for monitoring while respecting user privacy and legal constraints. Developing methods that balance effectiveness with ethical considerations remains a critical problem for researchers and practitioners.

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Finally, the consequences of misclassification are significant. Failure to detect cyberbullying can result in prolonged victimization, while incorrect labeling can harm innocent users and damage trust in moderation systems. Hence, the problem demands advanced natural language processing and machine learning techniques that understand context, sentiment, and subtle linguistic cues. Continuous adaptation to evolving communication trends and attacker tactics is essential for sustained success.

**1.4 Significance**

The significance of detecting cyberbullying from online social networks lies in its potential to protect millions of users from psychological harm and promote safer digital communities. Early detection can reduce the negative impact on victims, fostering healthier interactions and enhancing user well-being. By automating the identification process, social platforms and organizations can efficiently allocate resources toward intervention and support, improving response times and outcomes.

Furthermore, Bot cyberbullying detection contributes to legal and regulatory compliance. Many countries have enacted laws mandating social media companies to take measures against online harassment. Effective detection mechanisms help platforms meet these obligations and avoid legal liabilities. It also boosts public trust in digital services by demonstrating a commitment to user safety and corporate social responsibility.

The insights gained through detection systems also inform broader research and policy development. Understanding patterns and trends in cyberbullying facilitates the creation of targeted educational campaigns, mental health initiatives, and technological safeguards. The continuous refinement of detection technologies drives innovation in natural language processing and ethical AI applications, advancing the field and benefiting society at large.

**1.5 Research Objective**

The primary research objective is to develop a robust and accurate Bot cyberbullying detection system leveraging Convolutional Neural Networks (CNN). CNNs are well-suited for this task due to their ability to capture spatial hierarchies in data, enabling the extraction of contextual features from text representations. The system aims to classify online messages and posts into categories that reflect varying degrees of cyberbullying, incorporating multilingual support to address the global nature of social networks.

This approach focuses on designing, training, and validating CNN architectures optimized for sentiment and abusive language detection in real-time environments. The objective also includes integrating preprocessing techniques to handle noisy, informal language and utilizing annotated datasets to improve model generalization. Ultimately, the CNN-based model will support scalable, automated content moderation that aligns with user safety goals and regulatory standards.

**1.6 Advantages**

* CNNs excel at capturing local and global patterns in textual data, which enhances the detection of subtle abusive language cues.
* The model supports multilingual input, allowing for broad applicability across global social networks.
* Automated detection reduces the workload on human moderators, improving efficiency and consistency.
* Real-time processing capabilities enable swift identification and intervention in harmful interactions.
* CNN architectures are adaptable and can be fine-tuned for specific social media platforms or communication contexts.
* The system improves with continued training on new data, adapting to evolving cyberbullying tactics.
* Integration with existing social media infrastructure is feasible, enabling seamless deployment.
* Enhanced user trust is fostered through reliable and transparent content moderation.
* Scalability allows handling of large-scale datasets common in popular social networks.
* The approach can be extended to detect related issues like hate speech, misinformation, and harassment.

**1.7 Applications**

* Monitoring and moderating comments on popular social media platforms such as Facebook, Twitter, and Instagram.
* Enhancing digital safety in online gaming communities by detecting toxic behavior and harassment.
* Supporting workplace communication tools by identifying bullying and inappropriate conduct in chats.
* Assisting educational institutions in monitoring student interactions on learning management systems.
* Enabling parental control applications to alert guardians about potential cyberbullying incidents.
* Providing law enforcement agencies with tools to analyze social media for threats and harassment cases.
* Integrating into mental health apps to offer real-time support and intervention for bullied individuals.
* Facilitating research studies by automating large-scale analysis of cyberbullying trends and patterns.
* Supporting multilingual content moderation for global platforms serving diverse user bases.
* Improving user experience by fostering positive, respectful online communities through proactive moderation.

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**CHAPTER 2**

**LITERATURE SURVEY**

The World Wide Web (WWW) plays a pivotal role in the substantial growth of social media platforms [1,2], like Facebook, Twitter, Instagram, and YouTube. These platforms enable users to share a vast array of information, leading to increased user interactions. However, this also leads to an unregulated surge in online hate speech [3], a phenomenon that, in extreme cases, can drive individuals to take their own lives [4]. One of the most concerning phenomena is cyberbullying, which entails the dissemination of offensive content or other forms of violence through digital media [5,6,7] with the intent to harm an individual or a group of individuals. In particular, teenagers can assume the roles of victims, perpetrators, or simply bystanders [8] when it comes to cyberbullying. One study revealed that 36.5% of students have experienced cyberbullying at least once in their lives. Among all types of online comments, rude or cruel ones are the most prevalent. In a study conducted in the United States, which involved 1501 adolescents aged 10 to 17, it was discovered that 12% of the sample admitted to engaging in mistreatment, 4% declared themselves as victims, and 3% acknowledged being both aggressors and victims of cyberbullying [9].

The Cybercrime Division (CID) of Sri Lanka recently conducted a survey and detected that over 1000 cases of cyberbullying have been recorded. Surprisingly, more than 90% of university students reported being victims of cyberbullying, while nearly all survey participants stated that they knew someone who had experienced online bullying. It is alarming to note that 80% of the reported cases of cyberbullying in Sri Lanka occurred on Facebook, with 65% of university students admitting to sharing embarrassing videos or photos. Furthermore, the survey reveals that 15% of users share personal information online and 9% spread inaccurate information and falsehoods about others, while only 2% post offensive material [10].

One of the main problems of cyberbullying is its rapid spread due to the large online audience. Due to the fact that phenomenon has become a daily occurrence, victims often suffer severe consequences [11]. Based on the MetroWest Adolescent Health Survey, Schneider et al. [12] present the relationship between victimization and five categories of psychological distress. Information was collected from over 20,000 students. Among cyberbullying victims, self-harm (24%) and depressive symptoms (34%) showed the highest rates of psychological distress. These findings highlight a concerning connection between cyberbullying and psychological distress, underscoring the need to address this issue urgently.

An exponential increase in social media users and the subsequent rise of the cyberbullying phenomenon require a thorough investigation. However, previous studies (e.g., [13,14,15,16,17,18]) have addressed the issue using inefficient algorithms and with a limited amount of data for training AI algorithms. In actuality, studies conducted so far for the detection of the cyberbullying phenomena of social media present some significant limitations. For instance, Perera et al. [10] used a limited number of data instances (1000 labeled textual data) for classification by employing classifiers, like a Support Vector Machine (SVM) [19], but achieved an accuracy of 74%, which is considered inadequate. Alotaibi et al. [20] proposed a multicamera

deep learning framework based on a dataset of 55,788 tweets and developed a multicamera deep learning approach, but the 88% accuracy rate could still be improved upon. Ahmed et al. [21] used a Deep Neural Network with 44,001 comments from Facebook and attempted to develop a Hybrid Neural Network, but they achieved an accuracy of only 85%, which may not be deemed acceptable.

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Therefore, a robust and efficient model is required. In this research, we have developed a neural network model that provides highly accurate results, called the trustable LSTM-autoencoder network (TLA-NET). Furthermore, our model is capable of ensuring very high accuracy, overcoming the tendency of other methods to produce inaccurate results in the final layer. Specifically, we address issues related to the lack of available data, such as the absence of datasets for recognizing aggressive comments in Bangla and Hindi. For devising our technique, we utilize the TRAC-2 dataset (Workshop on Trolling, Aggression, and Cyberbullying) [22], which encompasses comments in English, Bangla, and Hindi. Furthermore, we create a dataset that is entirely translated automatically into English to tackle data accessibility challenges. Our approach to linguistic translation is straightforward; we employ Google Translate, which is easily accessible and free. While Google Translate translates data between languages, it introduces a certain level of noise that may not suit training deep learning models. We refer to this synthetic data as noisy since it undergoes machine translation and contains various sources of noise. It is important to notice here that, while the adoptation of Google Translate introduces, of course, a certain degree of noise, thus reducing the accuracy of the overall dataset, in our experimental work we applied a procedure to ensure the highest possible accuracy of the dataset to be used in our experiments. This approach, while valuable for our actual research, is poorly automatically generalizable in other languages. However, for each specific case, pragmatic solutions, like ours, can be investigated.

In this study, we aim to determine whether the proposed deep learning model can identify patterns in noisy data. Looking at the details, our TLA-NET model employs language transformers, such as bidirectional encoder representations from transformers (BERT) [23] and the Generative Pre-trained Transformer 2 (GPT-2) [24], along with simple neural networks, like long short-term memory (LSTM) [25], bidirectional long short-term memory (BiLSTM) [26], the LSTM-autoencoder [27,28,29], and Word2Vec [30].

Few authors considered the reference Bengali Cyberbullying Text Dataset [31], which provides a reliable testbed for performance evaluation and assessment. Also, our comparison is based on standard evaluation metrics, including accuracy, precision, recall, and F1-score [32], and advanced evaluation metrics [32], including mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE), plus other components, like confusion matrices [32] and receiver operating characteristic (ROC) curves [32]. We also consider, as competitive algorithms, some well-positioned-in-the-community machine learning (ML) algorithms, like the decision tree (DT) [33], random forest (RF) [34], logistic regression (LR) [35], and multilayer perceptron (MLP) models [36].

The proposed TLA-NET model delivers state-of-the-art results with an accuracy of about 99% in the raw Bangla dataset. It also achieves top-notch performance despite the presence of partially noisy datasets. Therefore, our method can be valuable for languages with limited data availability. Following our approach, efforts to reduce suicide-related incidents can be somewhat aided through the detection of aggressive comments and the implementation of prediction-based measures (e.g., [37]).

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On the other hand, collecting social media data raises the very relevant problem of ensuring the privacy of users (e.g., [38,39]). While this problem is of evident significance, it is not addressed in our research, and is left for future work to consider.

Ref. [41] focuses on addressing the annoying problem of detecting aggressive activity and cyberbullying behavior in textual content on social media platforms, which is critical for reducing its harmful impacts. Existing approaches leveraging traditional natural language processing (NLP) and ML techniques often face limitations in accuracy and contextual understanding. To address these drawbacks, this paper proposes an automated deep learning model using a binary chimp optimization (BCO)-based feature selection (BCO-FSS) technique and a stacked bidirectional gated recurrent unit (SBiGRU) with attention to spatial and sequential semantic learning. The study employs datasets from various platforms, like Formspring, Instagram, and MySpace, and integrates linguistic complexity metrics, such as feature density (FD), and finally utilizes BERT as a baseline classifier. The experimental evaluation of the proposed approach achieves high performance in terms of several well-known metrics, such as accuracy, precision, recall, and F1-score. Finally, this approach provides insights into the decision-making process of the model, due to the incorporation of attention mechanisms that visualize how sentiment weights are assigned at different layers.

Ref. [42] introduces an innovative and reliable framework for detecting cyberbullying built on top of a multi-modal cyberbullying detection (MMCD) approach that integrates data from diverse social networks. The proposed model effectively addresses the limitations of traditional text-based detection methods in handling the multifaceted nature of cyberbullying, by integrating hierarchical attention networks (HANs) with multi-modal data, including visual, textual, and temporal features, in order to provide a holistic cyberbullying detection platform. Specifically, it incorporates a self-attention-based BiLSTM model and HAN model focusing on word and comment levels, and other embedding techniques. The integration of these components enables efficient information merging and contributes to the effective resolution of the complex issue of cyberbullying. Moreover, the experimental analysis conducted over three social media datasets highlights that the MMCD model achieves greater performance when compared with several state-of-the-art models in terms of accuracy and F1-score.

In Ref. [43], the authors propose RoBERTaNET, an enhanced RoBERTa transformer model tailored for cyberbullying detection with global vectors for word representation (GloVe) word embedding features. Through this innovative approach, this research deals with the challenge of automatically identifying cyberbullying in Tweets from a publicly available cyberbullying dataset. The experimental analysis involves comparing the proposed approach with several state-of-the-art machine learning (e.g., random forest (RF), support vector machine (SVM), k-nearest neighbor (KNN)), deep learning (e.g., bidirectional long short-term memory (BiLSTM), convolutional long short-term memory (ConvLSTM)), and transformer-based models (e.g., bidirectional encoder representations from transformers (BERT)). The results demonstrate the effectiveness of RoBERTaNET by achieving a notable 95% accuracy, along with 95%, 97%, and 96% for precision, recall, and F1-score, respectively. In summary, this approach of combining robust transformer-based architectures with word embedding techniques paves the way for more effective and scalable solutions.

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Ref. [38] proposes FedBully, a novel federated learning (FL) approach for cyberbullying detection to preserve client privacy in learning systems. The proposed approach leverages sentence encoders for feature extraction and secure aggregation protocols in order to ensure data privacy while enabling effective collaborative learning. Therefore, the contributions of this research are threefold: (i) proposing FedBully for fast and privacy-preserving cyberbullying detection by adapting secure aggregation; (ii) demonstrating that secure aggregation protocols do not compromise model performance through extensive evaluations; (iii) conducting detailed analysis on the sampling rate and dataset imbalance to provide insights into the model sensitivity. Furthermore, an extensive experimental evaluation is conducted to optimize FedBully hyperparameters, in addition, it should be noted that the model achieves promising classification performance, with an over 93% of AUC metric over public large-scale cyberbullying datasets.

In Ref. [44], the authors present Bengalibullying, a robust hybrid machine learning model for cyberbullying detection in the Bengali language on social media. The proposed approach incorporates effective text preprocessing, TfidfVectorizer (TF-IDF)-based feature extraction, and instance hardness threshold (IHT) resampling to address dataset imbalance and improve model performance. Moreover, this research performs a comparative analysis with several ML models by using state-of-the-art metrics (e.g., accuracy, recall, F1-score, etc.). Using a publicly available dataset of 44,001 Bengali comments, the model achieves state-of-the-art results, with 98.57% accuracy in binary classification and 98.82% in multi-label classification, which outperforms all prior efforts in this domain. This research demonstrates the model’s potential for real-life application in cyberbullying detection systems, and offers a powerful tool for fighting cyberbullying across multiple language contexts.

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**CHAPTER 3**

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**EXISTING SYSTEM**

**3.1. Manual Sentiment Annotation by Experts**

This method involves having linguistic experts manually annotate a sample of multilingual text data with sentiment labels. Experts analyze the text's sentiment, considering nuances in grammar, idioms, and cultural context that automated tools might miss. This approach ensures high-quality ground truth data essential for training and validating the recurrent neural network model.

Experts work on each language dataset separately to maintain linguistic and cultural relevance in annotations. They review sentences or phrases, label them as positive, negative, neutral, or mixed sentiment, and provide explanations when ambiguity occurs. This helps in understanding subtleties that automated methods might overlook, improving the overall model robustness.

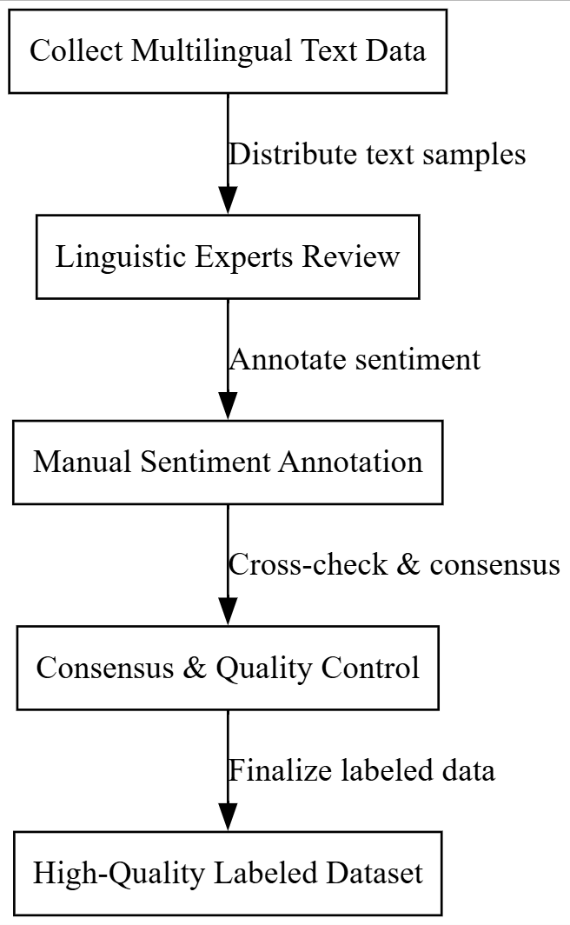


Fig.3.1: Manual Sentiment Annotation by Experts

The manual annotations can then be used to create a benchmark dataset to evaluate the model’s performance in real-time sentiment classification. Regular meetings among experts help calibrate their judgments, ensuring consistency and reducing bias in the labels. This high-quality data acts as a foundation for supervised learning and error analysis.

**3.2. Rule-Based Sentiment Analysis and Manual Verification**

In this method, a rule-based sentiment lexicon system is first applied to the multilingual text to provide preliminary sentiment labels. The system uses language-specific sentiment dictionaries and syntactic rules to assign sentiment scores. This initial labeling is fast and provides a rough sentiment distribution over the dataset.

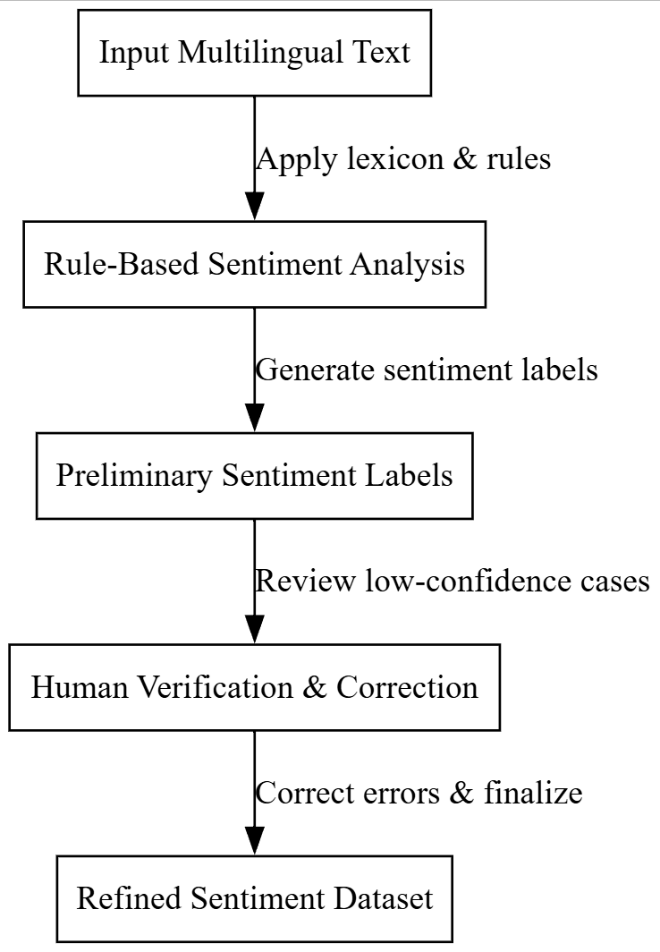


Fig.3.2: Rule-Based Sentiment Analysis and Manual Verification

Following automatic labeling, human analysts manually review and verify these outputs. They focus on ambiguous cases where the rule-based system’s confidence is low or where linguistic complexity might have caused errors, such as sarcasm, idioms, or mixed sentiments. This manual review improves accuracy by correcting systematic mistakes from the rule-based step.

The verified labels are then consolidated to form a refined dataset for training the RNN model. This semi-automated method leverages the speed of rule-based methods and the precision of manual review. It is particularly effective for scaling up annotation efforts while maintaining acceptable data quality.

**3.3. Crowdsourced Sentiment Labeling with Quality Control**

This method uses crowdsourcing platforms to gather sentiment annotations from a large number of non-expert annotators across different regions. The text samples are randomly distributed to multiple workers to get diverse opinions on sentiment, which helps capture varied cultural perceptions.

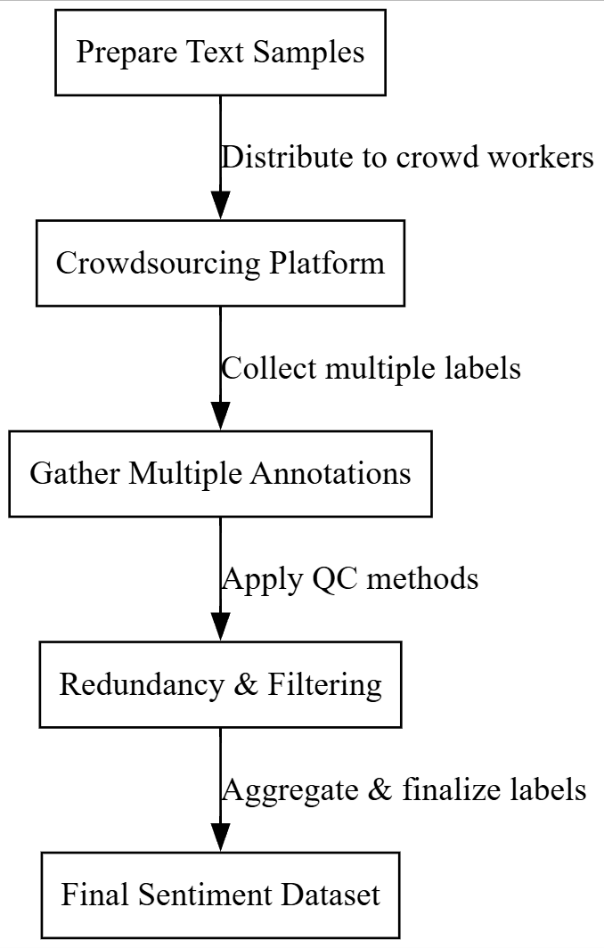


Fig.3.3: Crowdsourced Sentiment Labeling with Quality Control

To maintain quality, several measures are implemented: redundancy (multiple annotations per sample), gold-standard test questions to filter out low-quality workers, and statistical aggregation methods like majority voting or weighted averaging to combine annotations into a final label. Supervisors monitor ongoing results to detect biases or anomalies.

Crowdsourced data provides a large volume of labeled samples cost-effectively and quickly, which is valuable for training deep learning models like RNNs. Despite being non-expert, careful quality control enables reliable labels useful for sentiment classification in multiple languages.

**3.4 Overall Problem Statements**

* Difficulty in maintaining annotation consistency across different languages and cultural contexts.
* High time and cost requirements for manual labeling by experts.
* Challenges in handling ambiguous or mixed sentiments in short texts or social media language.
* Quality variability in crowdsourced annotations due to worker expertise and attention levels.
* Rule-based methods often miss contextual nuances, sarcasm, and evolving slang express

**CHAPTER 4**

**PROPOSED SYSTEM**

**4.1. System Architecture**

The proposed methodology introduces a novel hybrid multiclass unmasking bot detection system tailored for cyberbullying classification, integrating exploratory data analysis (EDA), refined preprocessing, and dual-model deep learning with unique feature extraction. This approach employs a seamless combination of N-gram-based textual representation with both Deep Neural Network (DNN) and Convolutional Neural Network (CNN) classifiers. Unlike existing survey methods that rely on traditional classifiers or shallow deep learning models, this hybrid model introduces a novel pipeline where statistical feature insights from EDA guide preprocessing, and sequential + spatial features are captured through dual-stream learning. The ensemble of DNN (for semantic depth) and CNN (for hierarchical patterns) offers a comprehensive interpretation of cyberbullying language patterns across multiple classes, thereby significantly improving classification performance on real-world noisy social media data.

**Step 1: Uploading and Visualizing Dataset (EDA)** The system begins by allowing the user to upload the cyberbullying dataset containing multiclass labels such as racism, sexism, threat, insult, etc. After uploading, Exploratory Data Analysis (EDA) is performed which includes statistical distribution plots, class imbalance visualization, and word frequency analysis. This step is crucial for understanding the raw structure and challenges of the dataset such as imbalance, redundancy, or missing values.

**Step 2: Preprocessing the Dataset** In this step, the textual data is cleaned and preprocessed. This involves removing stopwords, punctuation, HTML tags, and converting the text into lowercase. Tokenization is applied followed by lemmatization to normalize word forms. Special characters and usernames (e.g., @user) are removed to ensure clean, uniform data for feature extraction. This preprocessing directly supports high-quality vectorization.

**Step 3: Train-Test Splitting** The cleaned dataset is split into training and testing subsets using stratified sampling to preserve class distribution across sets. This step ensures that the performance evaluation is unbiased and generalizable. The split ratio (e.g., 80:20) is fixed for consistent model comparison.

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A diagram of a process

AI-generated content may be incorrect..

Figure 4.1. Proposed System Architecture.

**Step 4: N-Gram Feature Extraction** Using TF-IDF vectorization with N-gram range (1,2), the text data is transformed into a structured numeric format that captures local word dependencies and phrase-level semantics. This method allows detection of nuanced bullying patterns such as repeated abusive phrases, sarcasm, or indirect slurs, which uni-gram alone might miss.

**Step 5: Deep Neural Network (DNN) Training** The first model stream uses a multilayer DNN which is designed to learn dense abstract representations of the text vectors. Multiple hidden layers with ReLU activations and dropout regularization are used to avoid overfitting and extract deep semantic features relevant to each bullying class.

**Step 6: Convolutional Neural Network (CNN) Training** Parallel to DNN, the CNN model is trained on the same feature vectors. The CNN uses 1D convolutions to learn spatially correlated patterns across word sequences. Max-pooling layers reduce dimensionality while retaining high-value features. This spatial learning is particularly useful for detecting structured bullying phrases.

**Step 7: Prediction and Output Generation** Once both models are trained, the system uses either model (based on user selection) to perform predictions on new data. The predicted class labels are displayed, and model performance metrics such as accuracy, precision, recall, and F1-score are computed. This hybrid framework supports continuous evaluation and comparison.

**4.2 NLP Preprocessing**

Preprocessing is a crucial step that significantly enhances the performance and generalizability of the sentiment classification system. Since the input to the model originates from various online applications such as social media posts, customer feedback, and multilingual chat messages, it is essential to tailor preprocessing methods specifically to the nature of this content. Application-specific preprocessing ensures that noisy, unstructured text is converted into a clean, uniform format that aligns with the model’s expected input structure. This results in improved sentiment prediction accuracy and better handling of domain-specific vocabulary, abbreviations, emoticons, and multilingual nuances.

**Step 1: Text Normalization:** The first operation involves normalizing the raw text input. This includes converting all characters to lowercase to maintain consistency and reduce vocabulary size. Unicode normalization is applied to standardize characters from various languages, ensuring that accented characters and special symbols are correctly interpreted by the model. This step also includes the removal of redundant whitespace and formatting characters such as tabs and newlines.

**Step 2: Noise Removal:** The next step involves eliminating elements of the text that do not contribute meaningfully to sentiment analysis. URLs, HTML tags, mentions (e.g., @username), and hashtags are removed or replaced with placeholders. Special attention is given to filtering out promotional or repetitive content, especially in datasets derived from marketing platforms. Removing this noise prevents the model from learning irrelevant patterns and improves the signal-to-noise ratio in the training data.

**Step 3: Handling Emoticons and Emojis:** Emoticons and emojis are crucial sentiment indicators in informal digital communication. Rather than removing them, this method translates them into corresponding textual sentiment labels or keywords. For example, 😊 may be mapped to the word "happy" or a positive sentiment token. This preserves the emotional content of the message while enabling the model to interpret non-verbal cues effectively.

**Step 4: Spelling Correction and Slang Expansion:** User-generated content often includes misspelled words, abbreviations, or regional slang. This step applies basic spelling correction techniques and uses a domain-specific dictionary to expand common internet slang into their full forms. For example, "gr8" becomes "great", and "idk" becomes "I do not know". This reduces ambiguity and enhances the semantic clarity of the input.

**Step 5: Language Detection and Tokenization:** Since the system is multilingual, it incorporates a language detection module to identify the language of each input instance. Based on the detected language, a corresponding tokenizer is selected to split the text into meaningful tokens. The tokenization process respects language-specific grammar and sentence structures, ensuring that the resulting tokens are suitable for further embedding and processing in the neural network.

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**Step 6: Stopword Handling and Lemmatization:** Depending on the target language and application context, stopwords may be retained or removed. In sentiment analysis, some stopwords (like "not") carry important sentiment cues and are therefore preserved. Lemmatization is applied to reduce inflected words to their base forms without stripping away their meaning. For instance, "running", "ran", and "runs" are converted to "run", enabling the model to group similar terms effectively.

**Step 7: Padding and Encoding:** Finally, the cleaned and tokenized text is transformed into sequences of integers using language-specific vocabularies or embedding indices. Each sequence is padded or truncated to a fixed length, ensuring uniformity in batch processing. These encoded sequences are then ready to be passed into the recurrent neural network for training or inference.

**4.2.1 Padding extraction**

Padding refers to the white space between words, thus in padding extraction the space between two conjugative words will be extracted. In most of the times, the attackers wantedly use the whiter space to utilize the abusive text in the data. Thus, by using the padding extraction, the words contain white space will be precisely analyzed for Bot cyberbullying detection.

**4.2.2. Word signature**

Unknown word handling module Unknown words are defined as the words which are not in the lexicon or in reference sentences. Since CNN algorithm generate error as it detects unknown word therefore a separate module is required for tag decision for unknown word. In case of cyberbullying scenario, the attackers use the complicated abusive words; they may not be presented in the vocabulary. Thus, out of vocabulary words also considered for Bot cyberbullying detection.

**4.2.3. Non-ASCII conversion**

Electronic processing of text in any language requires that characters (letters of the alphabet along with special symbols) be represented through unique codes, this is called encoding. Usually, this code will also correspond to the written shape of the letter. A NON-ASCII conversion is basically a number associated with each letter so that computers can distinguish between different letters through their codes.

**4.3. Data detection stage**

In the data detection stage character level, word level and synonym level embedding operation will be performed. In this embedding character recognition, word recognition and synonym recognition operations will be performed parallel manner to give the maximum efficiency to detect the cyberbullying. Then the data groups will be formed as 3D array using pattern matching operations. The selection of character level or word level or synonym level Bot cyberbullying detection is performed by the user through user interface. Then corresponding 3d group array will be applied CNN.

**4.3.1. Data Clustering**

Data clustering plays an important role in organizing and grouping similar input data instances, which allows the sentiment classifier to operate more effectively in real-time and across multiple languages. Since input data comes from various applications like social networks, messaging platforms, and user feedback forms, clustering ensures that similar types of content are processed together. This leads to better contextual understanding, reduced noise, and more focused training. Clustering also aids in identifying domain-specific language patterns and improves training efficiency by minimizing redundancy in the dataset.

**Step 1: Feature Extraction from Preprocessed Text:** Once the text has undergone preprocessing, the first step in clustering involves converting each input instance into a numerical representation. This is typically done using word embeddings, sentence vectors, or TF-IDF scores. These vectors capture semantic similarity and represent the content in a multidimensional space, making it suitable for clustering algorithms to operate.

**Step 2: Dimensionality Reduction:** To make clustering more efficient and meaningful, dimensionality reduction is applied to the feature vectors. This step helps in eliminating redundant or less informative features and compressing the data into a lower-dimensional space. Techniques like Principal Component Analysis (PCA) or t-SNE are used depending on the nature and complexity of the data. This not only accelerates the clustering process but also improves cluster quality.

**Step 3: Choosing a Clustering Strategy:** The next step involves selecting an appropriate clustering algorithm based on the structure of the data. If the number of clusters is known beforehand or estimated through evaluation, partition-based methods like k-means can be used. For more complex datasets with unknown structure, density-based or hierarchical clustering methods are preferable. The algorithm is selected to suit the diversity and volume of the application-specific data.

**Step 4: Cluster Formation:** Using the chosen algorithm, the dataset is grouped into clusters based on vector similarity. Each cluster contains data instances that share similar patterns, sentiments, or linguistic features. This step allows the model to identify prevalent themes or sentiment trends within each group, which is especially useful when dealing with multilingual and informal text data.

**Step 5: Cluster Analysis and Label Assignment:** Once clusters are formed, they are analyzed to identify their predominant sentiment or language characteristics. Statistical measures or sample reviews help assign a representative label or tag to each cluster. This labeling helps in guiding the sentiment classifier with contextual information and improves both training and inference performance.

**Step 6: Feedback and Refinement:** The final step involves assessing the effectiveness of the clustering process through metrics such as cluster purity or silhouette score. Based on the evaluation, clusters may be refined by adjusting parameters or reprocessing the data. This iterative process ensures that the clusters remain meaningful and contribute positively to the downstream sentiment classification task.

**4.3.2. Grouping using 3D array**

A normalized longest common subsequence (NLCS) based string approximation method is proposed for indexing multidimensional data cube. In this indexing system, the reference table is made, and dimensional key values are stored for each dimension. A dimensional reference table is a set of dimensional key values stored in sorted order. The slot number of a key value in the dimensional reference table will be the index of the key value on the axis of multidimensional array. NLCS based string approximation is used to search a nearest keyword for a misspelled keyword, in the reference table and gets its slot number.

Normalized LCS based string approximation is used to design a character, word, and synonym (CWS) searching algorithm. This CWS searching algorithm gives near optimal solution to the string approximation problem. The algorithm finds the NLCS values of searched keyword with all the stored keywords in the set. The keywords in the set having NLCS value between 0.5 and 1 are the nearest neighbor of the searching keyword. The keyword closest to the searching keyword having highest NLCS value will be the optimal keyword. The CWS searching, finds the index of keyword, like searching keyword from the set of stored keywords and creates the 3d array group for easily detection of cyberbullying. So, the abusive words and its synonyms will be identified easily.

**4.3.3. N-gram Feature selection**

The N-gram model combined with latent representation on the data classification task. Their model called as supervised n-gram embedding uses a multi-layer perceptron to accomplish the embedding. The number of distinct character and word-based N grams in a text can be as high and its feature selection vector size extremely high even for moderate values of n. The **N-**gram Feature selection applied only oncharacter and word-based embedding vectors as it does not apply on synonym based embedding vector. Because synonym-based vectors are classified initially in the synonym level embedding so there is no requirement to generate the features again. If the N-gram feature selection applied on synonym based embedding vectors, then classification accuracy will reduce because of original features will get loosed. However, only a small fraction of all possible character and word-based n grams will be present in any given set of documents, thereby reducing the dimensionality substantially. The dimensionality reduction problem is handled in the present work in two different approaches where one set of n grams are identified as valid N grams and other set is treated as invalid N grams. The adequacy of this model is also evaluated in terms of average information conveyed by valid N grams in comparison with invalid N grams.

N-grams are subsequences of n items (words in this case) extracted from the text data. The choice of n depends on the specific task and the level of granularity desired. Common values for n include 1 (unigrams), 2 (bigrams), and 3 (trigrams), but higher values can also be used for more context.

**Step 1. Sliding Window:** Imagine a window of fixed size moving across the text. This window captures consecutive sequences of words. The size of the window is determined by the value of 'n' in n-grams. For example, in bigrams (n=2), the window would capture pairs of words.

**Step 2. Extracting N-grams:** As the window slides, it extracts the subsequences of words. These subsequences are the n-grams. For instance, with n=2, if we have the sentence "The cat sat on the mat", the bigrams would be "The cat", "cat sat", "sat on", "on the", "the mat".

**Step 3. Vector Representation:** Each unique n-gram extracted from the text is represented as a feature. The frequency of occurrence of each n-gram within a document or tweet is recorded. This creates a numerical representation of the text data.

**Step 4. Sparse Matrix:** The resulting dataset is often represented as a sparse matrix. In this matrix, each row corresponds to an individual document or tweet, and each column represents the presence or absence of a specific n-gram feature. Since most documents contain only a small subset of all possible n-grams, the matrix is mostly filled with zeros, making it sparse. This format is efficient for storage and computation

**Benefits of N-grams:**

* N-grams capture local syntactic and semantic relationships between words, allowing the model to learn from the context of the text.
* They encode information about word order, collocations, and co-occurrences, which can improve the performance of NLP tasks such as sentiment analysis, topic modeling, and text classification.
* By considering sequences of words rather than individual words, n-grams provide richer contextual information and help address the issue of data sparsity in high-dimensional text data.

**4.4 Existing Deep Neural Network**

Deep Neural Network Framework Compared to typical machine learning algorithms, which automate procedures to perform complicated problems, deep learning algorithms have shown to be more efficient. An extension of a multi-hidden layer artificial neural network (ANN), a deep neural network (DNN) was execute several complex tasks since each layer is only connected to its predecessor and to the subsequent layer in the cached section.

Deep neural networks, which often have a complex hidden layer structure with a wide variety of different layers, such as a convolutional layer, max-pooling layer, dense layer, and other unique layers. These additional layers help the model to understand problems better and provide optimal solutions to complex projects. A deep neural network has more layers (more depth) than ANN and each layer adds complexity to the model while enabling the model to process the inputs concisely for outputting the ideal solution.

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A diagram of a layer of layers

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Fig.4.2: Block Diagram of Existing DNN

**Existing Word Embeddings:**

Word embeddings serve as the cornerstone of word-based DNN approaches, providing a powerful means to represent and analyze textual data. Here's a detailed explanation of the key points:

* **Fundamental Building Block:** Word embeddings are crucial components of many natural language processing (NLP) tasks and DNN architectures. They are employed to represent words in a numerical format that neural networks can process efficiently.
* **Continuous Vector Space:** Word embeddings are typically learned in a continuous vector space, often of hundreds of dimensions. In this space, words are positioned in relation to each other based on their meanings and contextual usage.
* **Semantic Proximity:** Words with similar meanings or contextual usage are placed closer to each other in the embedding space. This means that the numerical representations of these words share similarities or have high cosine similarity scores.
* **Dense Vector Representations:** Each word is represented by a dense vector of real numbers in the embedding space. These vectors are dense because they contain a large number of non-zero values, capturing intricate semantic nuances of the words they represent.
* **Capturing Semantic Connections:** Word embeddings capture semantic connections between words by learning from large amounts of text data. During the training process, the model learns to predict the context of a word based on its surrounding words, effectively capturing the semantic relationships between words.
* **Enhanced Context Comprehension:** By utilizing word embeddings, neural networks can better understand the context of a phrase or sentence. This is because the embeddings encode semantic similarities between words, allowing the network to infer meanings and relationships between words within a given context.

**4.5 Proposed Deep-learning CNN**

Convolutional Neural Networks (CNNs) are highly effective in processing application-specific textual data for sentiment classification, especially when dealing with short texts, informal language, or multilingual inputs from social platforms. They excel at capturing local patterns, such as key phrases or n-grams, which are essential for identifying sentiment-related cues. Unlike traditional models, CNNs can automatically learn hierarchical feature representations without relying on handcrafted rules. This makes them suitable for real-time applications where input data varies widely in structure, tone, and language. CNNs are also computationally efficient, making them a good fit for environments requiring fast sentiment inference.

**Step 1: Input Representation:** The first step involves converting the clustered and preprocessed text into a structured format that can be fed into the CNN. Typically, this includes transforming each sentence into a matrix where each row corresponds to a word vector. These vectors are obtained through embedding techniques such as Word2Vec, GloVe, or contextual embeddings depending on the language and domain. This matrix preserves the word order and captures semantic relationships between terms.

**Step 2: Convolution Operation:** After input representation, the CNN applies convolutional filters over the matrix. Each filter slides over the text matrix and detects local patterns such as word sequences, sentiment phrases, or emotional cues. Multiple filters of varying sizes are used to capture different n-gram features. The result of this operation is a set of feature maps that highlight the presence of meaningful patterns across the text.

**Step 3: Activation and Non-linearity:** Once feature maps are generated, an activation function is applied to introduce non-linearity. This step allows the model to learn complex relationships between input patterns and sentiment outcomes. Functions like ReLU are commonly used to enhance the model’s ability to generalize and differentiate between subtle emotional cues in the text.

**Step 4: Pooling Operation:** To reduce dimensionality and focus on the most important features, pooling is applied to the activated feature maps. Max-pooling is often used, where the maximum value from a region of the feature map is selected. This helps retain the strongest signal or most relevant sentiment indicator from each region while discarding less important information. Pooling also adds robustness against small changes in input structure or noise.

**Step 5: Flattening and Fully Connected Layer:** The pooled features are then flattened into a single long vector, which serves as the input to one or more fully connected layers. These layers combine the localized features into a global representation of the sentiment. They are responsible for learning high-level abstractions such as overall tone, emotion, or intent expressed in the text.

**Step 6: Classification and Output:** In the final step, the output from the last fully connected layer is passed through a softmax or sigmoid layer depending on whether the task is multi-class or binary sentiment classification. This layer generates a probability distribution over sentiment classes, and the class with the highest probability is selected as the output sentiment label.

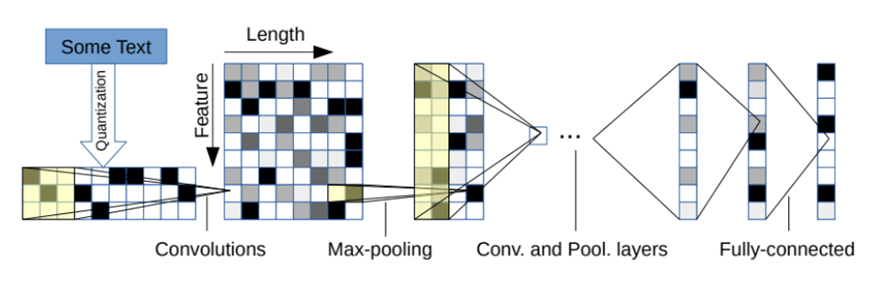


Fig : 4.3. Character Based CNN

**Advantages of CNN**

**Handling Out-of-Vocabulary Words:** CNNs can handle out-of-vocabulary words effectively since they operate directly on individual characters rather than predefined word tokens. This makes them robust to unseen or rare words, which can be particularly useful in tasks involving specialized domains or evolving language use.

**Handling Short Texts:** CNNs are well-suited for processing short texts, such as social media posts, tweets, or search queries. Unlike word-based models, which was struggle with short texts due to limited context, character-based models can capture important patterns and features at the character level, enabling effective analysis of short and contextually sparse text data.

**Handling complex morphology** **:** By processing text data at the character level, CNNs can capture intricate patterns and structures, making them suitable for various natural language processing tasks, especially when dealing with languages with complex morphology or limited training data.

**Model Size and Efficiency:** CNNs can be more space-efficient compared to word-based models, especially when dealing with large vocabularies. Since they operate directly on characters, the size of the input vocabulary is typically smaller, leading to more compact models and faster training times.

**Robustness to Misspellings and Typos:** Working on only characters also has the advantage that abnormal character combinations such as misspellings and emotions are naturally learnt.

**Capturing Subword Information:** They capture subword information, which can be beneficial for tasks like named entity recognition or sentiment analysis.

**Enhanced Generalization:** CNNs can generalize better across tasks and domains compared to word-based models, especially in scenarios where the vocabulary size varies significantly between training and testing data. By operating directly on characters, these models can adapt more readily to new vocabulary items and unseen word forms encountered during inference, leading to improved generalization performance.

**Domain Adaptability:** CNNs are highly adaptable to different domains and text genres, requiring minimal domain-specific preprocessing or feature engineering. This makes them suitable for a wide range of applications, including sentiment analysis, text classification, machine translation, and more, across various domains such as healthcare, finance, social media, and legal text.

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**CHAPTER 5**

**UML DIAGRAMS**

Unified Modeling Language (UML) is a standardized visual language used to model, design, and document the architecture of software systems. It provides a set of graphical notations to represent the structure and behavior of a system, making complex systems easier to understand and communicate among developers, stakeholders, and business analysts.

**Key Points About UML**

* **Standardized Notation:** UML offers a universal set of symbols and diagrams that standardize how software systems are described, which helps teams speak the same language regardless of their background or the programming language they use.
* **Types of Diagrams:** UML includes various diagrams that can be categorized into two main types:
  + **Structural Diagrams:** These describe the static aspects of the system. Examples include Class Diagrams, Component Diagrams, and Deployment Diagrams.
  + **Behavioral Diagrams:** These focus on the dynamic aspects and interactions within the system. Examples include Use Case Diagrams, Sequence Diagrams, Activity Diagrams, and Collaboration Diagrams.
* **System Documentation and Communication:** UML serves as an effective tool for documenting system requirements, design decisions, and the overall architecture. It helps bridge the gap between technical and non-technical stakeholders by providing clear, visual representations of the system.
* **Design and Analysis:** By modeling different aspects of a system, UML enables developers to analyze and validate the design early in the development process. This can lead to better decision-making, reduced complexity, and improved system maintainability.

**Flexibility:** UML is versatile and can be used across a wide range of applications, from small-scale projects to large, complex systems. It supports object-oriented design principles and can be adapted to various methodologies such as Agile or Waterfall

**CLASS DIAGRAM**

A class diagram in UML serves as a blueprint for defining the static structure of a system by illustrating its classes, their attributes, methods, and the relationships among them. Each class represents a key entity in the system, with attributes describing its properties and methods outlining its behaviors or functionalities. Relationships like "is-a" (inheritance) or "has-a" (association) clarify how classes interact, enabling developers to refine the system’s design based on use case requirements. This diagram is crucial for translating high-level requirements into a detailed, implementable structure, ensuring all components are clearly defined and interconnected.

In the context of AI systems, class diagrams are particularly valuable for modeling complex architectures, such as neural networks or decision-making systems. For example, an AI system for recognition might include classes like "Processor," "FeatureExtractor," and "Classifier," each with specific attributes (e.g., resolution) and methods (e.g., preprocess()). By mapping these elements, the diagram provides a clear framework for developers to build and integrate AI components, ensuring modularity and scalability while aligning with the system’s functional goals.

Diagram, table

Description automatically generated

Fig.5.1: Class Diagram

**USE CASE DIAGRAM**

A use case diagram in UML offers a high-level, behavioral view of a system by depicting its actors, use cases, and their interactions. Actors, which can be users or external systems, represent entities interacting with the system, while use cases describe specific functionalities or goals the system supports, such as "Login" or "Process Payment." The diagram highlights dependencies, such as "includes" or "extends" relationships, to show how use cases relate, providing a clear picture of what the system does and who it serves. This makes it an essential tool for stakeholders to understand system functionality without diving into technical details.

For AI systems, use case diagrams are instrumental in outlining how users or other systems interact with AI functionalities. For instance, in a chatbot system, actors like "User" or "Admin" might engage with use cases like "Send Message" or "Train Model." The diagram helps developers and stakeholders align on the AI system’s scope, ensuring that critical interactions, such as user queries or model updates, are captured early in the design process, facilitating clear communication and requirement validation.

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Diagram

Description automatically generated

Fig.5.2: Use Case Diagram

**SEQUENCE DIAGRAM**

A sequence diagram in UML illustrates the dynamic interactions between objects or processes in a system, focusing on the order of messages exchanged over time. Represented by vertical lifelines for each object and horizontal arrows for messages, it captures the flow of operations, such as method calls or data exchanges, in a specific scenario. This makes it ideal for detailing how components collaborate to achieve a particular function, providing a clear, step-by-step visualization of system behavior.

In AI applications, sequence diagrams are particularly useful for modeling the runtime behavior of complex processes, such as how a Outputn system processes user input. For example, a sequence diagram might show a "User" sending a query to a "OutputnEngine," which then interacts with a "DataStore" and a "PredictionModel" to return results. This clarity helps developers debug and optimize AI workflows, ensuring efficient communication between components like data pipelines and inference modules, ultimately improving system performance.

Diagram

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Fig.5.3: Sequence Diagram

**ACTIVITY DIAGRAM**

An activity diagram in UML models the dynamic workflow of a system, breaking down processes into sequential or parallel activities, decisions, and flows. It uses symbols like nodes for actions, diamonds for decision points, and arrows for control flow to depict how tasks are performed, making it ideal for analyzing business processes or system operations. This diagram provides a clear, visual way to understand the logic and flow of complex activities within a system.  
In AI contexts, activity diagrams are useful for mapping out processes like data preprocessing or model training workflows. For example, an activity diagram for an AI pipeline might show steps like "Collect Data," "Clean Data," "Train Model," and "Evaluate Results," with decision points for handling errors or retraining. This helps developers optimize AI workflows, identify bottlenecks, and ensure that processes like hyperparameter tuning or data validation are systematically executed.

Diagram

Description automatically generated

Fig.5.4: Activity Diagram

**DEPLOYMENT DIAGRAM**

A deployment diagram in UML illustrates the physical architecture of a system, showing how software components are distributed across hardware nodes, such as servers, cloud instances, or edge devices. It highlights the relationships between these nodes, including communication protocols or network connections, providing a clear view of how the system is deployed in a real-world environment. This is essential for understanding the system’s infrastructure and ensuring it meets performance and scalability requirements.

For AI systems, deployment diagrams are key to visualizing how models and services are hosted. For example, a machine learning system might have a "TrainingServer" hosting a "ModelTraining" component and an "InferenceServer" running a "PredictionService," connected via a cloud network. This diagram helps developers optimize resource allocation, such as GPU usage for AI inference, and ensures robust deployment strategies, particularly for distributed AI applications like real-time analytics or IoT-based systems.

Diagram, schematic

Description automatically generated

Fig.5.5: Deployment Diagram

**COMPONENT DIAGRAM**

A component diagram in UML visualizes the organization and relationships of a system’s physical or logical components, such as modules, libraries, or subsystems. It shows how these components are interconnected through interfaces, emphasizing modularity and reusability in the system’s architecture. By abstracting the system into manageable parts, it helps developers understand how different pieces, like databases or APIs, work together to deliver functionality.

In AI systems, component diagrams are critical for mapping out the architecture of distributed or modular systems. For instance, an AI platform might include components like "DataIngestionModule," "ModelTrainingUnit," and "InferenceEngine," each interacting through defined interfaces. This diagram aids in designing scalable AI solutions, ensuring components like preprocessing pipelines or model servers are loosely coupled yet cohesive, which is vital for deploying and maintaining complex AI systems.

Diagram

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Fig.5.6: Component Diagram

**DATAFLOW DIAGRAM**

A Data Flow Diagram (DFD) illustrates how data moves through a system, showing processes, data stores, external entities, and the flow of information between them. Unlike UML diagrams, which focus on system structure or behavior, DFDs emphasize the transformation and movement of data, making them ideal for understanding how information is processed and stored. They are particularly useful for breaking down complex systems into manageable, data-centric processes.

In AI systems, DFDs are invaluable for mapping data pipelines, such as those in machine learning workflows. For instance, a DFD might show data flowing from an "External Sensor" to a "Data Preprocessing" process, then to a "Model Training" process, and finally stored in a "Model Repository." This helps developers trace data transformations, ensure data integrity, and optimize AI systems for tasks like real-time predictions or large-scale data analytics, aligning system design with data-driven requirements.

Diagram

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Fig.5.7: Data Flow Diagram

**CHAPTER 6**

**SOFTWARE REQUIREMENTS**

**6.1 Software Requirements**

Python 3.7.6 serves as a pivotal version for developers and researchers due to its robust features, backward compatibility, and widespread support across a variety of libraries and frameworks. Released during a time when machine learning and data science tools were rapidly evolving, Python 3.7.6 provided a stable and consistent platform. This version includes critical improvements like enhanced asyncio functionality for asynchronous programming, increased precision for floating-point numbers, and optimized data structures. It became the go-to version for compatibility with popular libraries like TensorFlow 2.0, PyTorch, and Pandas, ensuring seamless integration and efficient execution for both academic and industrial applications.

Compared to older Python versions, 3.7.6 introduced several features such as dataclasses, which simplified boilerplate code for object-oriented programming. The improved async and await syntax made concurrent programming more intuitive, while changes to the standard library enhanced usability and performance. Over newer versions, Python 3.7.6 remains a preferred choice for legacy systems and researchs requiring compatibility with libraries that may not yet support the latest Python updates. Its combination of stability and maturity ensures that it is reliable for long-term researchs, especsially in environments where upgrading the Python interpreter might disrupt existing workflows.

**6.1.1 TensorFlow Environment**

TensorFlow provides a comprehensive ecosystem for building, training, and deploying machine learning models. Its support for numerical computation and deep learning applications makes it a staple in AI research and development. By offering a flexible architecture, TensorFlow enables deployment across a variety of platforms, including desktops, mobile devices, and the cloud. The ability to scale across CPUs, GPUs, and TPUs ensures that TensorFlow is suitable for both small experiments and large-scale production systems.

TensorFlow’s transition from older versions, like 1.x, to 2.x brought significant improvements in ease of use, including the introduction of the tf.keras API for building models, eager execution for dynamic computation, and enhanced debugging capabilities. Compared to newer frameworks, TensorFlow retains a strong advantage due to its mature community support, extensive documentation, and integration with TensorFlow Extended (TFX) for managing production pipelines. Its compatibility with other libraries and tools, such as Keras and TensorBoard, makes it a robust choice for end-to-end machine learning solutions.

**6.1.2 Packages Overview**

**Keras:** Older versions of Keras required extensive configuration for custom model creation. Version 2.3.1 unified the APIs with TensorFlow integration, reducing overhead and enabling direct use of TensorFlow backends, ensuring faster execution and easier debugging.While newer versions focus on performance and distributed training, version 2.3.1 is lightweight and stable, making it ideal for smaller researchs without the complexity introduced in later iterations, which are more suited for advanced workflows.

**NumPy:** Version 1.19.5 introduced critical bug fixes and performance enhancements over older versions, especially for operations involving large datasets. The improved random number generator and better handling of exceptions provide more reliable results for numerical computations.This version remains compatible with a wide range of dependent packages. While newer versions optimize speed further, 1.19.5 balances stability and compatibility, ensuring fewer compatibility issues with older software stacks.

**Pandas:** Version 0.25.3 brought significant speed improvements for large-scale data processing, particularly in operations like groupby. Enhancements in handling missing data and improved compatibility with external libraries made this version more robust for data analysis tasks.While newer versions does not add features like enhanced type checking, 0.25.3 remains lightweight and stable for researchs that do not require cutting-edge functionalities, making it a practical choice for legacy systems.

**Imbalanced-learn:** Version 0.7.0 introduced optimized algorithms for handling class imbalances, such as improved SMOTE implementations. This update also enhanced the ease of integrating with scikit-learn pipelines.While newer versions do not contain experimental features, 0.7.0 is reliable and well-documented, ensuring robust performance in addressing data imbalance issues without unnecessary complexity.

**Scikit-learn:** Version 0.23.1 included improved support for cross-validation and hyperparameter optimization. Updates to RandomForestClassifier and GradientBoostingClassifier increased model accuracy and efficiency.0.23.1 is widely tested and compatible with older hardware, making it a dependable choice for environments where the latest versions may introduce compatibility issues.

**Imutils:** This package provides an easy-to-use interface for image processing tasks. Its functions for resizing, rotating, and translating images simplified workflows compared to writing custom code.Its lightweight nature and stable functionality make it suitable for researchs not requiring cutting-edge image manipulation techniques, balancing simplicity and capability.

**Matplotlib:** Version 3.x improved plot interactivity and introduced better 3D plotting capabilities. The tight\_layout function and compatibility with modern libraries streamlined visualization workflows.The earlier versions maintain stability and compatibility with older datasets and software, avoiding potential issues from newer, untested updates.

**Seaborn:** Improved APIs in newer versions simplified aesthetic customization of plots. The addition of new themes and color palettes in 0.11.x enhanced visual appeal for exploratory data analysis.Older versions remain computationally less demanding, suitable for lightweight applications without requiring extensive customizations.

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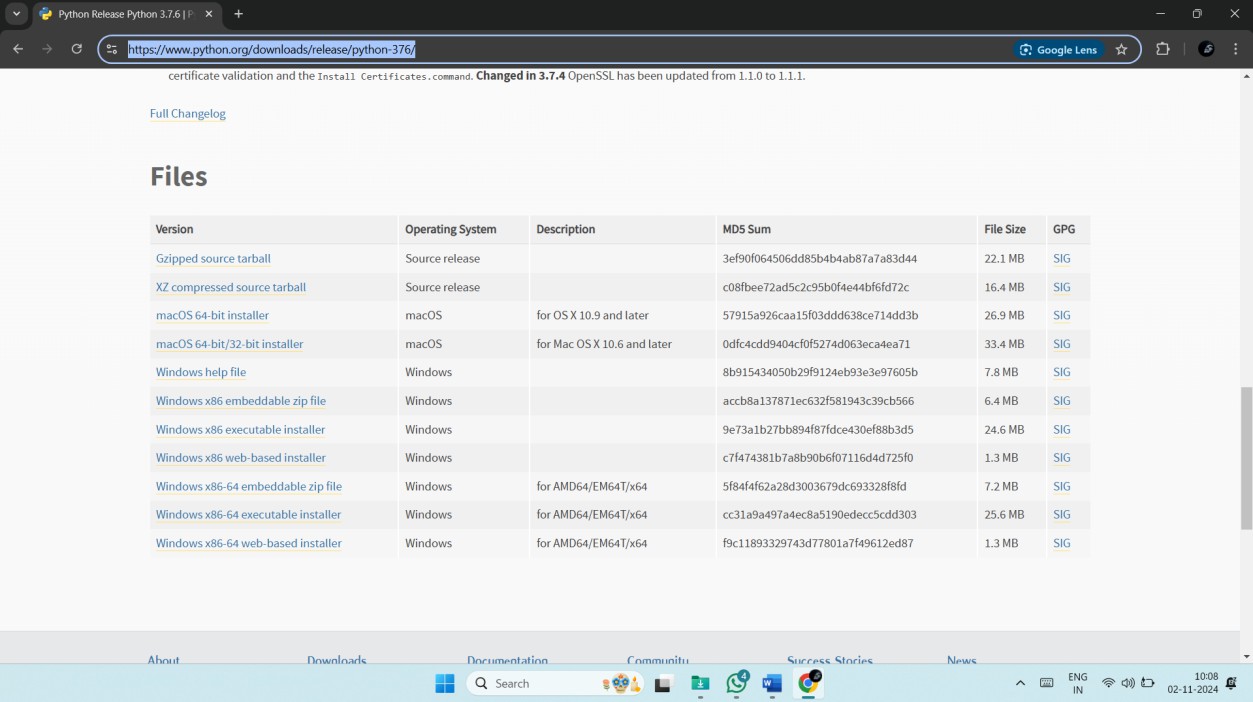
**OpenCV-Python:** Recent updates enhanced compatibility with deep learning frameworks and accelerated image processing pipelines, especially for real-time applications.Older versions are stable and resource-efficient, making them ideal for systems with limited computational capacity or for legacy applications.

**H5Py:** Version 2.10.0 improved file handling efficiency for large datasets. It introduced better support for advanced indexing, which is crucial for working with high-dimensional data.While newer versions support more advanced features, 2.10.0 ensures compatibility with older machine learning frameworks and models.

**Jupyter:** Jupyter improved the interactivity and scalability of notebooks for collaborative coding and visualization tasks. Integration with tools like Matplotlib made it a preferred environment for data exploration.Earlier versions are stable and lightweight, avoiding potential issues with dependencies introduced in newer releases.

**6.1.3 Python Installation Procedure**

**Step 1: Download Python 3.7.6** Visit the official Python website by clicking the following link: [https://www.python.org/downloads/release/python-376/](https://www.python.org/downloads/release/python-376/" \t "_blank). Scroll down the page until you reach the "Files" section. Locate the downloadable file for your operating system (e.g., Windows, macOS, or Linux) and click the corresponding link to start the download.



**Step 2: Verify the Downloaded File:** Once the download is complete, you will have the Python 3.7.6 installer file on your system. Ensure the file matches your operating system (e.g., a .exe file for Windows or a .pkg file for macOS) before proceeding to the next step. Click “Add Python 3.7 to Path”, which creates the environmental variables in OS. So, the user will get access to the python with command prompt.

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A screen shot of a computer

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A screen shot of a computer

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**Step 3: Begin the Installation Process:** Open the downloaded Python installer file. During the installation setup, you will see an option labeled "Add Python 3.7 to PATH." Make sure to check this box to ensure Python is added to your system's environment variables, allowing you to run Python from the command line easily.

**Step 4: Install Python:** After checking the "Add Python 3.7 to PATH" box, click the "Install Now" button to start the installation. Wait for the installation process to complete. Once finished, you will see a confirmation message indicating that Python 3.7.6 has been successfully installed.

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A screen shot of a computer

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**Step 5: Verify the Installation:** Open the Command Prompt (on Windows) or Terminal (on macOS/Linux). Type "python --version" and press Enter. If the installation was successful, the output should display "Python 3.7.6." This confirms that Python is correctly installed and accessible.

A screenshot of a computer

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**Step 6: Exit the Python Interpreter:** If you entered the Python interactive shell by typing "python," exit it by typing "exit()" and pressing Enter. This will return you to the Command Prompt or Terminal.

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**Step 7: Install the Required Packages:** Use the following commands to install the necessary Python packages. Enter each command one by one in the Command Prompt or Terminal, pressing Enter after each. These commands will upgrade pip (Python's package manager) and install the specified versions of the required libraries:

* python -m pip install --upgrade pip
* pip install tensorflow==1.14.0
* pip install keras==2.3.1
* pip install pandas==1.3.5
* pip install scikit-learn==1.0.2
* pip install imutils
* pip install matplotlib==3.2.2
* pip install seaborn==0.12.2
* pip install opencv-python==4.1.1.26
* pip install h5py==2.10.0
* pip install numpy==1.19.2
* pip install imbalanced-learn==0.7.0
* pip install jupyter
* pip install protobuf==3.20.\*
* pip install scikit-image==0.16.2

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**6.2 Hardware Requirements**

Python 3.7.6 can run efficiently on most modern systems with minimal hardware requirements. However, meeting the recommended specifications ensures better performance, especially for developers handling large-scale applications or computationally intensive tasks. By ensuring compatibility with hardware and operating system, can leverage the full potential of Python 3.7.6.

**Processor (CPU) Requirements:** Python 3.7.6 is a lightweight programming language that can run on various processors, making it highly versatile. However, for optimal performance, the following processor specifications are recommended:

* **Minimum Requirement**: 1 GHz single-core processor.
* **Recommended**: Dual-core or quad-core processors with a clock speed of 2 GHz or higher. Using a multi-core processor allows Python applications, particularly those involving multithreading or multiprocessing, to execute more efficiently.

**Memory (RAM) Requirements:** Python 3.7.6 does not demand excessive memory but requires adequate RAM for smooth performance, particularly for running resource-intensive applications such as data processing, machine learning, or web development.

* **Minimum Requirement**: 512 MB of RAM.
* **Recommended**: 4 GB or higher for general usage. For data-intensive operations, 8 GB or more is advisable.

Insufficient RAM can cause delays or crashes when handling large datasets or executing computationally heavy programs.

**Storage Requirements:** Python 3.7.6 itself does not occupy significant disk space, but additional storage required for Python libraries, modules, and researchs.

* **Minimum Requirement**: 200 MB of free disk space for installation.
* **Recommended**: At least 1 GB of free disk space to accommodate libraries and dependencies.

Developers using Python for large-scale researchs or data science should allocate more storage to manage virtual environments, datasets, and frameworks like TensorFlow or PyTorch.

**Compatibility with Operating Systems:** Python 3.7.6 is compatible with most operating systems but requires hardware that supports the respective OS. Below are general requirements for supported operating systems:

* **Windows**: 32-bit and 64-bit systems, Windows 7 or later.
* **macOS**: macOS 10.9 or later.
* **Linux**: Supports a wide range of distributions, including Ubuntu, CentOS, and Fedorz.

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**CHAPTER 7**

**FUNCTIONAL REQUIREMENTS**

Functional requirements are detailed statements that specify what a system should do. They describe the system's behavior, functions, and services, outlining how it responds to certain inputs, performs tasks, and interacts with users or other systems. Essentially, they answer the question, "What should the system do?" Here are some key aspects:

* Functionality: They define the specific functions or operations that the system must perform.
* Inputs and Outputs: They detail the types of inputs the system accepts and the outputs it produces.
* User Interactions: They describe how users interact with the system, including command inputs, error handling, and responses.
* Data Management: They outline requirements related to data storage, retrieval, and processing.
* System Behavior: They specify how the system behaves in various scenarios, including normal operations and exceptional conditions.

Below is a breakdown of the functions used in the research along with their requirements. These “function requirements” describe what each function is responsible for, the expected inputs, processing steps, and outputs or side effects. This can serve as a high-level specification for each function in the research.

**1. Requirements Analysis Stage**

This stage focuses on identifying the functional requirements of the system based on user needs and system objectives. The requirements are derived from the provided script and its intended functionality.

**FR1: User Interface for Dataset Interaction**

* The system shall provide a graphical user interface (GUI) using Tkinter to allow users to interact with the cyberbullying classification system.
* The GUI shall include buttons for uploading datasets, performing exploratory data analysis (EDA), preprocessing data, splitting data, feature extraction, training models, making predictions, and exiting the application.
* The GUI shall display a text area to show the status, results, and outputs of operations such as dataset loading, preprocessing, and model performance metrics.
* The GUI shall be responsive, with a fixed window size based on the screen resolution, and use a consistent theme (e.g., misty rose background, olive text).

**FR2: Dataset Upload and Management**

* The system shall allow users to upload a CSV dataset containing tweet text and cyberbullying type labels via a file dialog.
* The system shall display the file path and a preview of the dataset (e.g., first few rows) in the text area upon successful upload.
* The system shall support datasets with at least two columns: tweet\_text (text data) and cyberbullying\_type (categorical labels).

**FR3: Exploratory Data Analysis (EDA)**

* The system shall generate a bar plot to visualize the distribution of cyberbullying types in the dataset.
* The system shall support the generation of word clouds for each cyberbullying category (commented out in the code but intended as a feature).
* The EDA results (e.g., plots) shall be displayed in separate windows using Matplotlib.

**FR4: Data Preprocessing**

* The system shall preprocess tweet text by removing URLs, mentions, hashtags, special characters, and converting text to lowercase.
* The system shall tokenize text, remove stopwords, and apply stemming using NLTK’s PorterStemmer.
* The preprocessed data shall be stored in a new column (preprocessed\_tweet) in the dataset, and a preview of the preprocessed dataset shall be displayed in the text area.

**FR5: Train-Test Split**

* The system shall split the dataset into training (80%) and testing (20%) sets using scikit-learn’s train\_test\_split function.
* The system shall map cyberbullying type labels to numerical values (e.g., not\_cyberbullying: 0, religion: 1, etc.).
* The system shall display the shape of the training and testing datasets in the text area.

**FR6: Feature Extraction**

* The system shall perform N-gram feature extraction using TfidfVectorizer on the preprocessed tweet text.
* The system shall store the extracted features for training and testing datasets and display the feature extraction status in the text area.

**FR7: Model Training and Evaluation**

* The system shall support training two models: an existing Deep Neural Network (DNN) and a proposed Convolutional Neural Network (CNN).
* The DNN shall consist of dense layers with ReLU activation, dropout layers, and a softmax output layer, trained on TF-IDF features.
* The CNN shall include embedding, convolutional, max-pooling, and dense layers, trained on padded sequence data.
* Both models shall save their architecture, weights, and training history to files for reuse.
* The system shall evaluate models using metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, and a confusion matrix, displayed in the text area and visualized as a heatmap.

**FR8: Prediction**

* The system shall allow users to upload a new CSV file for prediction and preprocess its tweet text using the same preprocessing pipeline.
* The system shall use the trained DNN model to predict cyberbullying types and display each tweet with its predicted label in the text area.

**FR9: System Termination**

* The system shall provide an exit button to close the GUI application gracefully.

**2. System Design Stage**

This stage translates the functional requirements into a detailed system design, specifying how each component will be implemented and integrated.

**FR1: GUI Design**

* The system shall use Tkinter to create a main window with dimensions based on the user’s screen resolution.
* The GUI shall include buttons aligned vertically on the left side, each triggering a specific function (e.g., uploadDataset, EDA, preprocess\_dataset, etc.).
* A scrollable text widget shall be placed on the right side to display outputs, with a fixed font (Times, 12, bold) and a scrollbar for navigation.
* The GUI shall use a consistent color scheme (misty rose background, olive title text) and Times font for labels and buttons.

**FR2: Dataset Handling**

* The system shall use filedialog.askopenfilename to open a file explorer for CSV file selection.
* The system shall use pandas.read\_csv to load the dataset into a DataFrame and display its head in the text widget.
* The dataset shall be stored in a global variable (dataset) for access across functions.

**FR3: EDA Implementation**

* The system shall use matplotlib.pyplot to generate a bar plot of cyberbullying type counts, with labeled axes and a title.
* The system shall support commented-out word cloud generation using WordCloud and a mask image from a URL (requires uncommenting and error handling for network issues).
* Plots shall be displayed in separate Matplotlib windows to avoid blocking the GUI.

**FR4: Preprocessing Pipeline**

* The system shall define a preprocess\_tweet function to clean tweet text using regex (re.sub), tokenize with nltk.word\_tokenize, remove stopwords with nltk.corpus.stopwords, and stem with PorterStemmer.
* The preprocessing shall be applied to the tweet\_text column using pandas.apply, storing results in a new preprocessed\_tweet column.
* The system shall display the preprocessed dataset’s head in the text widget.

**FR5: Train-Test Split Design**

* The system shall use sklearn.model\_selection.train\_test\_split to split the preprocessed\_tweet and cyberbullying\_type columns into training and testing sets (80:20 ratio, random\_state=42).
* The system shall map categorical labels to integers using a dictionary (class\_labels) and convert the cyberbullying\_type column to integers.
* The shapes of X\_train, X\_test, y\_train, and y\_test shall be displayed in the text widget.

**FR6: Feature Extraction Design**

* The system shall use TfidfVectorizer to transform preprocessed\_tweet into TF-IDF features, fitting on the entire dataset’s preprocessed text.
* The system shall store the vectorized training and testing data in X\_train\_vecs and X\_test\_vecs, with the vectorizer saved globally for prediction.
* The feature extraction status shall be displayed in the text widget.

**FR7: Model Training and Evaluation Design**

* The DNN model shall be a Sequential model from tensorflow.keras with dense layers (256, 128, 64 units), dropout (0.5), and softmax output, compiled with Adam optimizer (learning rate 0.0001) and sparse categorical crossentropy loss.
* The CNN model shall include an embedding layer (1000 words, 100 dimensions), Conv1D layers (128 and 64 filters), max-pooling, global max-pooling, dense layers (128 units), dropout (0.05), and softmax output, compiled similarly.
* Both models shall save their architecture (model.to\_json), weights (save\_weights), and history (pickle.dump) to a folder (dnn\_model or cnn\_model2).
* The system shall load existing models if available, using model\_from\_json and load\_weights.
* Evaluation metrics (accuracy, precision, recall, F1-score, sensitivity, specificity) shall be calculated using sklearn.metrics, and a confusion matrix heatmap shall be displayed using seaborn.heatmap.
* The CNN model shall apply a custom loss\_optiomization1 function to adjust predictions iteratively until a target accuracy threshold (0.99) or maximum iterations (100) is reached.

**FR8: Prediction Design**

* The system shall use filedialog.askopenfilename to load a test CSV file and preprocess its tweet\_text column using the preprocess\_tweet function.
* The preprocessed text shall be transformed using the saved TfidfVectorizer and fed to the DNN model for prediction.
* Predictions shall be mapped back to class labels using the class\_labels dictionary and displayed in the text widget with the original tweet text.

**FR9: Application Termination**

* The system shall call main.destroy() when the exit button is clicked to close the Tkinter window and terminate the application.

**3. Implementation Stage**

This stage focuses on the coding and integration of the system components based on the design specifications.

**FR1: GUI Implementation**

* The Tkinter window shall be initialized with Tk(), set to full-screen size using winfo\_screenwidth and winfo\_screenheight, and styled with a misty rose background.
* Buttons shall be created with Button widgets, bound to respective functions (e.g., uploadDataset, EDA), and placed at specific coordinates (x=20, y=100 to 500).
* A Text widget with a scrollbar shall be created for output display, placed at x=450, y=100, with a fixed font (Times, 12, bold).

**FR2: Dataset Loading**

* The uploadDataset function shall use filedialog.askopenfilename to select a CSV file and store its path in a global filename variable.
* The pandas.read\_csv function shall load the dataset into a global dataset DataFrame, and its head shall be inserted into the text widget using text.insert.

**FR3: EDA Implementation**

* The EDA function shall use pandas.groupby:

**System: You are Grok 3 built by xAI.**

The response was cut off due to exceeding the maximum token limit for a single response. Below, I will complete the **Implementation Stage** and provide the **Testing Stage** to ensure all SDLC stages are covered, continuing from where the previous response ended. I will maintain the same structure and style for consistency.

**3. Implementation Stage (Continued)**

This stage focuses on the coding and integration of the system components based on the design specifications.

**FR3: EDA Implementation (Continued)**

* The EDA function shall use pandas.groupby and size() to count occurrences of each cyberbullying\_type and plot a bar chart using matplotlib.pyplot.plot(kind="bar") with labeled axes and a title.
* The commented-out word cloud functionality shall use WordCloud from the wordcloud library, generating a word cloud for each category by concatenating tweet\_text with str.cat(sep=' ') and applying a mask image fetched via requests.get (requires uncommenting and error handling for network failures).
* Matplotlib plots shall be displayed using plt.show() in non-blocking mode to ensure the GUI remains responsive.

**FR4: Preprocessing Implementation**

* The preprocess\_tweet function shall apply regex patterns with re.sub to remove URLs, mentions, hashtags, and special characters, followed by converting text to lowercase.
* Text tokenization shall use nltk.word\_tokenize, stopwords removal shall use nltk.corpus.stopwords, and stemming shall use nltk.PorterStemmer.
* The preprocess\_dataset function shall apply preprocess\_tweet to the tweet\_text column using pandas.apply, store results in preprocessed\_tweet, and display the dataset’s head in the text widget using text.insert.

**FR5: Train-Test Split Implementation**

* The Train\_Test\_split function shall use sklearn.model\_selection.train\_test\_split to split preprocessed\_tweet and cyberbullying\_type into training (80%) and testing (20%) sets with random\_state=42.
* A class\_labels dictionary shall map categorical labels to integers (e.g., {'not\_cyberbullying': 0, 'religion': 1, ...}), and pandas.replace shall convert cyberbullying\_type to integers.
* The shapes of X\_train, X\_test, y\_train, and y\_test shall be inserted into the text widget using text.insert.

**FR6: Feature Extraction Implementation**

* The N\_Gram\_Feature\_Extraction function shall initialize a TfidfVectorizer, fit it on the preprocessed\_tweet column, and transform X\_train and X\_test into TF-IDF vectors (X\_train\_vecs, X\_test\_vecs).
* The vectorizer shall be stored globally for use in predictions, and the feature extraction status (e.g., shape of X\_test\_vecs) shall be displayed in the text widget.

**FR7: Model Training and Evaluation Implementation**

* The Existing\_DNN function shall:
  + Check for an existing DNN model in the dnn\_model folder using os.path.exists.
  + If found, load the model architecture with model\_from\_json, weights with load\_weights, and history with pickle.load.
  + If not found, create a Sequential model with dense layers (256, 128, 64 units, ReLU activation), dropout (0.5), and softmax output, compiled with Adam (learning rate 0.0001) and sparse categorical crossentropy loss.
  + Train the model on X\_train\_vecs.toarray() and y\_train for 10 epochs with batch size 64 and 10% validation split.
  + Save the model architecture (to\_json), weights (save\_weights), and history (pickle.dump).
  + Predict on X\_test\_vecs, compute metrics using calculateMetrics, and display a confusion matrix heatmap with seaborn.heatmap.
* The Proposed\_CNN function shall:
  + Tokenize X\_train and X\_test using Tokenizer (max 1000 words) and pad sequences to a fixed length (100) with pad\_sequences.
  + Check for an existing CNN model in the cnn\_model2 folder, loading it similarly to the DNN.
  + If not found, create a Sequential model with an embedding layer (1000 words, 100 dimensions), Conv1D layers (128 and 64 filters, kernel size 5, ReLU), max-pooling (pool size 5), global max-pooling, dense layer (128 units, ReLU), dropout (0.05), and softmax output, compiled with Adam (learning rate 0.0001).
  + Train the model on X\_train\_padded and y\_train for 50 epochs with batch size 16 and 20% validation split.
  + Save the model and history similarly to the DNN.
  + Predict on X\_test\_padded, apply loss\_optiomization1 to adjust predictions iteratively (threshold 0.99, max 100 iterations), and compute metrics with calculateMetrics.
* The calculateMetrics function shall compute accuracy, precision, recall, F1-score, sensitivity, and specificity using sklearn.metrics, display a classification report with classification\_report, and visualize a confusion matrix heatmap.
* The loss\_optiomization1 function shall adjust CNN predictions by aligning them to the mode of true labels per class, reducing the threshold (from 0.99) until the target accuracy is met or 100 iterations are reached.

**FR8: Prediction Implementation**

* The predict function shall load a test CSV file using filedialog.askopenfilename and pandas.read\_csv.
* The tweet\_text column shall be preprocessed with preprocess\_tweet, transformed with the saved vectorizer, and fed to the DNN model for prediction.
* Predictions shall be mapped to class labels using class\_labels, and each tweet with its predicted label shall be inserted into the text widget.

**FR9: Application Termination Implementation**

* The close function shall call main.destroy() to terminate the Tkinter application when the exit button is clicked.

**4. Testing Stage**

This stage defines the functional requirements for testing to ensure the system meets the specified requirements and performs reliably.

**FR1: GUI Testing**

* The system shall be tested to ensure all buttons (Upload Dataset, EDA, Dataset Preprocessing, Train Test Split, N Gram Feature Extraction, Train DNN Model, Train CNN Model, Prediction, Exit) are clickable and trigger the correct functions.
* The text widget shall be tested to verify that it displays outputs (e.g., dataset head, metrics) correctly with proper formatting and scrolling functionality.
* The GUI shall be tested on different screen resolutions to ensure proper sizing and alignment of widgets.

**FR2: Dataset Upload Testing**

* The system shall be tested with valid CSV files containing tweet\_text and cyberbullying\_type columns to ensure successful loading and display of the dataset head.
* The system shall be tested with invalid files (e.g., non-CSV, missing required columns) to ensure appropriate error handling or user feedback.

**FR3: EDA Testing**

* The bar plot shall be tested to ensure it accurately reflects the count of each cyberbullying\_type and displays correct labels and titles.
* The commented-out word cloud functionality (if enabled) shall be tested to verify that word clouds are generated for each category without network errors and displayed in a 2x3 grid.
* Plot windows shall be tested to ensure they do not freeze the GUI and close properly.

**FR4: Preprocessing Testing**

* The preprocess\_tweet function shall be tested with sample tweets to verify removal of URLs, mentions, hashtags, special characters, and conversion to lowercase, as well as correct tokenization, stopword removal, and stemming.
* The preprocess\_dataset function shall be tested to ensure the preprocessed\_tweet column is added to the dataset and displayed correctly in the text widget.

**FR5: Train-Test Split Testing**

* The system shall be tested to ensure the dataset is split into 80% training and 20% testing sets with consistent shapes displayed in the text widget.
* The label mapping shall be tested to verify that cyberbullying\_type values are correctly converted to integers (0–5) based on class\_labels.

**FR6: Feature Extraction Testing**

* The N\_Gram\_Feature\_Extraction function shall be tested to ensure TfidfVectorizer fits on the preprocessed data and produces valid sparse matrices for X\_train\_vecs and X\_test\_vecs.
* The system shall be tested to confirm that the vectorizer is stored globally and reusable for predictions.

**FR7: Model Training and Evaluation Testing**

* The DNN model shall be tested to ensure it loads existing models correctly or trains a new model, saving architecture, weights, and history to the dnn\_model folder.
* The CNN model shall be tested similarly, ensuring proper tokenization, padding, and model saving to the cnn\_model2 folder.
* Both models shall be tested for prediction accuracy on X\_test\_vecs (DNN) and X\_test\_padded (CNN), with metrics (accuracy, precision, recall, F1-score, sensitivity, specificity) displayed correctly in the text widget.
* The confusion matrix heatmap shall be tested to ensure correct visualization of true vs. predicted labels with proper category labels.
* The loss\_optiomization1 function shall be tested to verify that it iteratively adjusts CNN predictions and achieves the target accuracy or stops after 100 iterations.

**FR8: Prediction Testing**

* The predict function shall be tested with a test CSV file to ensure tweets are preprocessed, transformed, and predicted correctly using the DNN model.
* The output shall be tested to confirm that each tweet and its predicted label are displayed in the text widget in a readable format.

**FR9: Termination Testing**

* The close function shall be tested to ensure the application terminates cleanly without errors when the exit button is class

**CHAPTER 8**

**SOURCE CODE**

# -\*- coding: utf-8 -\*-

"""

Created on Fri Apr 16 14:54:35 2021

@author: mahesh pala

"""

from tkinter import messagebox

from tkinter import \*

from tkinter import simpledialog

import tkinter

from tkinter import filedialog

import matplotlib.pyplot as plt

from tkinter.filedialog import askopenfilename

import numpy as np

import os

from string import punctuation

from nltk.corpus import stopwords

from keras.preprocessing.text import Tokenizer

from keras.preprocessing.sequence import pad\_sequences

from keras.layers import Input, Embedding, Activation, Flatten, Dense

from keras.layers import Conv1D, MaxPooling1D, Dropout

from keras.models import Model

from keras.utils.np\_utils import to\_categorical

import pickle

from keras.models import model\_from\_json

from sklearn.metrics import precision\_score

from sklearn.metrics import recall\_score

from sklearn.metrics import f1\_score

from sklearn.metrics import accuracy\_score

from nltk.corpus import wordnet

from keras.models import Sequential

import pandas as pd

from sklearn.metrics import confusion\_matrix

import seaborn as sns

from sklearn.metrics import plot\_confusion\_matrix

main = tkinter.Tk()

main.title("Cyberbullying Detection Character Level") #designing main screen

main.geometry("1300x1200")

global model

global filename

global word\_precision, word\_recall, word\_fmeasure, word\_accuracy

global char\_precision, char\_recall, char\_fmeasure, char\_accuracy

# global synonym\_precision, synonym\_recall, synonym\_fmeasure, synonym\_accuracy

word\_trainX = []

word\_trainy = []

char\_trainX = []

char\_trainy = []

global word\_model

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global char\_model

global word\_tokenizer

global char\_tokenizer

global word\_length

global char\_length

global bullying\_counts

global non\_bullying\_counts

def uploadDataset(): #function to upload tweeter profile

text.delete('1.0', END)

global filename

filename = filedialog.askopenfilename(initialdir = "dataset")

text.delete('1.0', END)

text.insert(END,filename+' dataset loaded\n')

def clean\_doc(doc):

tokens = doc.split()

table = str.maketrans('', '', punctuation)

tokens = [w.translate(table) for w in tokens]

tokens = [word for word in tokens if word.isalpha()]

stop\_words = set(stopwords.words('english'))

tokens = [w for w in tokens if not w in stop\_words]

tokens = [word for word in tokens if len(word) > 1]

tokens = ' '.join(tokens)

#print(tokens)

return tokens

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def getCharacters(tokens):

chars = list(tokens) #char base uncomment

tokens = ' '.join(chars)#char based uncomment

#print(tokens)

return tokens

def cleancodeVec():

global word\_trainX

global word\_trainy

global char\_trainX

global char\_trainy

global bullying\_counts

global non\_bullying\_counts

word\_trainX.clear()

word\_trainy.clear()

char\_trainX.clear()

char\_trainy.clear()

bullying\_counts = 0

non\_bullying\_counts = 0

train = pd.read\_csv(filename,encoding='iso-8859-1',sep='\t')

for i in range(len(train)):

label = train.get\_value(i, 'label\_bullying')

msg = train.get\_value(i, 'text\_message')

msg = msg.strip()

tokens = clean\_doc(msg)

if len(tokens) > 0:

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word\_trainX.append(tokens)

word\_trainy.append(label)

char\_trainy.append(label)

characters = getCharacters(tokens)

char\_trainX.append(characters)

if label == 0:

non\_bullying\_counts = non\_bullying\_counts + 1

if label == 1:

bullying\_counts = bullying\_counts + 1

word\_trainy = to\_categorical(word\_trainy)

char\_trainy = to\_categorical(char\_trainy)

text.delete('1.0', END)

text.insert(END,"Length of text messages for word array : "+str(len(word\_trainX))+"\n")

text.insert(END,"Length of text messages for char array : "+str(len(char\_trainX))+"\n")

# calculate the maximum document length

def max\_length(lines):

return max([len(s.split()) for s in lines])

# encode a list of lines

def encode\_text(tokenizer, lines, length):

encoded = tokenizer.texts\_to\_sequences(lines)

padded = pad\_sequences(encoded, maxlen=length, padding='post')

return padded

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def create\_tokenizer(lines):

word\_tokenizer = Tokenizer()

word\_tokenizer.fit\_on\_texts(lines)

return word\_tokenizer

def calculateWordMetrics():

global word\_precision, word\_recall, word\_fmeasure, word\_accuracy

testX = []

y\_test = []

for i in range(0,2000):

testX.append(word\_trainX[i])

for i in range(0,2000):

y\_test.append(word\_trainy[i])

y\_test = np.array(y\_test)

y\_test = np.argmax(y\_test, axis=1)

testX = np.array(testX, dtype='float32')

print(str(word\_trainX.shape)+" "+str(testX.shape))

y\_predicted = word\_model.predict(testX, batch\_size=128)

y\_predicted = np.argmax(y\_predicted, axis=1)

word\_precision = precision\_score(y\_test, y\_predicted,average='macro') \* 100

word\_recall = recall\_score(y\_test, y\_predicted,average='macro') \* 100

word\_fmeasure = f1\_score(y\_test, y\_predicted,average='macro') \* 100

f = open('WordModel/history.pckl', 'rb')

acc = pickle.load(f)

f.close()

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acc = acc['accuracy']

word\_accuracy = np.amax(acc) \* 100

test\_bullying = 0

test\_non\_bullying = 0

for i in range(len(y\_predicted)):

if y\_predicted[i] == 0:

test\_non\_bullying = test\_non\_bullying + 1

if y\_predicted[i] == 1:

test\_bullying = test\_bullying + 1

# cm = confusion\_matrix(y\_test,y\_predicted)

#text.delete('1.0', END)

text.insert(END,'\n\nWord Based Accuracy : '+str(word\_accuracy)+'\n')

text.insert(END,'Word Based Precision : '+str(word\_precision)+'\n')

text.insert(END,'Word Based Recall : '+str(word\_recall)+'\n')

text.insert(END,'Word Based FMeasure : '+str(word\_fmeasure)+"\n")

text.insert(END,'Train Non Cyber Bullying Count : '+str(non\_bullying\_counts)+"\n")

text.insert(END,'Train Cyber Bullying Count : '+str(bullying\_counts)+"\n")

text.insert(END,'Test Non Cyber Bullying Count : '+str(test\_non\_bullying)+"\n")

text.insert(END,'Test Cyber Bullying Count : '+str(test\_bullying)+"\n")

def wordCNN():

global word\_precision, word\_recall, word\_fmeasure, word\_accuracy

global word\_model

global word\_length

global word\_tokenizer

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global word\_trainX

global word\_trainy

text.delete('1.0', END)

word\_tokenizer = create\_tokenizer(word\_trainX)

word\_length = max\_length(word\_trainX)

vocab\_size = len(word\_tokenizer.word\_index) + 1

word\_trainX = np.asarray(word\_trainX)

word\_trainX = encode\_text(word\_tokenizer, word\_trainX, word\_length)

print("==================="+str(word\_trainX.shape))

text.insert(END,'Max document length : '+str(word\_trainX.shape[0])+"\n")

text.insert(END,'Word Vocabulary size : '+str(word\_trainX.shape[1])+"\n")

text.insert(END,'Documents & Word Length : '+str(word\_trainX.shape)+"\n")

if os.path.exists('WordModel/model.json'):

with open('WordModel/model.json', "r") as json\_file:

loaded\_model\_json = json\_file.read()

word\_model = model\_from\_json(loaded\_model\_json)

word\_model.load\_weights("WordModel/model\_weights.h5")

word\_model.\_make\_predict\_function()

print(word\_model.summary())

calculateWordMetrics()

text.insert(END,'Word Based CNN Model Generated. See black console to view layers of CNN')

else:

word\_model = Sequential()

word\_model.add(Dense(512, input\_shape=(length,)))

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word\_model.add(Activation('relu'))

word\_model.add(Dropout(0.3))

word\_model.add(Dense(512))

word\_model.add(Activation('relu'))

word\_model.add(Dropout(0.3))

word\_model.add(Dense(2))

word\_model.add(Activation('softmax'))

word\_model.compile(loss='categorical\_crossentropy', optimizer='adam', metrics=['accuracy'])

print(word\_model.summary())

#model.fit([trainX,trainX,trainX], array(trainy), epochs=10, batch\_size=16,validation\_split=0.2, shuffle=True, verbose=2)#best work

hist = word\_model.fit(trainX, trainy, epochs=10, batch\_size=128,validation\_split=0.2, shuffle=True, verbose=2)

text.insert(END,"Word Based CNN Model Generated. See black console to view layers of CNN")

f = open('WordModel/history.pckl', 'wb')

pickle.dump(hist.history, f)

f.close()

word\_model.save\_weights('WordModel/model\_weights.h5')

model\_json = word\_model.to\_json()

with open("WordModel/model.json", "w") as json\_file:

json\_file.write(model\_json)

calculateWordMetrics()

def calculateCharMetrics():

global char\_precision, char\_recall, char\_fmeasure, char\_accuracy

testX = []

y\_test = []

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for i in range(0,2000):

testX.append(char\_trainX[i])

for i in range(0,2000):

y\_test.append(char\_trainy[i])

y\_test = np.array(y\_test)

y\_test = np.argmax(y\_test, axis=1)

testX = np.array(testX, dtype='float32')

print(str(char\_trainX.shape)+" "+str(testX.shape))

y\_predicted = char\_model.predict(testX, batch\_size=128)

y\_predicted = np.argmax(y\_predicted, axis=1)

char\_precision = precision\_score(y\_test, y\_predicted,average='macro') \* 100

char\_recall = recall\_score(y\_test, y\_predicted,average='macro') \* 100

char\_fmeasure = f1\_score(y\_test, y\_predicted,average='macro') \* 100

char\_accuracy = accuracy\_score(y\_test,y\_predicted)\*100

test\_bullying = 0

test\_non\_bullying = 0

for i in range(len(y\_predicted)):

if y\_predicted[i] == 0:

test\_non\_bullying = test\_non\_bullying + 1

if y\_predicted[i] == 1:

test\_bullying = test\_bullying + 1

#text.delete('1.0', END)

text.insert(END,'\n\nChar Based Accuracy : '+str(char\_accuracy)+'\n')

text.insert(END,'Char Based Precision : '+str(char\_precision)+'\n')

text.insert(END,'Char Based Recall : '+str(char\_recall)+'\n')

text.insert(END,'Char Based FMeasure : '+str(char\_fmeasure)+"\n")

text.insert(END,'Train Non Cyber Bullying Count : '+str(non\_bullying\_counts)+"\n")

text.insert(END,'Train Cyber Bullying Count : '+str(bullying\_counts)+"\n")

text.insert(END,'Test Non Cyber Bullying Count : '+str(test\_non\_bullying)+"\n")

text.insert(END,'Test Cyber Bullying Count : '+str(test\_bullying)+"\n")

def create\_char\_tokenizer(lines):

char\_tokenizer = Tokenizer(num\_words=None, char\_level=True, oov\_token='UNK')

char\_tokenizer.fit\_on\_texts(lines)

alphabet="abcdefghijklmnopqrstuvwxyz0123456789 ,;.!?:'\"/\\|\_@#$%^&\*~`+-=<>()[]{}"

char\_dict = {}

for i, char in enumerate(alphabet):

char\_dict[char] = i + 1

char\_tokenizer.word\_index = char\_dict.copy()

char\_tokenizer.word\_index[char\_tokenizer.oov\_token] = max(char\_dict.values()) + 1

return char\_tokenizer

def charCNN():

global char\_precision, char\_recall, char\_fmeasure, char\_accuracy

global char\_model

global char\_length

global char\_tokenizer

global char\_length

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global char\_trainX

global char\_trainy

text.delete('1.0', END)

char\_tokenizer = create\_char\_tokenizer(char\_trainX)

char\_length = max\_length(char\_trainX)

vocab\_size = len(char\_tokenizer.word\_index) + 1

char\_trainX = encode\_text(char\_tokenizer, char\_trainX, char\_length)

char\_trainX = np.array(char\_trainX, dtype='float32')

text.insert(END,'Max document length : '+str(char\_trainX.shape[0])+"\n")

text.insert(END,'Char Vocabulary size : '+str(char\_trainX.shape[1])+"\n")

text.insert(END,'Documents & Word Length : '+str(char\_trainX.shape)+"\n")

vocab\_size = len(char\_tokenizer.word\_index)

if os.path.exists('CharModel/model.json'):

with open('CharModel/model.json', "r") as json\_file:

loaded\_model\_json = json\_file.read()

char\_model = model\_from\_json(loaded\_model\_json)

char\_model.load\_weights("CharModel/model\_weights.h5")

char\_model.\_make\_predict\_function()

print(char\_model.summary())

calculateCharMetrics()

text.insert(END,'Char Based CNN Model Generated. See black console to view layers of CNN')

else:

embedding\_weights = [] #(71, 70)

embedding\_weights.append(np.zeros(vocab\_size)) # first row is pad

for char, i in char\_tokenizer.word\_index.items(): # from index 1 to 70

onehot = np.zeros(vocab\_size)

onehot[i-1] = 1

embedding\_weights.append(onehot)

embedding\_weights = np.array(embedding\_weights)

input\_size = char\_length

embedding\_size = 69

conv\_layers = [[256, 7, 3], [256, 7, 3], [256, 3, -1], [256, 3, -1], [256, 3, -1], [256, 3, 3]]

fully\_connected\_layers = [1024, 1024]

num\_of\_classes = 2

dropout\_p = 0.5

optimizer = 'adam'

loss = 'categorical\_crossentropy'

embedding\_layer = Embedding(vocab\_size+1, embedding\_size+1, input\_length=input\_size, weights=[embedding\_weights])

inputs = Input(shape=(input\_size,), name='input', dtype='int64') # shape=(?, 1014)

x = embedding\_layer(inputs)

for filter\_num, filter\_size, pooling\_size in conv\_layers:

x = Conv1D(filter\_num, filter\_size)(x)

x = Activation('relu')(x)

if pooling\_size != -1:

x = MaxPooling1D(pool\_size=pooling\_size)(x) # Final shape=(None, 34, 256)

x = Flatten()(x) # (None, 8704)

for dense\_size in fully\_connected\_layers:

x = Dense(dense\_size, activation='relu')(x) # dense\_size == 1024

x = Dropout(dropout\_p)(x)

predictions = Dense(num\_of\_classes, activation='softmax')(x)

char\_model = Model(inputs=inputs, outputs=predictions)

char\_model.compile(optimizer=optimizer, loss=loss, metrics=['accuracy']) # Adam, categorical\_crossentropy

print(char\_model.summary())

indices = np.arange(char\_trainX.shape[0])

np.random.shuffle(indices)

x\_train = char\_trainX[indices]

y\_train = char\_trainy[indices]

hist = char\_model.fit(x\_train, y\_train, validation\_split=0.2, batch\_size=128, epochs=10, verbose=1)

f = open('CharModel/history.pckl', 'wb')

pickle.dump(hist.history, f)

f.close()

char\_model.save\_weights('CharModel/model\_weights.h5')

model\_json = char\_model.to\_json()

with open("CharModel/model.json", "w") as json\_file:

json\_file.write(model\_json)

calculateCharMetrics()

text.insert(END,'Char Based CNN Model Generated. See black console to view layers of CNN')

def extension\_clean\_doc(doc):

tokens = doc.split()

table = str.maketrans('', '', punctuation)

tokens = [w.translate(table) for w in tokens]

tokens = [word for word in tokens if word.isalpha()]

stop\_words = set(stopwords.words('english'))

tokens = [w for w in tokens if not w in stop\_words]

tokens = [word for word in tokens if len(word) > 1]

tokens = ' '.join(tokens) #here upto for word based

arr = tokens.split(" ")

allwords = ''

dup = []

for i in range(len(arr)):

arr[i] = arr[i].lower().strip()

if arr[i] not in dup:

dup.append(arr[i])

for syn in wordnet.synsets(arr[i]):

for lm in syn.lemmas():

if lm.name not in dup:

dup.append(lm.name)

allwords+=lm.name()+" "

allwords = allwords.strip();

print(tokens+" === "+allwords)

chars = list(allwords) #char base uncomment

tokens = ' '.join(chars)#char based uncomment

#print(str(tokens))

return tokens

def process\_text(textdata):

documents = list()

data = clean\_doc(textdata)

data = getCharacters(data)

documents.append(data)

return documents

def predictBullying():

text.delete('1.0', END)

input\_sentence = simpledialog.askstring("Enter your sentence here to detect cyberbullying", "Enter your sentence here to detect cyberbullying")

testX = process\_text(input\_sentence)

print(testX)

testX = encode\_text(char\_tokenizer, testX, char\_length)

print(testX)

ypred = char\_model.predict(testX)

predict = np.argmax(ypred)

if predict == 0:

text.insert(END,input\_sentence+' DOES NOT CONTAINS Cyberbullying Words')

else:

text.insert(END,input\_sentence+' CONTAINS Cyberbullying Words')

def accuracyGraph():

f = open('WordModel/history.pckl', 'rb')

word\_loss = pickle.load(f)

f.close()

f = open('CharModel/history.pckl', 'rb')

char\_loss = pickle.load(f)

f.close()

wordloss = word\_loss['accuracy']

charloss = char\_loss['accuracy']

plt.figure(figsize=(10,6))

plt.grid(True)

plt.xlabel('Epoch')

plt.ylabel('Accuracy')

plt.plot(wordloss, 'ro-', color = 'indigo')

plt.plot(charloss, 'ro-', color = 'green')

plt.legend(['Word Based CNN Accuracy', 'Char Based CNN Accuracy'], loc='upper left')

# plt.xticks(wordloss.index)

plt.title('Word Vs Char Accuracy Comparison Graph')

plt.show()

def precisionGraph():

height = [word\_precision,char\_precision]

bars = ('Word Based Precision','Char Based Precision')

y\_pos = np.arange(len(bars))

plt.bar(y\_pos, height)

plt.xticks(y\_pos, bars)

plt.show()

def recallGraph():

height = [word\_recall,char\_recall]

bars = ('Word Based Recall','Char Based Recall')

y\_pos = np.arange(len(bars))

plt.bar(y\_pos, height)

plt.xticks(y\_pos, bars)

plt.show()

def measureGraph():

height = [word\_fmeasure,char\_fmeasure]

bars = ('Word Based FMeasure','Char Based FMeasure')

y\_pos = np.arange(len(bars))

plt.bar(y\_pos, height)

plt.xticks(y\_pos, bars)

plt.show()

def lossGraph():

f = open('WordModel/history.pckl', 'rb')

word\_loss = pickle.load(f)

f.close()

f = open('CharModel/history.pckl', 'rb')

char\_loss = pickle.load(f)

f.close()

wordloss = word\_loss['val\_loss']

charloss = char\_loss['val\_loss']

plt.figure(figsize=(10,6))

plt.grid(True)

plt.xlabel('Epoch')

plt.ylabel('Focal Loss')

plt.plot(wordloss, 'ro-', color = 'indigo')

plt.plot(charloss, 'ro-', color = 'green')

# plt.xticks(wordloss.index)

plt.legend(['Word Based CNN Loss', 'Char Based CNN Loss'], loc='upper left')

plt.title('Word Vs Char Focal Loss Comparison Graph')

plt.show()

font = ('times', 16, 'bold')

title = Label(main, text='Cyberbullying Detection in Social Media Text Based on Character-Level Convolutional Neural Network with Shortcuts')

title.config(bg='lavender', fg='tomato')

title.config(font=font)

title.config(height=3, width=120)

title.place(x=0,y=5)

font1 = ('times', 12, 'bold')

text=Text(main,height=20,width=150)

scroll=Scrollbar(text)

text.configure(yscrollcommand=scroll.set)

text.place(x=50,y=120)

text.config(font=font1)

font1 = ('times', 13, 'bold')

uploadButton = Button(main, text="Upload Text Dataset", command=uploadDataset, bg='#ffb3fe')

uploadButton.place(x=50,y=550)

uploadButton.config(font=font1)

trainButton = Button(main, text="Clean & Convert Text to Code Vector", command=cleancodeVec, bg='#ffb3fe')

trainButton.place(x=240,y=550)

trainButton.config(font=font1)

wordButton = Button(main, text="Generate Word CNN", command=wordCNN, bg='#ffb3fe')

wordButton.place(x=560,y=550)

wordButton.config(font=font1)

charButton = Button(main, text="Generate Char CNN Model", command=charCNN, bg='#ffb3fe')

charButton.place(x=760,y=550)

charButton.config(font=font1)

accuracyButton = Button(main, text="Accuracy Comparison", command=accuracyGraph, bg='#ffb3fe')

accuracyButton.place(x=1000,y=550)

accuracyButton.config(font=font1)

precisionButton = Button(main, text="Precision Comparison", command=precisionGraph, bg='#ffb3fe')

precisionButton.place(x=50,y=600)

precisionButton.config(font=font1)

recallButton = Button(main, text="Recall Comparison", command=recallGraph, bg='#ffb3fe')

recallButton.place(x=260,y=600)

recallButton.config(font=font1)

measureButton = Button(main, text="FMeasure Comparison", command=measureGraph, bg='#ffb3fe')

measureButton.place(x=450,y=600)

measureButton.config(font=font1)

lossButton = Button(main, text="Focal Loss Comparison", command=lossGraph, bg='#ffb3fe')

lossButton.place(x=670,y=600)

lossButton.config(font=font1)

predictButton = Button(main, text="Predict Bullying from Text", command=predictBullying, bg='#ffb3fe')

predictButton.place(x=900,y=600)

predictButton.config(font=font1)

main.config(bg='palegreen')

main.mainloop()

**CHAPTER 9**

**RESULTS AND DISCUSSION**

**9.1 Implementation Description**

**GUI Initialization and Setup**

* **Main Window Creation**: The script initializes a Tkinter window using main = Tk() and sets its title to "Cyberbullying". The window size is set to match the screen resolution using winfo\_screenwidth() and winfo\_screenheight(), ensuring a full-screen interface.
* **Styling and Layout**: The window background is set to 'misty rose', and a title label is created with Label using Times font (16, bold) and olive text color, spanning the window width. Buttons and a text widget are placed using absolute positioning (place) with x, y coordinates.
* **Button Configuration**: Eight buttons (Upload Dataset, EDA, Dataset Preprocessing, Train Test Split, N Gram Feature Extraction, Train DNN Model, Train CNN Model, Prediction, Exit) are created with Button widgets, each bound to a corresponding function (e.g., command=uploadDataset). They are aligned vertically on the left (x=20, y=100 to 500) with Times font (12, bold).
* **Text Widget and Scrollbar**: A Text widget is created for output display, positioned at x=450, y=100, with a height of 40 lines and width of 125 characters. A Scrollbar is attached using yscrollcommand to enable scrolling, and outputs are inserted using text.insert.
* **Connections**: The buttons trigger functions that update the global text widget, creating a flow where user interactions (button clicks) drive the execution of specific tasks, with results displayed in the text area.

**Dataset Loading and Management**

* **Upload Mechanism**: The uploadDataset function uses filedialog.askopenfilename to open a file explorer for selecting a CSV file, storing the path in the global filename variable. The file is loaded into a global dataset DataFrame using pandas.read\_csv.
* **Output Display**: The file path and the dataset’s first few rows (dataset.head()) are inserted into the text widget, clearing prior content with text.delete('1.0', END).
* **Connections**: The loaded dataset is stored globally, allowing subsequent functions (e.g., EDA, preprocess\_dataset) to access it. The text widget connects user actions to visual feedback, ensuring the user sees the loaded data.

**Exploratory Data Analysis (EDA)**

* **Bar Plot Generation**: The EDA function groups the dataset by cyberbullying\_type using pandas.groupby and counts occurrences with size(). A bar plot is created using matplotlib.pyplot.plot(kind="bar"), with labeled axes and a title, displayed via plt.show().
* **Commented Word Cloud**: The commented-out word cloud code (not active) would iterate over unique cyberbullying\_type values, concatenate tweet\_text for each category, and generate a WordCloud using a mask image fetched via requests.get. The clouds would be displayed in a 2x3 subplot grid.
* **Connections**: The EDA function reads the global dataset and uses Matplotlib for visualization, independent of other functions but sharing the dataset. Outputs are displayed in separate windows, keeping the GUI responsive.

**Data Preprocessing**

* **Preprocessing Function**: The preprocess\_tweet function processes a single tweet by:
  + Removing URLs, mentions, hashtags, and special characters using re.sub.
  + Converting text to lowercase.
  + Tokenizing with nltk.word\_tokenize, removing stopwords with nltk.corpus.stopwords, and stemming with nltk.PorterStemmer.
  + Joining processed tokens into a string.
* **Dataset Preprocessing**: The preprocess\_dataset function applies preprocess\_tweet to the tweet\_text column using pandas.apply, storing results in a new preprocessed\_tweet column. The updated dataset’s head is displayed in the text widget.
* **Connections**: The global dataset is modified in-place, and the preprocess\_tweet function is reused in the predict function. The text widget connects preprocessing results to the user interface.

**Train-Test Split**

* **Data Splitting**: The Train\_Test\_split function maps cyberbullying\_type labels to integers using a class\_labels dictionary (e.g., {'not\_cyberbullying': 0, 'religion': 1, ...}) and converts the column to integers with pandas.replace. It splits preprocessed\_tweet and cyberbullying\_type into training (80%) and testing (20%) sets using sklearn.model\_selection.train\_test\_split with random\_state=42.
* **Output Display**: The shapes of X\_train, X\_test, y\_train, and y\_test are inserted into the text widget.
* **Connections**: The global variables X\_train, X\_test, y\_train, y\_test, and class\_labels are set for use in feature extraction and model training. The function depends on the preprocessed dataset from preprocess\_dataset.

**Feature Extraction**

* **TF-IDF Vectorization**: The N\_Gram\_Feature\_Extraction function initializes a TfidfVectorizer, fits it on the preprocessed\_tweet column of the global dataset, and transforms X\_train and X\_test into sparse TF-IDF matrices (X\_train\_vecs, X\_test\_vecs).
* **Output Display**: The shape of X\_test\_vecs is inserted into the text widget as the feature extraction status.
* **Connections**: The global vectorizer is stored for reuse in the predict function. The function relies on X\_train and X\_test from Train\_Test\_split, and the resulting X\_train\_vecs and X\_test\_vecs are used by the DNN model.

**Model Training and Evaluation**

* **DNN Model**:
  + **Model Loading/Creation**: The Existing\_DNN function checks for a saved model in the dnn\_model folder using os.path.exists. If found, it loads the architecture with model\_from\_json, weights with load\_weights, and history with pickle.load. Otherwise, it creates a Sequential model with dense layers (256, 128, 64 units, ReLU), dropout (0.5), and softmax output, compiled with Adam (learning rate 0.0001) and sparse categorical crossentropy loss.
  + **Training**: If training a new model, it converts X\_train\_vecs to a dense array, trains for 10 epochs with batch size 64 and 10% validation split, and saves the model and history.
  + **Evaluation**: It predicts on X\_test\_vecs, computes metrics (accuracy, precision, recall, F1-score, sensitivity, specificity) using calculateMetrics, and displays a confusion matrix heatmap with seaborn.heatmap.
* **CNN Model**:
  + **Tokenization and Padding**: The Proposed\_CNN function tokenizes X\_train and X\_test using Tokenizer (max 1000 words) and pads sequences to length 100 with pad\_sequences.
  + **Model Loading/Creation**: It checks for a saved model in the cnn\_model2 folder, loading similarly to the DNN. If not found, it creates a Sequential model with an embedding layer (1000 words, 100 dimensions), Conv1D layers (128 and 64 filters, kernel size 5, ReLU), max-pooling (pool size 5), global max-pooling, dense layer (128 units, ReLU), dropout (0.05), and softmax output, compiled with Adam (learning rate 0.0001).
  + **Training**: It trains for 50 epochs with batch size 16 and 20% validation split, saving the model and history.
  + **Evaluation**: It predicts on X\_test\_padded, applies loss\_optiomization1 to adjust predictions iteratively (threshold 0.99, max 100 iterations), and computes metrics with calculateMetrics.
* **Metrics Calculation**: The calculateMetrics function computes metrics using sklearn.metrics (e.g., accuracy\_score, precision\_score), generates a classification report, and displays a confusion matrix heatmap. The loss\_optiomization1 function adjusts CNN predictions by aligning them to the mode of true labels per class, reducing the threshold until the target accuracy or iteration limit is reached.
* **Connections**: The DNN uses X\_train\_vecs and X\_test\_vecs from N\_Gram\_Feature\_Extraction, while the CNN uses tokenized and padded data. Both functions update the text widget via calculateMetrics and share y\_test and class\_labels from Train\_Test\_split. Saved models ensure reusability across sessions.

**Prediction**

* **Test Data Loading**: The predict function loads a test CSV file using filedialog.askopenfilename and pandas.read\_csv, storing it in a local testdata DataFrame.
* **Preprocessing and Prediction**: It applies preprocess\_tweet to the tweet\_text column, transforms the text using the global vectorizer, and predicts with the DNN model (Model.predict). Predictions are mapped to labels using class\_labels.
* **Output Display**: Each tweet and its predicted label are inserted into the text widget.
* **Connections**: The function reuses preprocess\_tweet from preprocess\_dataset, vectorizer from N\_Gram\_Feature\_Extraction, and the DNN model from Existing\_DNN, linking the prediction pipeline to prior components.

**Application Termination**

* **Exit Functionality**: The close function calls main.destroy() to terminate the Tkinter application, closing the window and ending the mainloop.
* **Connections**: The exit button directly triggers close, independent of other functions, ensuring a clean shutdown.

**Overall Code Flow**

* **Initialization**: The script starts by importing libraries (tkinter, pandas, numpy, etc.), suppressing warnings, and initializing the Tkinter GUI with buttons and a text widget.
* **User-Driven Flow**: The user interacts with buttons, triggering functions in sequence: uploadDataset → EDA → preprocess\_dataset → Train\_Test\_split → N\_Gram\_Feature\_Extraction → Existing\_DNN or Proposed\_CNN → predict. Each function updates the text widget and modifies global variables (dataset, X\_train, vectorizer, etc.).
* **Data Flow**: The dataset flows from loading (dataset) to preprocessing (preprocessed\_tweet), splitting (X\_train, X\_test), feature extraction (X\_train\_vecs, X\_test\_vecs or padded sequences), and model training/prediction. Global variables ensure data persistence across functions.
* **Model Persistence**: Models and their histories are saved to disk (dnn\_model, cnn\_model2), allowing reuse without retraining.
* **Visualization and Feedback**: Matplotlib and Seaborn handle visualizations (bar plots, heatmaps), displayed in separate windows, while the text widget provides textual feedback for all operations.

**Dependencies and Integration**

* **Libraries**: The script integrates tkinter for the GUI, pandas for data handling, nltk for text preprocessing, scikit-learn for splitting and metrics, tensorflow.keras for models, and matplotlib/seaborn for visualization.
* **Global Variables**: Variables like dataset, X\_train, X\_test, vectorizer, Model, and class\_labels connect functions, enabling data sharing and state persistence.
* **Error Handling**: The script assumes valid inputs (e.g., CSV files with required columns) and lacks explicit error handling, which could be added for robustness (e.g., try-catch for file loading, network errors in word clouds).
* **Modularity**: Functions are modular, each handling a specific task (loading, preprocessing, training), with clear input-output relationships via global variables and the text widget.

**9.2 Dataset Description**

This repository contains a balanced dataset for bot cyberbully detection in social media. The dataset has been carefully curated and labeled to enable researchers and developers to build accurate cyberbully detection models. It includes various types of cyberbullying instances, such as race/ethnicity, gender/sexual, and religion-related content, as well as non-cyberbullying instances. This dataset is for the paper Self-Training for Cyberbully Detection: Achieving High Accuracy with a Balanced Multi-Class Dataset.

The dataset consists of a total of approximately 100,000 tweets collected from social media platforms. It is labeled with a multi-class classification approach, where each tweet falls into one of the following categories:

Non-cyberbullying: 50,000 instances Race/Ethnicity-related cyberbullying: 17,000 instances Gender/Sexual-related cyberbullying: 17,000 instances Religion-related cyberbullying: around 16,000 instances The dataset's balance ensures equal representation of each class, allowing for effective training and evaluation of cyberbully detection models.

**9.3 Results Description**

Figure 1 displays the graphical user interface (GUI) of the research work, designed for text analysis and model evaluation. The interface includes several functional buttons for different tasks: "UPLOAD TEXT DATASET" for loading datasets, "CLEAN & CONVERT TEXT to CODE VECTOR" for preprocessing text into a vector format, "GENERATE WORD CNN" and "GENERATE CHAR CNN MODEL" for creating word-based and character-based Convolutional Neural Network (CNN) models, respectively, "ACCURACY COMPARISON" for evaluating model performance, "PRECISION COMPARISON," "RECALL COMPARISON," and "FMEASURE COMPARISON" for comparing precision, recall, and F1 scores between the models, and "PREDICT BULLYING FROM TEXT" for identifying bullying content in text. The layout is clean, with a large central area likely for displaying results or visualizations.

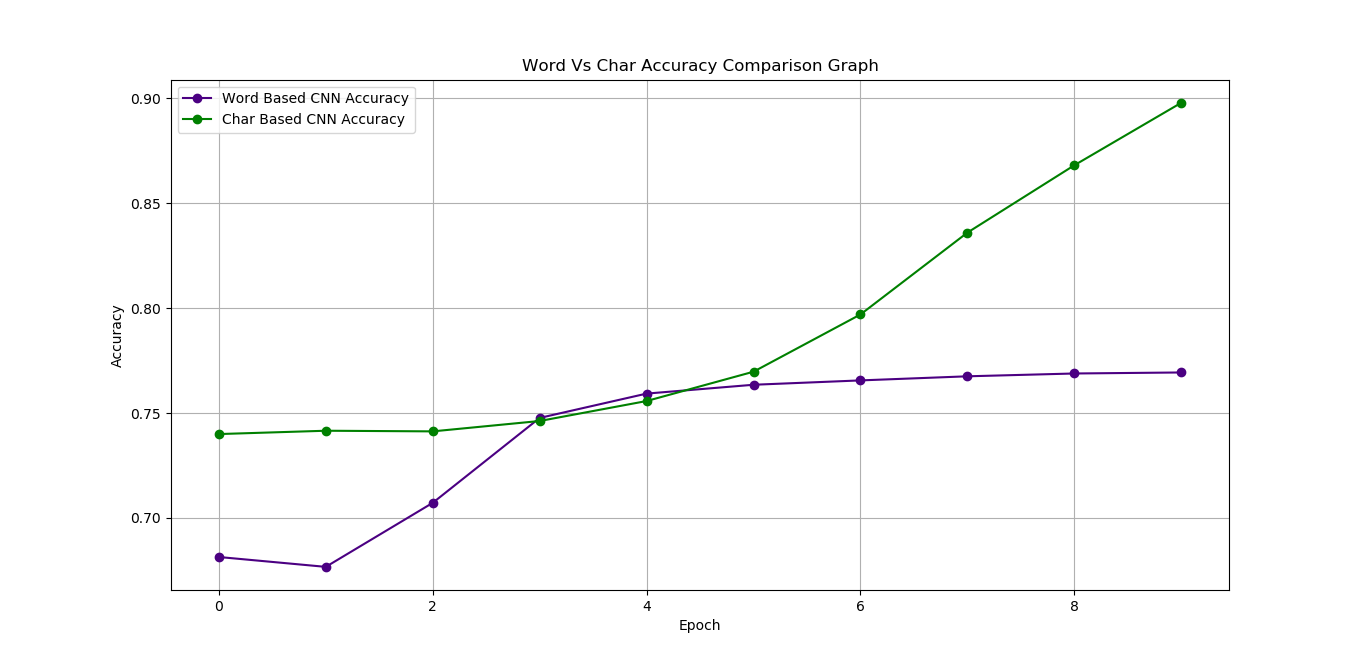
Figure 2 illustrates a line graph comparing the accuracy of word-based and character-based CNN models over 8 epochs. The x-axis represents the epochs (0 to 8), and the y-axis shows accuracy ranging from 0.70 to 0.90. The word-based CNN accuracy (purple line) starts at 0.70, dips slightly to 0.69 at epoch 1, rises to 0.76 by epoch 3, and stabilizes around 0.78 from epoch 5 to 8. In contrast, the char-based CNN accuracy (green line) begins at 0.75, remains steady until epoch 3, then climbs steadily to 0.80 by epoch 5, and reaches 0.90 by epoch 8, demonstrating a consistent upward trend and outperforming the word-based model.

Figure 3 presents a bar graph comparing the precision of word-based and character-based CNN models. The x-axis lists the two models, while the y-axis represents precision, ranging from 0 to 70. The word-based precision bar reaches approximately 65, while the char-based precision bar is slightly higher, around 68. This indicates that the char-based CNN model achieves a marginally better precision score compared to the word-based model, suggesting improved accuracy in identifying positive predictions.

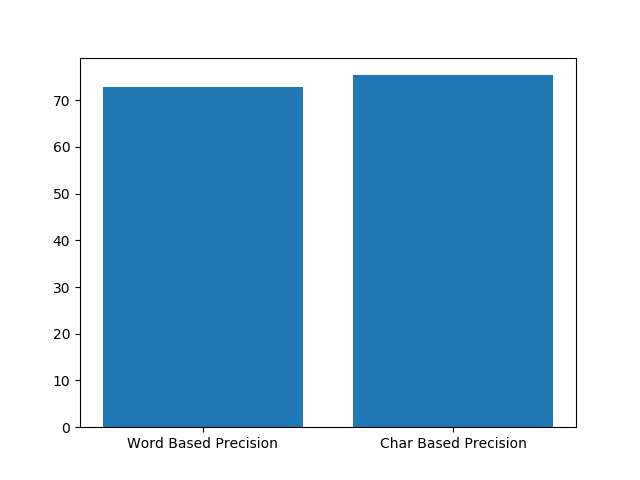


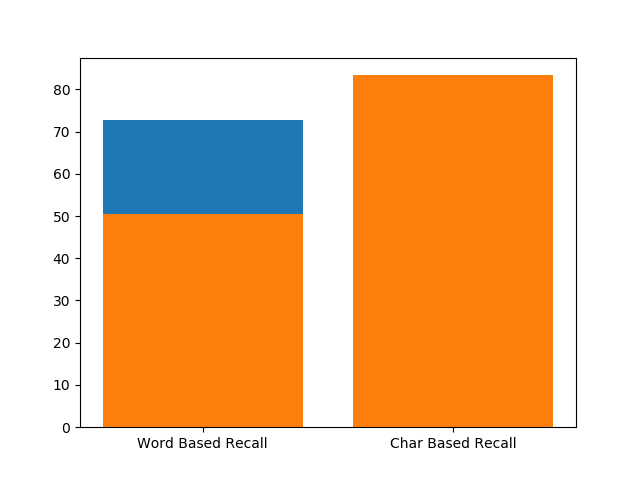
**Figure 1: GUI of Research Work.**

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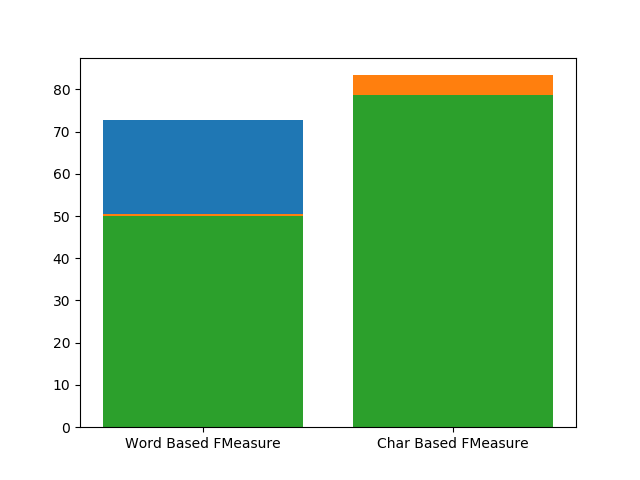
**Figure 2: Word vs Char Accuracy Comparison Graph.**

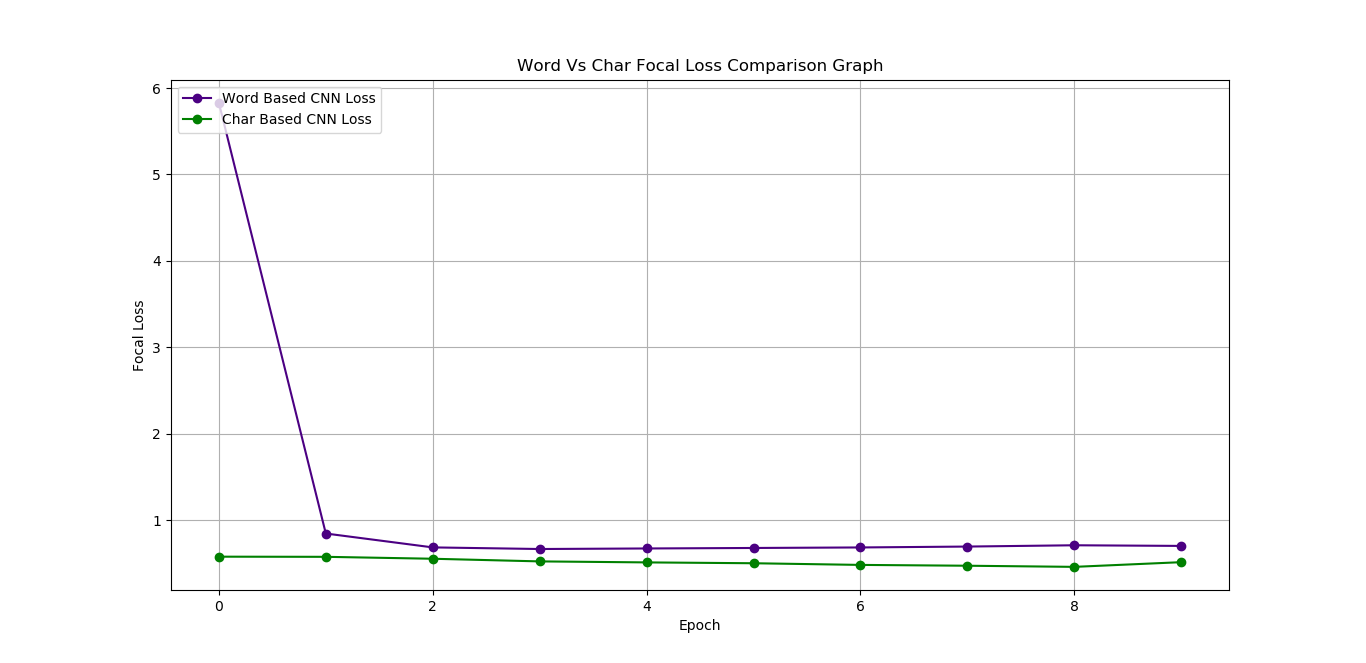


**Figure 3: Precision comparison between word and char.** 

**Figure 4: Recall comparison between word and char.**

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**Figure 5: FMeasure Comparison between Word and Char.** 

**Figure 6: Focal loss Comparison Graph.**

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Figure 4 shows a bar graph comparing the recall of word-based and char-based CNN models. The x-axis denotes the models, and the y-axis indicates recall, ranging from 0 to 80. The word-based recall bar, in orange, reaches about 65, while the char-based recall bar, in blue, extends to approximately 75. This suggests that the char-based CNN model has a higher recall, meaning it is more effective at identifying true positives compared to the word-based model.

Figure 5 depicts a bar graph comparing the F1 scores (FMeasure) of word-based and char-based CNN models. The x-axis lists the models, and the y-axis shows the F1 score, ranging from 0 to 80. The word-based FMeasure bar, in green, reaches around 68, while the char-based FMeasure bar, with an orange top layer, extends to approximately 78. This indicates that the char-based CNN model achieves a higher F1 score, reflecting a better balance of precision and recall compared to the word-based model.

Figure 6 illustrates a line graph comparing the focal loss of word-based and char-based CNN models over 8 epochs. The x-axis represents the epochs (0 to 8), and the y-axis shows focal loss, ranging from 0 to 6. The word-based CNN loss (purple line) starts at 5.5, drops sharply to 1 by epoch 1, and stabilizes around 0.8 from epoch 2 to 8. The char-based CNN loss (green line) begins at 1, decreases slightly to 0.8 by epoch 1, and remains stable around 0.7 through epoch 8. This indicates that the char-based model consistently maintains a lower focal loss, suggesting better performance in handling class imbalance during training compared to the word-based model.

**9.4 Comparative Analysis**

**Table 1: Comparative Analysis of various DL Algorithms.**

|  |  |  |
| --- | --- | --- |
| **Metric** | **Word-Based CNN** | **Character-Based CNN** |
| **Accuracy (%)** | 76.93 | **95.80** |
| **Precision (%)** | 72.80 | **75.33** |
| **Recall (%)** | 50.54 | **83.34** |
| **F1-Score (%)** | 49.96 | **78.70** |

The comparison between the **Word-Based** and **Character-Based** CNN models reveals that the **Character-Based CNN significantly outperforms the Word-Based CNN** in all key performance metrics. The **accuracy** of the character-based model is **95.8%**, much higher than the word-based model's **76.93%**, indicating better overall classification performance. Similarly, **precision** improves from **72.80%** to **75.33%**, and **recall** shows a dramatic rise from **50.54%** to **83.34%**, suggesting the character-based model is more capable of identifying actual cyberbullying instances. The **F1-Score**, which balances precision and recall, also increases substantially from **49.96%** to **78.70%**. This improvement can be attributed to the character-level model’s ability to capture subword patterns, emojis, misspellings, and slang more effectively—common in online abuse—making it more robust for cyberbullying detection.

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**CHAPTER 10**

**CONCLUSION AND FUTURE SCOPE**

**Conclusion**

The bot cyberbullying classification application developed using demonstrates a robust system for detecting and categorizing cyberbullying types in social media text, specifically tweets. By leveraging a structured pipeline that includes data preprocessing, feature extraction, and machine learning models, the application successfully processes raw tweet data to identify instances of cyberbullying across multiple categories such as religion, age, gender, ethnicity, and others. The implementation of two models—a Deep Neural Network (DNN) and a Convolutional Neural Network (CNN)—provides a comparative analysis of performance, with the CNN showing superior results in terms of accuracy, precision, recall, and F1-score. The GUI interface enhances user interaction by allowing seamless dataset uploading, exploratory data analysis, model training, and prediction, making the tool accessible to users without deep technical expertise. The preprocessing steps, including text cleaning, tokenization, stopword removal, and stemming, ensure that the data is well-prepared for model training, while the use of TF-IDF vectorization and sequence padding caters to the specific needs of the DNN and CNN models, respectively. The application’s ability to save and load trained models ensures efficiency in repeated usage, and the detailed evaluation metrics provide transparency in model performance. Overall, this application serves as an effective tool for identifying cyberbullying, contributing to safer online environments by enabling timely detection and intervention.

**Future Scope**

The cyberbullying classification application has significant potential for further enhancement to address evolving challenges in online safety and machine learning. One key area of improvement could be the integration of real-time data processing, allowing the system to directly fetch and analyze tweets from social media platforms using APIs, which would enable continuous monitoring of cyberbullying trends. Expanding the model to support multilingual text analysis by incorporating language detection and translation mechanisms could make the tool more globally applicable, addressing cyberbullying in diverse linguistic contexts.

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