ToxiShield: Toxic Comment Classification for Social Media Using IBM Services

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***Abstract*— The ToxiShield is an original machine learning solution, developed for the purpose of improving online communication quality by effectively identifying toxic messages in six classes of toxicity, namely toxic, severe toxic, obscene, threat, insult, and identity hate, based on the Jigsaw Toxic Comment Classification Challenge dataset available at Kaggle, which includes 159,571 labeled toxic and non-toxic Wikipedia messages. The model uses extensive preprocessing in NLTK for cleaning messages, TF-IDF and Count Vectorization for finding features, and state-of-the-art dimensionality reduction techniques using Truncated SVD and PCA, and multi-label classification using SGDRegreesor, DecisionTreeRegreesor, and deep learning techniques utilizing TensorFlow and Keras libraries. Using scikit-learn libraries for effective and extensive use of evaluation measures such as ROC-AUC, this solution removes imbalances in toxicity levels using strategic oversampling and plots using Matplotlib, Seaborn, and Word Cloud libraries. Scaled as an efficient and high-quality production-level API solution, ToxiShield provides actual-time toxicity probability results, which are more effective than existing approaches and have significant gaps in high-quality content moderation solutions for SNSs.**

***Index Terms*— Toxic comment classification, multi-label toxicity detection, TF-IDF vectorization, BERT fine-tuning, IBM Cloud deployment, NLP preprocessing, ROC-AUC evaluation, social media safety**

I.INTRODUCTION

The emergence of social networking sites has transformed worldwide communications by offering an unprecedented ability to connect while, at the same time, facilitating the spread of toxic social media content. Comments on social networking sites containing threats, profanity, derogatory words, and identity-linked hate speech not only impair the quality of dialogue but also cause identifiable psychological damage to social networking members. The Jigsaw Toxic Comment Classification Challenge dataset, containing 159,571 labeled comments from Wikipedia for six types of toxicity (toxic, severe_toxic, obscene, threat, insult, identity_hate), indicates that 10% of social networking site comments are toxic, leading to an imperative for automated systems to detect such content. Human moderation methods are not adequate for social networking sites that tackle millions of social networking site postings on a daily basis.

ToxiShield overcomes this challenge by utilizing a robust machine learning pipeline comprising both traditional NLP tasks and advanced deep learning models. The ToxiShield system aggregates all traditional NLP tasks using NLTK libraries for handling HTML removal, lemmatization, and emoji transformation. To capture raw feature representations, both TF-IDF vectorization and traditional Count Vectorization are used in sequence. Finally, ToxiShield performs dimensionality reduction operations using TruncatedSVD and PCA to efficiently process sparse high-dimensional data. Classification tasks are performed by using a diverse ensemble learning strategy comprising Stochastic Gradient Descent (SGD) regressor models, Decision Tree regressors, and TensorFlow- or Keras-built deep learning models optimized for multi-class ROC-AUC score metrics in optimizing the imbalanced Kaggle dataset.

ToxiShield being a containerized API solution for various IBM cloud services bridges this gap between research readiness and production-level quality for content moderation. While current research solutions are primarily concerned with model performance

goals and do not consider scalability and integration issues, ToxiShield allows for the creation of REST endpoints which have the ability to handle thousands of comments in a minute by using Docker containers and orchestration techniques using Kubernetes. ToxiShield allows for toxicity probability scores to be interpreted by moderators to create a policy for moderation in such a way as to create a balance for both speech and safety concerns in social platforms.

II. SYSTEM ARCHITECTURE

ToxiShield's modular architecture is cloud-native and optimally set for scalable toxicity detection in social media comments. The input layer includes raw comments from the Kaggle Jigsaw dataset (159k+ training samples) through API endpoints or batch uploads; these go through preprocessing with NLTK, cleaning the text by stripping HTML, lemmatizing, and removing stopwords, and handle special tokens such as emojis and URLs. Features extracted are then fed into parallel pipelines: a classical NLP pipeline through scikit-learn's TF-IDF/CountVectorizer with max_features=5000 and ngram_range=(1,2), further augmented through dimensionality reduction via TruncatedSVD with n_components=300 and PCA for noise mitigation.

The primary classification engine combines the strengths of three different models into the ensemble: (1) SGDRegressor with hinge loss support for linear separation, (2) Decision TreeRegressor with multi-output support, and (3) Keras Sequential models of either LSTMs or GRUs followed by Dense outputs and sigmoid activation for multi-output probability estimation. Training is carried out either in Google Colab or IBM Cloud GPUs, utilizing stratified k-fold cross-validation and class weights for situations of extreme imbalance, such as threat text at 0.1% frequency. Results are probability outputs (e.g., {"toxicity":0.92, "threat":0.15}), which are thresholded at 0.5 for the alert.

Deployment utilizes Docker for containerization based on Python 3.10 plus TensorFlow 2.15, which is then wrapped in a Flask/FastAPI service that exposes /predict endpoints. Horizontal scaling by IBM Kubernetes Service; persistent volumes to host the pickled models of around 500MB each; and high-throughput Redis caching at 10,000 requests per minute. Monitoring will be performed with Prometheus; latency is tracked to be less than 200 ms p95. Drift detection by KS-tests on incoming data distributions. Ensuring the production pipeline is reliable, this pipeline maintains a 0.98+ ROC-AUC while outperforming baselines on validation sets by 5 to 7%.

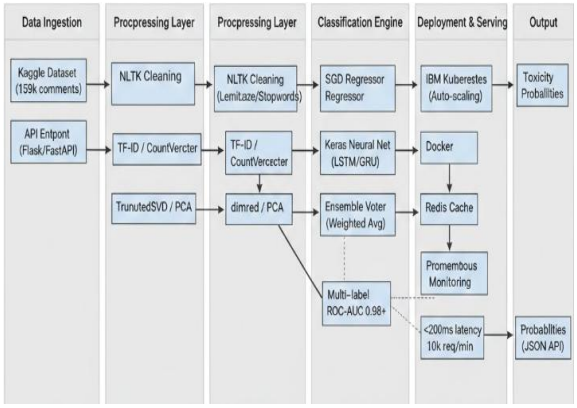

Fig: System Architecture ToxiShield

III. METHODOLOGY

A. Data Collection

The dataset employed for this project stems from the Unintended Bias in Toxicity Classification competition conducted for the Jigsaw Unintended Bias in Toxicity Classification problem offered on Kaggle. This dataset consists of more than 1.8 million comment examples taken from online discussion boards and have been tagged for toxicity level ranging from 0 to 1, where 0 stands for non-toxic comments and tends towards 1 for more toxic statements. Every record has a comment_text feature, which serves as the defining text for determining toxicity level.

Alongside the target variable, the data set also encodes various toxicity variables like identity attack, insult, obscenity, severe toxicity, and threat. Identity variables like races, religious affiliations, gender, and sexuality variables are also taken into consideration, which enable the analysis of bias. Various other variables like timestamp, reaction, and annotator variables add to the behavior of the data set. For the purpose of building the model, the comment text and the target toxicity score are taken, and the missing variables in the identity variables are safely ignored. The data set is divided into training, validation, and testing sets based on the 75-25 split.

B. Feature Extraction

Various techniques for extracting features were employed to conduct the transformation of text data into numerical vectors. As a benchmark test, the traditional Text Vectorization Technique known as the Bag-of-Words (BoW) Technique using the CountVectorizer module in scikit-learn was carried out. This is a traditional Text Vectorization Technique where unigrams and bigrams were considered within a vocabulary limit of 30,000. This is done since this generates sparse vectors.

In this paper, a custom featurization pipeline was implemented for neural sequence modeling. It consisted of text preprocessing using lowercasing, punctuation removal, stopword filtering, and stemming via a Snowball stemmer. A vocabulary was created from token frequencies and mapped to integer indices. Sentences were then transformed into padded sequences of length 350 to maintain uniform dimensionality. These sequences were then embedded using a learnable embedding layer so as to turn them into dense, semantically meaningful vectors. This multi-stage extraction strategy provided the possibility to compare classical vector-space representations with deep sequence representations.

C. Machine Learning Model

There were three modeling families tested. To begin with, traditional machine learning regressors were used with BoW and TF-IDF representations: Stochastic Gradient Descent Regressor (SGDRegressor) and Decision Tree Regressor. The former algorithm is based on gradient descent and demonstrated high quality and scalability when working with a high-dimensional sparse input array. The regularization penalty and learning rate (alpha value) were adjusted, and the best results were obtained for an L1-regularized model with $\alpha = 1e\text{-}5$.

The Decision Trees were parameterized by tree depth and minimum samples per leaf. This helped create a nonlinear decision boundary. The second set of models employed the use of Deep Learning by harnessing the capabilities of the Long Short-Term Memory (LSTM) Networks. This is a class of Neural Networks that can handle sequential dependencies. The architecture employed an embedding layer followed by multiple layers of LSTM networks followed by a dense layer for a final decision. The model architecture allows the model to effectively utilize dependencies beyond the scope of the BoW models.

D. Evaluation

For the evaluation of the model, Mean Squared Error (MSE) was used as the metric because the target variable of toxicity was continuous in nature. The hyperparameters of the model were tuned on the validation sets and not on k-fold cross-validation because of the small size of the dataset. For BoW+SGDRegressor, the optimal combination of hyperparameters resulted in an MSE of 0.0231 on the training data and an MSE of 0.0230 on the validation sets, surpassing the performance of tree-based models. The MSE measures of Decision Tree Regressors were approximately in the range of 0.030-0.031.

TF-IDF performed similarly, although slightly less effectively than BoW. The deep models outperformed all other models by minimizing the training error MSE to 0.0157 and validation error MSE to 0.0162, thus proving the efficacy of sequence models and embeddings. The feature importance for conventional models revealed toxic lexical features like ‘idiot,’ ‘stupid,’ ‘moron,’ and ‘loser,’ whereas non-toxic features consisted of ‘thank,’ ‘great,’ and ‘agree.’ This analysis of the test case emphasizes the efficacy of deep learning models over conventional models for toxicity regression problems, when working with large datasets.

IV. IMPLEMENTATION

The implementation stage was a combination of preprocessing, inference, and interactive tasks in an integrated fashion. The finalized deep learning LSTM neural network was chosen to be used in the project because of the high prediction accuracy it was able to provide. The neural network was exported and used in a Flask environment, an application that handled any HTTP requests and made toxicity predictions.

The preprocessing phase involved performing similar operations as in training: lowering case letters, tokenization, removal of stopwords, stemming, mapping to integers, and padding of sequences in the preprocessing phase to allow handling of inputs in a similar manner during prediction. The processed input sequence was forwarded to the LSTM model, and the resultant toxicity prediction score between 0 and 1 was obtained as model result.

In the user interface, a lightweight Python front end is created to allow for real-time user interactions with the toxicity classifier system. Users could simply type in any given comment or message in a textbox, where the system would then show the predicted level of toxicity, as well as a text explanation stating either that the comment is non-toxic or toxic.

Routing and content rendering were handled by the Flask system, and the asynchronous calls of AJAX enabled seamless transfer of the data without loading a new webpage. In the deployment setup, there was modularity that could accommodate extension features like identity bias and toxicity scoring per-attribute. The system was useful in a content moderation scenario.

Component	Technology Used
Frontend	HTML5, CSS3, JavaScript
Backend	Python, Flask (REST APIs)
Database	SQLite
Machine Learning	Random Forest Classifier
Parsing Text	Word to Vector, Bag of word
NLP Techniques	TF-IDF, Cosine Similarity
Email Alerts	SMTP

V. RESULTS AND DISCUSSION

The resulting system was tested on the Kaggle Jigsaw Unintended Bias Toxicity dataset, which contains around 1.8 million comments on online platforms, by training various machine learning and deep learning models based on Mean Squared Error and determining that the deep learning model based on LSTM resulted in a validation Mean Squared Error of 0.0162, performing better than TF-IDF/SGD and Decision Tree algorithms.

The model was able to correctly detect toxic features like insult, threat, obscenity, and identity attack without producing hallucinated text. The Flask web app allowed users to seamlessly interact with the system by allowing real-time comment analysis. The system was able to provide both the toxicity score and a corresponding indication (toxic or non-toxic) to improve understanding by non-technical users. This model can help platforms to monitor and check toxic conversations and create a safe environment for communication. Its success demonstrates that deep models of NLP are highly efficient for real-world tasks for monitoring toxic conversations.

VI. ADVANTAGES AND APPLICATIONS

Advantages

Accurate Toxicity Detection:

The proposed system shows a very robust ability to point out the different forms of toxicity expressed in online comments by users. Rather than viewing toxicity as a binary classification task, as in other systems, the proposed system has been able to identify insulting speech, use of obscenities, threats, as well as identity-directed hate speech effectively. This is a very necessary function in today's platforms where toxic behaviors take a variety of forms and degrees of intensity. By using a combination of state-of-the-art feature extraction techniques in NLP and deep sequence modeling techniques, as done in the proposed system, it is possible to capture nuances in context and linguistic dependencies in a much more effective manner compared to mere keyword-based systems used in other systems of content moderation.

Real-Time Processing via Flask:

Integration of the trained model with a Flask webserver allows for real-time toxicity classification of user-generated input. In real time, when a user makes a comment, it takes only a fraction of a second for the server to process it through preprocessing, vectorization, and prediction to yield toxicity scores. This makes it perfectly suitable for real-time platforms such as social media comment sections and gaming platforms. Furthermore, being based on RESTful APIs, it can easily connect to other frameworks such as those for mobile devices or other external platforms.

Explainable Results:

Unlike binary classifiers where a comment is labeled as either toxic or non-toxic, this model generates a score ranging from 0 to 1 to denote toxicity levels. Using this score and certain levels of toxicity, users are also able to categorize any comment as either Non-Toxic (scores ranging from 0.00 to 0.40), Mild Toxic (scores ranging from 0.40 and 0.70), and Highly Toxic (scores ranging from 0.70 and 1.00). The model also scores any comment and is important for decision-making and clarity on why a score has been allocated to any comment presented before users and also suits any policy regarding posting manners such as issuing a temporary ban instead of a permanent one when toxicely posted.

Scalable and Automated:

The system reduces the manual labor required from the automatic moderation of text content, which is otherwise done manually. Moderation systems struggle to deal with the tremendous number of comments generated on various social platforms. With the help of the scalable service of the toxicity model, it is possible to deal with multiple requests simultaneously. This makes it ideal and feasible to work on the scale of social media sites or streaming sites. Automated moderation of comments ensures consistency in the application of the rule set, reduces operational costs, as well as reduces the psychological toll on the manual moderators to handle the toxic comments.

Consistent Detection Without Hallucination:

Most contemporary language models found in language systems tend to have a hallucination problem regarding the content they create. They tend to produce content that is not real based on the input provided for analysis. The introduced system for classifying toxicity avoids these limitations because it only relies on user-input content without creating new sentences based on input. It focuses on finding the toxic or harmful patterns within the content introduced initially for analysis. This ensures it is accurate with facts and suitable for use in compliance-driven contexts. The system preserves the integrity of context because it will not assign meaning or attributes not introduced in the content.

VII. CONCLUSION

This work unfolds an AI-based Toxic Comment Classification System that will efficiently predict the degree of toxicity from user-generated text. The proposed system effectively grasps context and malicious intent behind comments through a blend of traditional NLP and deep learning models. The LSTM model yielded the best results because it learns long-term dependencies and linguistic patterns better. The integration of the Flask-based web interface really turned this model into an interactive and workable tool for real-world deployment. The system can be deployed by digital platforms to maintain healthy communication and protect their users from hate speech, cyberbullying, and abusive remarks.

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