AUTOMATED HATE SPEECH DETECTION IN ONLINE PLATFORMS

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Business Problem

Hate Speech Detection on Reddit

- Hate speech on Reddit can harm user safety, community health, and platform reputation.
- Effective detection is crucial for maintaining a safe and inclusive online environment.

Solution:

Building the Solution

Data Preparation:

- Collected and preprocessed Reddit comments.
- Addressed class imbalances using SMOTE

Model Development:

- Implemented ML models (SVM, SGD Classifier, Random forest etc.) and DL models (CNN, LSTM, BERT).
- BERT model achieved the best performance with 89% accuracy and an F1-score of 78%

Business Benefits

Enhanced User Safety:

- Protects users from harmful content, creating a safer environment.

Improved Community Health:

- Reduces toxicity, encouraging positive and constructive interactions.

Dataset Description:

Examples:

1. **Example 1:**
   - *Text:* "A subsection of retarded Hungarians? Ohh boy..."
   - *Hate Speech Index:* [1]
   - *Response:* "I don't see a reason why it's okay to insult..."
2. **Example 2:**
   - *Text:* "> 'y'all hear sumn?' by all means I live in a small town..."
   - *Hate Speech Index:* [3]
   - *Response:* "Persons with disabilities is the accepted term..."
3. **Example 3:**
   - *Text:* "Grammatical errors, overt racism, child prostitution..."
   - *Hate Speech Index:* NaN
   - *Response:* NaN

Benchmark Dataset

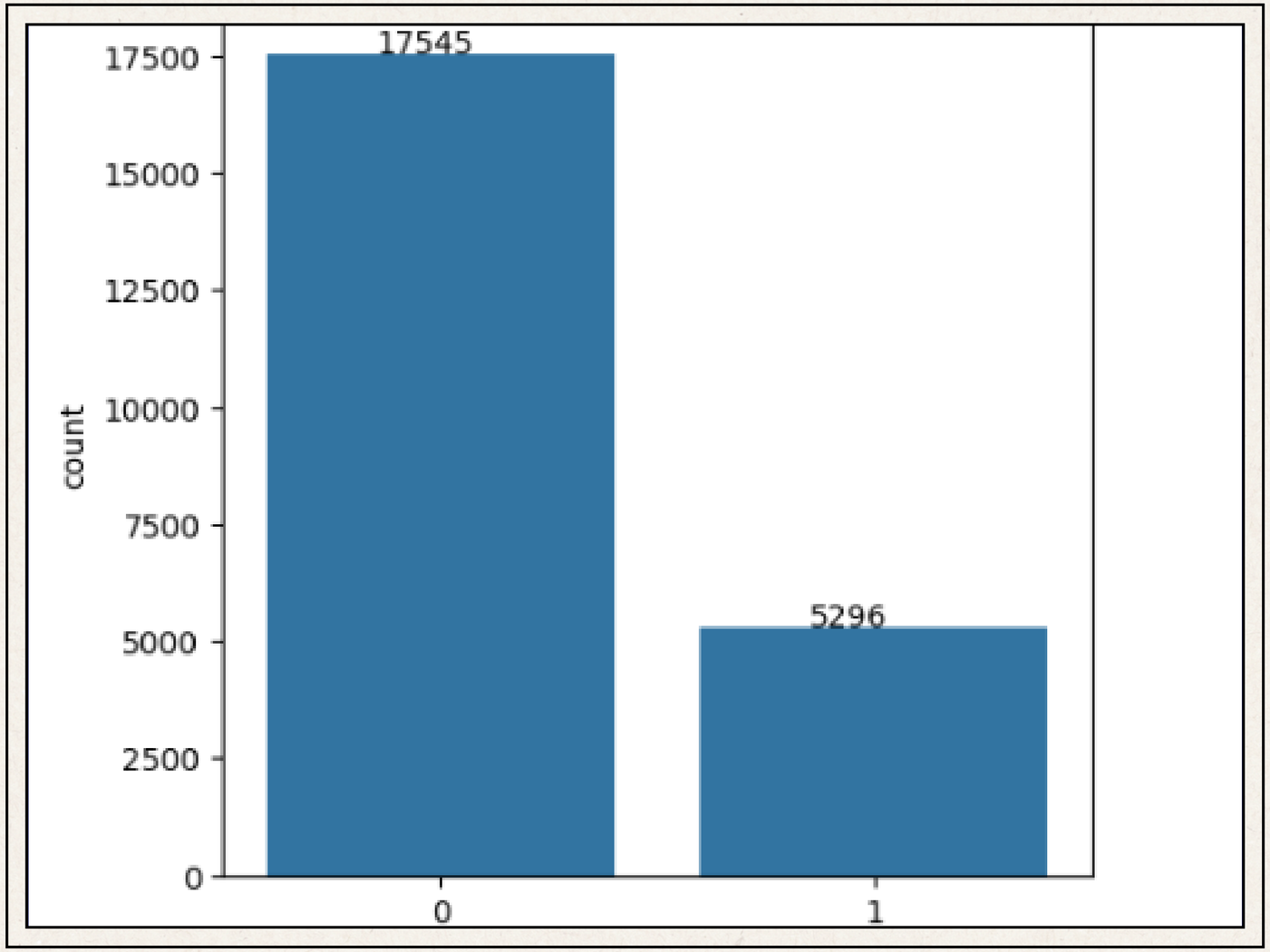
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5020 entries, 0 to 5019
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   id               5020 non-null   object
 1   text             5020 non-null   object
 2   hate_speech_idx  3847 non-null   object
 3   response         3847 non-null   object
dtypes: object(4)
memory usage: 157.0+ KB
```

Data Visualization

- Dataset Sizes and Distributions:
  Total Samples: 22,841

·Class Distribution:

- *Training Count*
  Non-Hate (0): 13,506 (76%)
  Hate (1): 3,408 (77%)
- *Testing Count*
  Non-Hate (0): 4,254 (24%)
  Hate (1): 1,032 (23%)



Data Preprocessing

1.Importing Necessary Libraries:

- Loaded essential libraries like pandas, numpy, sklearn, etc.
- Imported the dataset into a dataframe for analysis.

2.Checking for Missing Values:

- Identified and handled any missing values in the data.

3.Data Cleaning:

- Removed numbers and chat words.
- Handled emojis.
- Applied autocorrect for text normalization.

4.Handling Imbalanced Data:

- Applied SMOTE to balance the training data.
- Class Distribution after SMOTE:

  Non-Hate Speech (0): 13,539

  Hate Speech (1): 13,539

Tokenization and Embedding Techniques

Tokenization Techniques:

1. Tokenization:
    - Splitting text into individual words or tokens.

Embedding Techniques:

1.FastText (for ML Models):

- Usage: Applied FastText embeddings to represent words as dense vectors for machine learning models.

2.Word Embedding (for DL Models):

- Description: Converts words into continuous vector representations.
- Technique: Used pre-trained word embeddings or trained embeddings during model training.
- Advantages: Captures semantic meaning of words, improving model performance for text classification tasks.

Modeling

Various Machine Learning Models:

- Random Forest: Robust to overfitting, handles high-dimensional data, provides feature importance.
- Logistic Regression: Simple, interpretable, quick to train.
- Support Vector Machine (SVM): Effective for binary classification, robust with high-dimensional data.
- Gradient Boosting: Combines base estimators for improved accuracy, provides feature importance.
- K-Nearest Neighbors (KNN): Simple, effective for small datasets, predicts based on nearest data points.
- SGD Classifier: Efficient for large datasets.

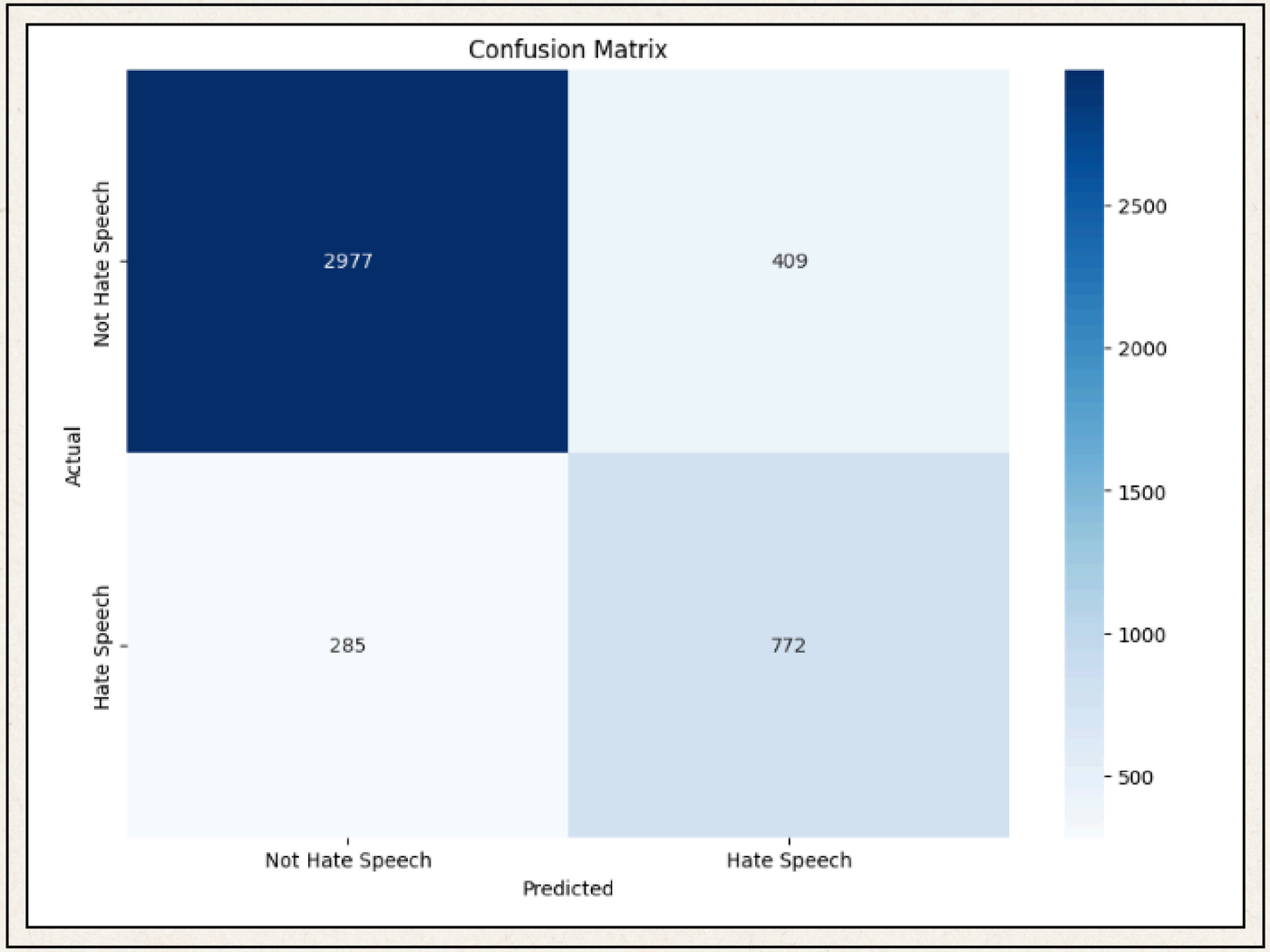
Deep Learning Models:

- Convolutional Neural Network (CNN): Captures spatial and contextual information, performs well in text classification.
- Long Short-Term Memory (LSTM): Suitable for sequential data, captures long-term dependencies.

Evaluation Metrics

We used several key metrics to evaluate our models:

- **Accuracy**: Measured the overall correctness of the model.
- **F1 Score:** Balanced precision and recall, especially important for imbalanced datasets.
- **Confusion Matrix:** Provided a detailed breakdown of model performance across classes



DL Model (LSTM):

- Accuracy: 84.38%
- Precision: 65.37%
- Recall: 73.04%
- F1 Score: 68.99%


Thank You