INFOSYS SPRINGBOARD INTERNSHIP

TOPIC: HATE SPEECH DETECTION ON TLEGRAM PLATFORM

Business Problem:

Hate speech on online platforms is a growing concern, especially on messaging apps like Telegram, where content can spread quickly and often without moderation. Hate speech can cause significant harm to individuals and communities, leading to psychological distress, social division, and, in some cases, real-world violence. For businesses, the presence of hate speech on their platforms can damage their reputation, lead to legal liabilities, and result in user attrition. Telegram must implement an effective hate speech detection system to maintain a safe and welcoming environment for all users, uphold its brand image, and comply with regulatory standards.

SOLUTION:

- **Dataset Collection:** Collect a comprehensive dataset of Telegram messages.
- **Data Preprocessing**: Clean and preprocess the text data.
- **BERT Tokenization:** Use the BERT tokenizer to convert messages into token IDS.
- **BERT Embeddings:** Pass tokenized messages through a pre-trained BERT model.
- **BiLSTM Layers:** Feed BERT embeddings into a neural network with three Bidirectional Long Short-Term Memory (BiLSTM) layers.
- **Model Training:** Train the model to understand nuanced patterns and context in the messages.

DATASET DESCRIPTION:

The GHC (Gab Hate Corpus) dataset:

- Source: Posts from Gab, a platform with lenient moderation, associated with high hate speech incidence.
- Purpose: Curated for hate speech detection research.
- Size: 22,037 posts.
- Annotations:
  - 'hd': Human Dignity
  - 'cv': Calls for Violence
  - 'vo': Vulgarity/Offensive Language
- Use: Essential for developing automated hate speech detection systems.

Example:

1).Text: "he most likely converted to islam due to his nature being suitable for islamic doctrine prophet muhammad was a psychopath"

• hd: 0 • cv: 0 • vo: 0 • label: 0 (No hate speech)

2).Text: "italy candidate says that all immigrants cannot be accepted if we want our white race our society to continue denounces nonwhite immigration as invasion closetheborder "

• hd: 1 • cv: 0 • vo: 0 • label: 1(Hate speech)

3).Text: "men have always gone to war to protect the women and children if the women are fat feminist toads and our children are a bunch of tranny shit turds then rest assured the military will dry the fuck up"

• hd: 1 • cv: 0 • vo: 1 • label: 1(Hate speech)

Data Distribution:

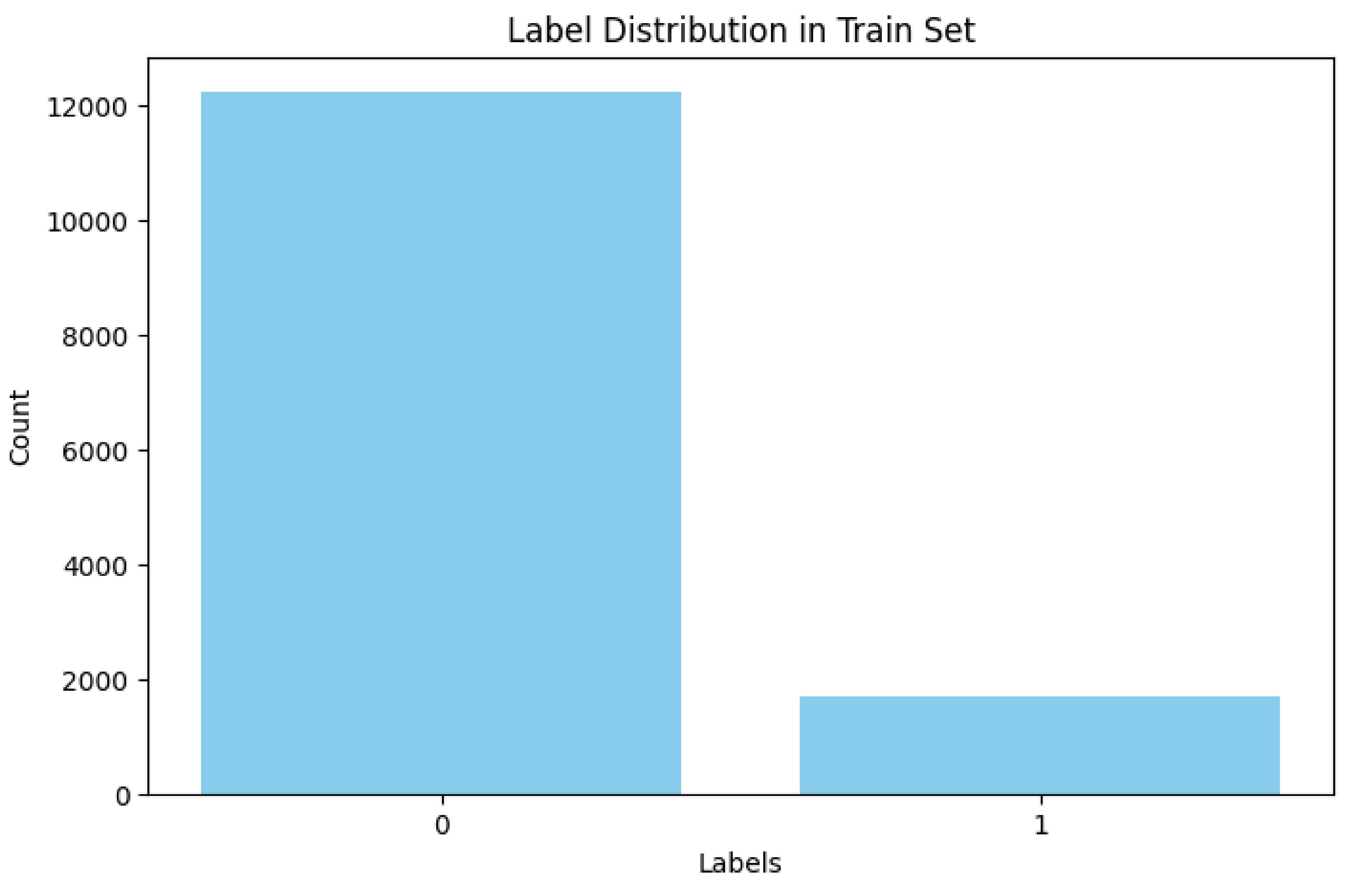
The dataset is specifically curated for hate speech detection and contains a total of 22,037 posts

Label wise splitting:

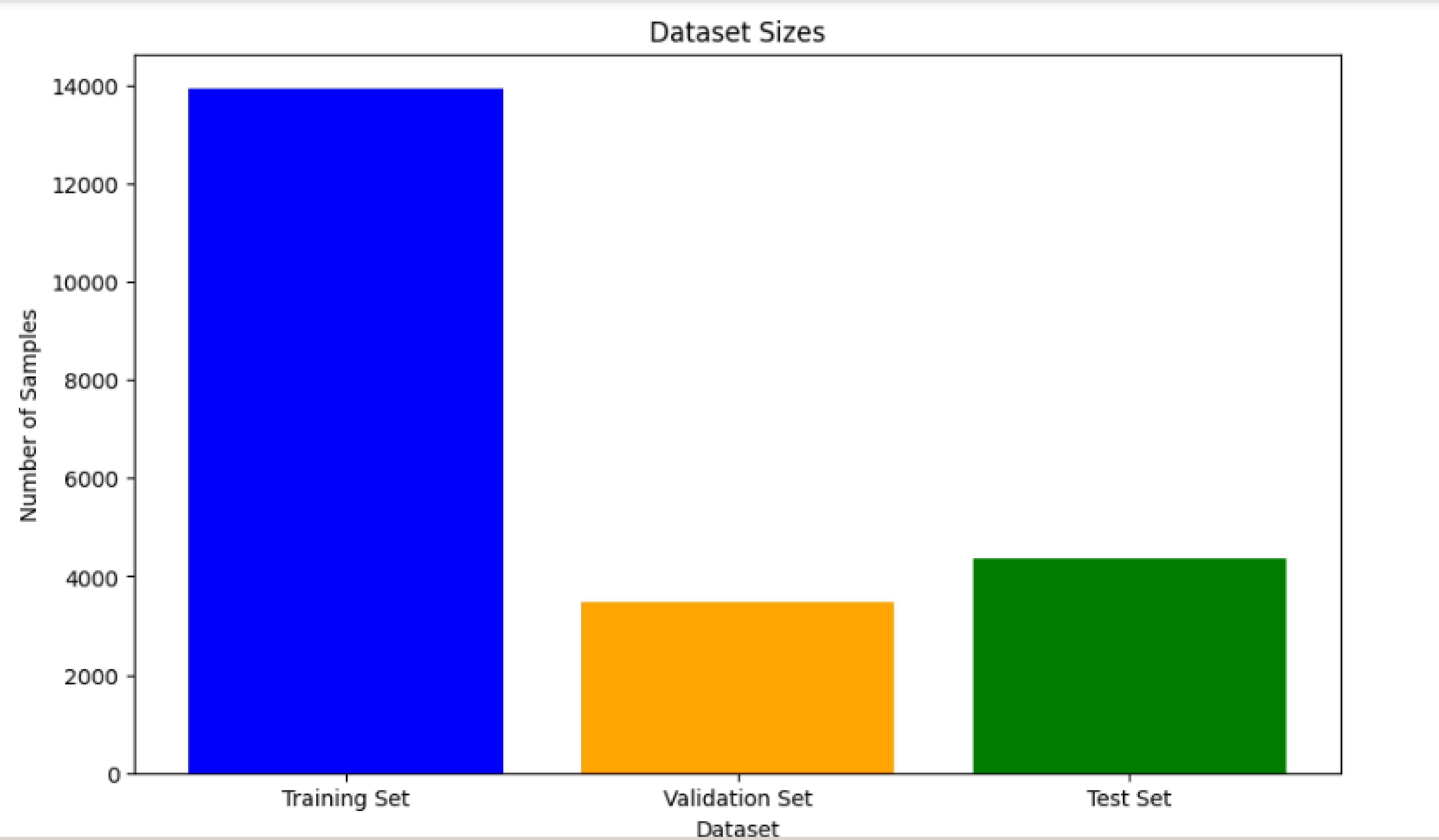
Label:-

0: 12240

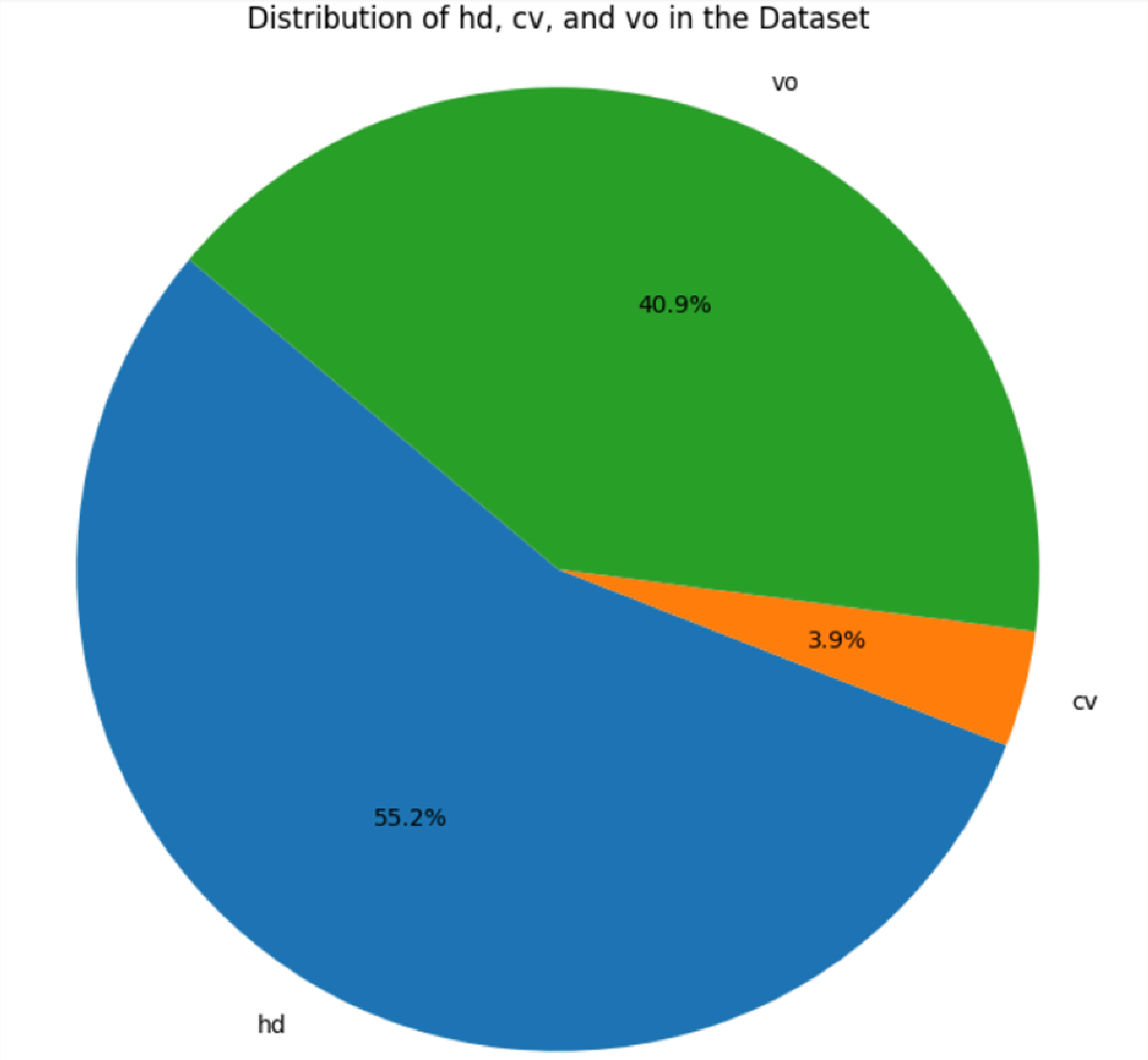
1 : 1696



- Train,test,validation distribution:



- Metadata distribution



DATA PREPROCESSING:

1. **Lowercasing**: Converting all text to lowercase ensures uniformity and reduces the complexity caused by case sensitivity.

2.**Punctuation Removal:** Punctuation often does not add value in hate speech detection and can be removed to simplify the text.

3. **Stopword Removal**: Stopwords are common words (like "and", "the", "is") that do not carry significant meaning and are often removed to focus on more meaningful words.

4.**Stemming**: Stemming reduces words to their root form. For example, "running" and "runner" are both reduced to "run"

5. **Lemmatization:** Lemmatization is similar to stemming but more accurate as it reduces words to their meaningful base form. For example, "better" is reduced to "good".

6. Removing URLs, Hastags , & mentions: Hashtags, and mentions (e.g., @username) are often irrelevant for hate speech detection and can be removed to clean the text.

7.Emoji Conversion: Emojis can carry sentiment and meaning, so converting them to text can help preserve their information.

8.Remove extra space: Trimming excess whitespace between words to maintain uniform spacing and improve readability.

TOKENISATION & EMBEDDING

For Machine Leaning:

Tokeniser:Whitespace Tokeniser:

With the help of whitespace tokeniser we get tokens from string of words or sentences without whitespaces, new line and tabs.

Embedding

1.One Hot Encodding: One-hot encoding is a technique used to convert categorical variables (like class labels) into a format that can be provided to machine learning algorithms to improve model performance.

2.Label Encodding:Label encoding is another technique used to convert categorical variables into numerical format. Unlike one-hot encoding, which creates binary columns for each category, label encoding assigns a unique integer to each category.

3.Word2vec Embedding: It represents words in a continuous vector space where words with similar meanings have similar representations.Word2Vec embeddings are powerful tools for capturing semantic meanings from text data

4. TF-IDF Embeddings: The values in TF-IDF vectors have clear meanings.Term Frequency (TF) measures the frequency of a term in a document, while Inverse Document Frequency (IDF) measures how unique or rare a term is across all documents. This helps in understanding the importance of terms within and across documents.

For Deep learning Models:

BERT Tokeniser:

- BERT uses a method called WordPiece tokenization. This method breaks words into subword units. For example, the word "unhappiness" might be tokenized into "un", "happiness".
- The tokenizer creates attention masks to indicate which tokens are actual words and which are padding. This helps the model differentiate between real content and padding during processing.

BERT Embeddings:

- BERT (Bidirectional Encoder Representations from Transformers) embeddings are a type of word embedding generated by the BERT model, which captures rich contextual information from both directions (left-to-right and right-to-left) in the text.

Modeling:

ML Models:

1. Logistic Regression
2. Random Forest
3. Naive Bayes(Multinomial)
4. SVM(Support Vector Machine)
5. Gradient Boosting

DL Models:

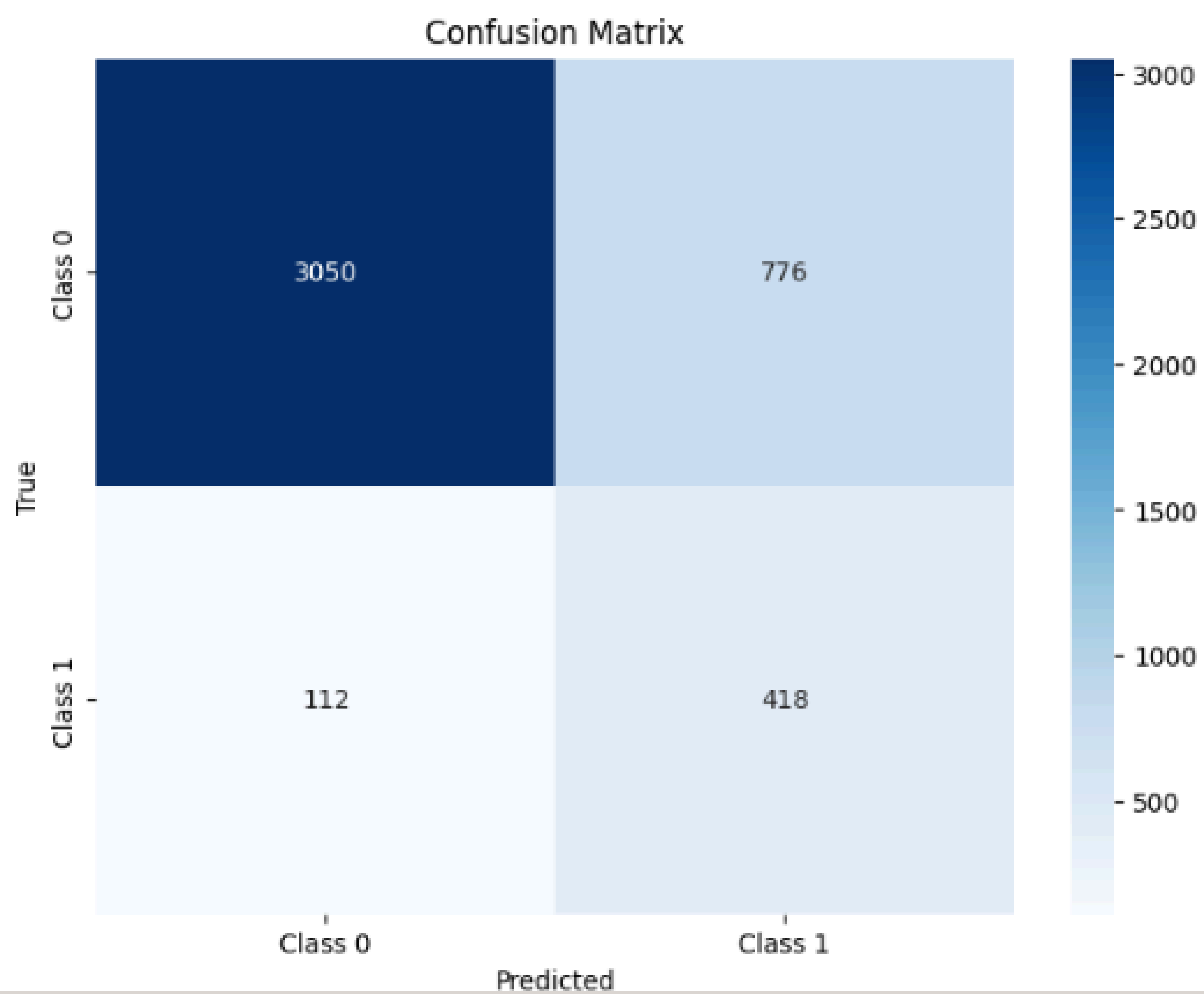
1. CNN
2. Bideirectional LSTM
3. CNN with LSTM
4. Bidirectional LSTM with BERT Embeddings

Finalised Model:

Bidirectional LSTM with BERT Embeddings

Reason:

- Provide deep contextualized representations of text
- Capture rich semantic meanings of words.
- Process information in both forward and backward directions.



EVALUATION METRICS:-

Recall:

Recall measures the effectiveness of a classification model in identifying all relevant instances from a dataset.

- **For DL Model**: 78%

	precision	recall	f1-score	support
Class 0	0.96	0.80	0.87	3826
Class 1	0.35	0.79	0.48	530
accuracy			0.80	4356
macro avg	0.66	0.79	0.68	4356
weighted avg	0.89	0.80	0.83	4356

ROC AUC Score:

AUC measures how well a model is able to distinguish between classes.

- **For DL Model:** 87%

THANK YOU

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