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ENHANCING HOPE SPEECH DETECTION IN SOCIAL MEDIA USING TRANSFORMER MODELS

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Abstract - *The proliferation of online communication has led to an increase in both positive and negative content. While considerable efforts have been directed toward detecting and mitigating hate speech, the identification and promotion of hope speech, which has the potential to foster positive social change, has garnered less attention. This study explores the application of various machine learning and deep learning models to detect hope speech in online textual content. The models evaluated include Logistic Regression (LR), Support Vector Machine (SVM), Bidirectional Encoder Representations from Transformers (BERT), and Recurrent Neural Networks (RNN). The models' performance was measured using metrics such as accuracy, precision, recall, and F1-score. BERT and RNN models outperformed LR and SVM, emphasizing the importance of contextual understanding in hope speech detection. This study demonstrates that deep learning models, particularly BERT, outperform traditional machine learning methods in detecting hope speech.*

Key Words: Hope Speech Detection, Machine Learning, Deep Learning, LR, SVM, BERT, RNN, TF-IDF, GloVe, Word2Vec and BERT Embeddings.

1.INTRODUCTION

Social media sites and online forums have replaced traditional ways of communication for millions of people globally in the current digital era. Social media provides a virtual platform for people to develop, exchange, and work with each other on ideas, facts, and opinions [1]. Even though English is the most widely used language on social media platforms, people from various linguistic backgrounds connect and exchange ideas in their native tongues.

Social media provides deep insights into people's behaviour and is a valuable source of scientific research on topics pertaining to Natural Language Processing (NLP). We exchange our experiences, including those that are necessary for everyone to have during difficult times, such as gratitude for achievements, joy, anger, sadness, and inspiration from defeats [1]. These remarks, sometimes known as "hope speech," convey the well-being of the speaker. "Not hope speech" refers to the other sorts of remarks that demoralize, mistreat, or discourage someone based on their gender, race, handicap, or other minority. The positive recommendations from other viewers improve the video's coherence or substance.[1] On the other hand, remarks like "not hope speech" might demotivate the speaker and reduce the importance of the topic. It important to recognize them in order to make an informed choice, given the greater effect of comments that express hope versus those that do not in social media settings.

Hope speech includes sayings that uplift, encourage, and assist people while promoting positivity and a sense of community. Detecting hope speech can benefit applications such as increasing mental health support, improving the overall ambiance of online platforms, and creating more engaging and supportive environments [2]. This investigates the concept of hope speech, the difficulties in identifying it, and techniques for anticipating hope speech.

1.1 Importance of Hope Speech

A hope speech is a type of speech intended to uplift, encourage, and assist people or groups. Hope speech, in contrast to other positive communication techniques, is concentrated on fostering a feeling of hope and optimism.[3] These speeches work well in a range of contexts, such as social movements, crisis communication, and mental health assistance.

In order to lessen the negative effects of poisonous content on the internet, hope speech is crucial. People's mental health can be greatly impacted by supportive and community-building relationships. [2] Online platforms may become safer, friendlier places where people feel appreciated and supported by encouraging hope speech. Furthermore, hope speech has the power to favorably affect society attitudes and behaviors.

Regardless of its importance, detecting hope speech poses special obstacles. Unlike harmful material, which may be easily classified based on negativity or aggressiveness, hope speech is distinguished by its constructive and uplifting quality, making it more nuanced and context-dependent.[3] Detecting and distinguishing hope speech necessitates sophisticated procedures and a comprehension of context, tone, and intent.

1.2 The Significance of Hope Speech Recognition

Identifying hope speech is important for a number of reasons:

- Mental Health: Positive reinforcement and supportive remarks can significantly improve mental health by providing encouragement and reducing emotions of loneliness.
- Social Cohesion: Hope speeches can bring communities together during turbulent social or political times by encouraging a sense of unity and group resilience.
- Counteracting Negativity: Hope speech can help create a more positive and constructive debate by balancing out damaging and negative speech in the huge ocean of online content.
- Platform Safety: By recognizing and encouraging hope speech, [2] social media platforms and online communities make its members feel safer and more welcome.

Morphological analysis and ML algorithms are two sophisticated approaches used by NLP (natural language processing) to understand and manage the complicated syntax and word formations.[8] By breaking down words and looking at the relationships among them, natural language processing (NLP) systems can produce and analyse text in a extensive variety of languages. Feature extraction techniques such as TF-IDF vectorization and Word2Vec embeddings, GloVe embeddings aid in the conversion of text input into numerical features that prototypes can process.

Machine Learning classifiers such as Support Vector Machines (SVM's) and Logistic Regression (LR) that extract features from the content to categorize the text data. Compared to more traditional machine learning prototypes similar to Support Vector Machines (SVM's) and Logistic Regression (LR), Deep Learning Prototypes like RNN (Recurrent Neural Networks) and BERT (Bidirectional Encoder Representations from Transformers) use large-scale datasets and complex architectures to better interpret and categorize hope speech.

2. Literature Survey

Hope discourse is characterized as dialect that passes on good faith, support, and positive estimations. Its location is vital for cultivating steady and elevating online communities. This writing audit gives an outline of existing strategies for trust discourse location, highlighting conventional machine learning and profound learning approaches. The chapter concludes with the inspiration and issue explanation for the current research.

The writing looks included investigating scholarly databases such as Google Researcher, IEEE Xplore, and ACM Advanced Library. Catchphrases utilized in the look included "trust discourse discovery," "opinion investigation," "content classification," "machine learning," "profound learning," "BERT," "RNN," "calculated relapse," and "bolster vector machines." The look cantered on articles distributed inside the final decade to guarantee the consideration of later headways in the field.

2.1 Machine Learning Approaches

Logistic Regression relapse is a broadly utilized strategy for parallel classification errands. It prototypes the likelihood that a given input has a place to a specific lesson. Thinks about such as Sharma et al. (2022) [4] have illustrated the viability of calculated relapse in recognizing confident discourse by leveraging highlights like term recurrence and estimation scores. Jurafsky and Martin (2020) [6] examine Calculated Relapse in their book on Discourse and Dialect Preparing, enumerating its application to opinion investigation and content classification. They give experiences into how Calculated Relapse can be utilized to classify content based on enthusiastic substance, counting trust. Ng and Jordan (2002) [7] investigated regularization procedures for Calculated Relapse, making strides its execution on high-dimensional content information. This approach can improve the prototype's capacity to foresee cheerful discourse by viably overseeing highlights extricated from content. Le and Mikolov (2014) [11] expanded Word2Vec with Passage Vectors, moving forward its capacity to capture document-level semantics. This expansion upgrades the prototype's capability to get it and produce content with particular passionate tones, counting hope.

Support Vector Machines are capable classifiers that discover the ideal hyperplane isolating diverse classes. SVMs have been connected to different content classification assignments, counting trust discourse discovery. Zhang et al. (2018) [13] highlighted the Vigor of SVMs in taking care of high-dimensional information, making them reasonable for feeling and sentiment-based content classification. Jones (2004) [5] utilized SVMs for estimation examination in motion picture surveys. Their approach highlighted the adequacy of SVMs in recognizing between diverse passionate tones, a guideline that can be adjusted for classifying content sentences based on cheerfulness. Joachims (1998) [9] connected SVMs to content classification, counting assumption investigation, illustrating their adequacy in isolating classes with a clear edge. SVMs appeared to be viable for categorizing content, counting positive and negative estimations, and identifying confident versus non-hopeful content. Jones (2004) [5] surveyed the application of TF-IDF in content classification, highlighting its adequacy in recognizing imperative terms for recognizing between distinctive sorts of substance. Joachims (1998) [9] Connected SVMs to content classification, counting estimation examination, illustrating their efficacy.

2.2 Deep Learning Approaches

RNNs, particularly LSTM (Long Short-Term Memory) and GRU (Gated Repetitive Unit), are outlined to handle successive information and capture transient conditions. Hochreiter and Schmid Huber (1997) [14] presented LSTMs, which have been successfully connected to estimation examination and feeling location errands, counting trust discourse discovery. Sebastiani (2002) [17] investigated different content classification methods, emphasizing the part of TF-IDF in include extraction and its effect on demonstrate execution. Sebastiani (2002) [17] investigated different content classification methods, emphasizing the part of TF-IDF in highlight extraction and its effect on demonstrate execution. Jones (2004) [5] checked on the application of TF-IDF in content classification, highlighting its viability in recognizing critical terms for recognizing between diverse sorts of substance. Gers et al. (2002) [19] investigated Gated Repetitive Units (GRUs), another RNN variation that moves forward learning proficiency. GRUs have been utilized in different NLP applications, counting recognizing passionate tones in text. Santos et al. (2017) [17] connected LSTMs to assumption investigation, illustrating their adequacy in capturing transient conditions in content, which is valuable for foreseeing cheerful speech.

BERT, displayed by Devlin et al. (2018) [20], is a transformer-based appear pre-trained on sweeping substance corpora. BERT has showed up predominant execution in distinctive NLP errands, checking estimation and feeling disclosure. Fine-tuning BERT for believe talk revelation can utilize its significant important understanding to fulfil tall accuracy. Liu et al. (2019) [10] evaluated BERT's execution on suspicion examination benchmarks, showing its ampleness in understanding nuanced eager substance. Research has shown that BERT outperforms conventional machine learning approaches in content classification tasks because of its ability to understand context and semantic relationships at a deeper level. For occasion, Liu et al. (2019) [10] assessed BERT's execution on opinion investigation benchmarks, exhibiting its prevalent capability in dealing with nuanced enthusiastic substance, counting trust discourse. Social media stages are overflowing with both positive and negative substance. BERT has been linked to the recognition of trust discourse in internet posts, giving insightful information about public opinion and facilitating the promotion of constructive conversation. For illustration, Huang et al. (2020) [21] utilized BERT to classify tweets and illustrated that the show may successfully distinguish tweets containing confident messages, hence contributing to endeavors in mental wellbeing and community bolster activities.

2.3 Motivation

Effective moderation is essential for encouraging positive online interactions. While many systems have been developed to detect toxicity, a common drawback is their inability to identify specific portions responsible for the sentiment. This gap is critical, as the ability to highlight these spans is highly beneficial for human moderators who need to manage lengthy comment threads. Addressing this gap by developing systems capable of recognizing and distinguishing hopeful instances within textual content is a crucial step toward successful semi-automated moderation. By achieving this goal, we bridge the gap between automated analysis and human intuition, providing moderators with detailed explanations of where hopefulness exists. This enables users to make more informed and focused decisions, thereby improving the overall quality of online interactions.

3. Problem Definition

The goal is to identify whether a particular social media content contains hope speech in order to solve the issue of binary categorization. Each input text is classed as either hope speech. Determine if a given text on social media contains hope speech, structured as a binary classification issue, with each input text classed as either hope speech (positive class) or not (negative class). Let $X = \{x1, x2, ..., xN\}$ be the set of input texts and $Y=\{y1,y2,...,yN\}$ be the corresponding labels, where $yi \in \{0,1\}$ indicates the presence or absence of hope speech. The contextualized embeddings Hi are extracted from the input texts using a transformer-based prototype called BERT. A BERT network then processes the extracted embeddings to create hidden representations hi. For every sentence, a dense layer with a sigmoid activation function produces the probability score $y\hat{}i$. The training process of the prototype aims To find a function $f: X \rightarrow Y$ that accurately determines whether or not texts contain hope speech. The aim is to enhance the identification of hope speech in social media information by optimizing the prototype parameters θ to make to reduce the loss function.

3.1 Dataset Construction

We collected the dataset from Chakravarthi, B. R. (2022) [15]. Their primary goal was gathering information from social media comments on YouTube, the most popular medium for expressing opinions worldwide. For English, information was gathered from YouTube video comments on current EDI subjects, such as women in STEM, LGBTIQ concerns, COVID-19, Black Lives Matter, the UK against China, the USA versus China, and Australia versus China. This data is unbalanced so to attain balance approach known as under sampling, we eliminated samples derived from the heavily represented class from the original, unbalanced data up to the classes of majority and minority had an equal separation of data. Under sampling offers a few benefits, including being reasonably easy to apply and having the potential to minimize training data, which can improve prototype run time. To predict the hope speech, we also built a dataset that we compared with the unbalanced, balanced dataset.

4. METHODOLOGY

The methodology for predicting hopeful speech in text sentences involves several key phases: data collection, preprocessing, feature extraction, prototype selection and training, evaluation, and deployment. Each phase is crucial for developing an accurate and efficient prediction system.

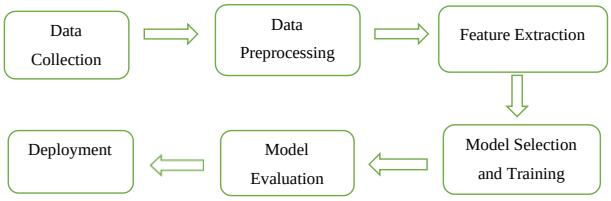

Fig 4.1 Data flow diagram

The system will process input text sentences and predict whether they exhibit a hopeful tone. It will include text preprocessing, feature extraction, prototype training, and prediction functionalities.

4.1 Data Collection

We collected the dataset from Chakravarthi, B. R. (2022) [15]. Their primary goal was gathering information from social media comments on YouTube, the most popular medium for expressing opinions worldwide. For English, information was gathered from YouTube video comments on current EDI subjects, such as women in STEM, LGBTIQ concerns, COVID-19, Black Lives Matter, the UK against China, the USA versus China, and Australia versus China. This data is unbalanced so to attain balance approach known as under sampling, we eliminated samples derived from the heavily represented class from the original, unbalanced data up to the classes of majority and minority had an equal separation of data. Under sampling offers a few benefits, including being reasonably easy to apply and having the potential to minimize training data, which can improve prototype run time. To predict the hope speech, we also built a dataset that we compared with the unbalanced, balanced dataset.

4.2 Data Preprocessing

We carry out a number of preprocessing procedures to get the data ready for hope speech detection before implementing the models. The pre-processing actions listed below are carried out:

- Replacing Tagged User Names: To exclude personally identifiable information from the text, we replace all tagged user names with the "@user" token.
- Eliminating Non-Alphanumeric Characters: All non-alphanumeric characters are eliminated, with the exception of full stops and punctuation symbols like "|" and "." This stage guarantees that the machine can correctly recognize the character sequence.
- Eliminating Flags, Emotions, and Emojis: Since these elements don't add to the semantic substance of hope speech, we also eliminate them from the text.
- URL Removal: All URLs are removed from the text in order to weed out any links that might not be pertinent to the detection of hope speech.

We make sure that the text data is clear and well-suited for the classification task by carrying out these preprocessing methods.

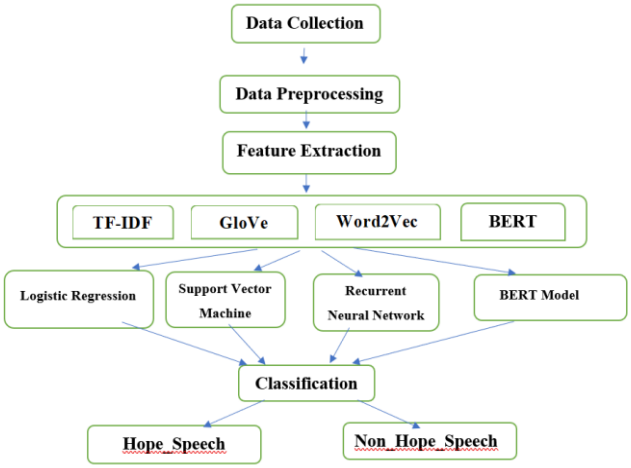

Fig 4.2 System Architecture

This diagram provides a modular and scalable approach to predicting hopeful speech in text, leveraging multiple NLP methods and machine learning.

4.3 Feature Extraction

In hope speech detection, GloVe embeddings provide a static word representation that captures general context from vast corpora, whereas TF-IDF emphasizes the value of single words in the text. Word2Vec offers dynamic embeddings based on local context, allowing for more comprehensive semantic understanding. BERT embeddings outperform because to their bidirectional nature, capturing deeper, context-aware meanings of words. When comparing these algorithms, BERT generally outperforms them because to its increased contextual awareness. however, combining these techniques can provide complementary capabilities for more robust identification.

4.4 Models

Speech detection can be approached using a variety of models, including Logistic Regression (LR), Support Vector Machines (SVM), Recurrent Neural Networks (RNN),

and BERT. Traditional machine learning models include linear regression and support vector machines. RNN is a deep learning model, whereas BERT is a transformer-based model.

- Logistic Regression (LR): An excellent starting point for classification tasks. It's simple, understandable, and frequently performs well on small to medium-sized data sets. LR provides a basic, interpretable baseline based on linear connections between variables and labels.
- Support Vector Machines (SVM): Effective in high-dimensional spaces and applicable to both regression and tasks involving classification. SVM provide a more complex method, managing non-linear boundaries and doing well on smaller datasets.
- Recurrent Neural Nets (RNNs): Recurrent Neural Networks (RNN) use sequential processing to record dependencies over time, which is essential for interpreting the flow of hope speech in context.
- Bidirectional Encoder Representations from Transformer (BERT): BERT is advanced, with its transformer-based architecture that captures bidirectional context, resulting in an extensive understand of language.

While LR and SVM work well for simpler tasks, RNNs have an advantage in sequence handling, and BERT frequently beats all, particularly in capturing complex, sensitive statements of hope speech. When comparing these models, BERT typically outperforms them because to its advanced contextual embeddings, albeit requiring more processing resources.

5. Experimental setup

The complete experimental methodology which has been used for the development of the prototype. For the experiment, traditional machine learning methods of Support Vector Machines (SVMs) and Logistic Regression (LR) are chosen. These prototypes' performance is evaluated using the F1 score, Precision, and Recall metrics. In order to achieve balanced data, we removed samples from the heavily represented class from the unbalanced data until the minority and majority classes had an equal distribution of data with 3,365 features, of which 1,804 were non_hope_speech and 1561 hope_speech. Initially, a total of unbalanced data 18,192 features, of which 16,630 were non_hope_speech and 1,562 hope_speech, were extracted from the processed data [15]. There were 1,098 hope speeches and 1512 non-hope speeches out of the 2,610 generated data points.

Following that, the training dataset was given into ML classifiers using feature extraction methods including TF-IDF, Word2Vec, and GloVe. We used every possible combination of feature extraction methods and carefully chosen classifiers. In addition, this problem is addressed by implementing Deep Learning neural networks such as Recurrent Neural Networks (RNN), Transformer-Based Bidirectional Encoder Representations (BERT), BERT with LSTM, and BERT embeddings with SVM classifier. Chapter 6 discusses the comparative results of the ML classifiers and Deep Learning classifier with feature extraction techniques including TF-IDF, Word2Vec, GloVe, and BERT embeddings on the created, unbalanced, and balanced dataset.

Table-5.1: Data distribution for the Unbalanced data.

Hope_speech	1562
Non_hope_speech	16630

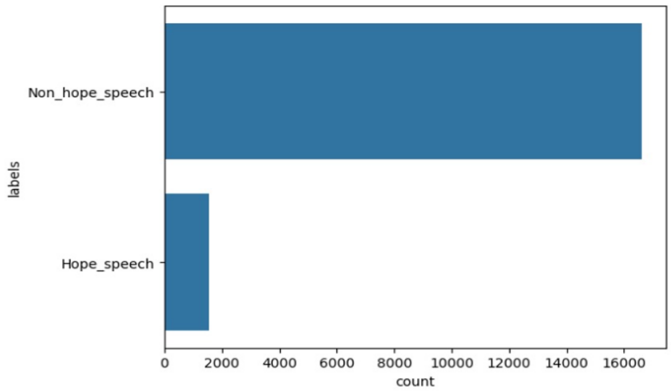

Chart-5.1: Data distribution for the Unbalanced data.

A total of original data with 18,192 features, of which 16,630 were Non_hope_speech and 1,562 Hope_speech, were extracted from the processed data [15].

Table-5.2: Data distribution for the Balanced data.

Hope_speech	1561
Non_hope_speech	1804

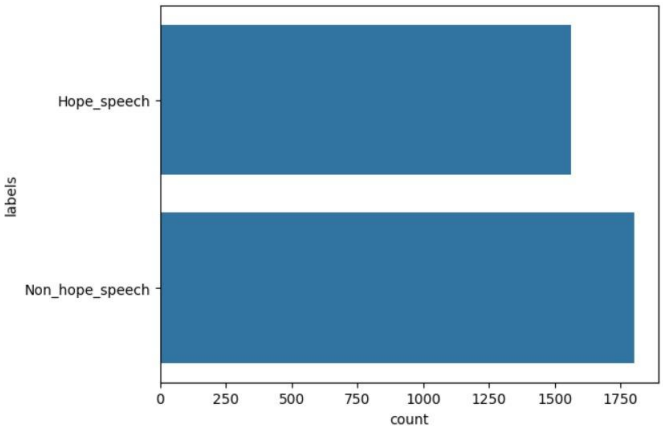

Chart-5.2: Data distribution for the Balanced database.

The unbalanced data was reduced until the minority and majority classes had an equal distribution of data with 3,365 features, of which 1,804 were Non_hope_speech and 1561 Hope_speech.

Table-5.3: Data distribution for the Generated data.

Hope_speech	1512
Non_hope_speech	1098

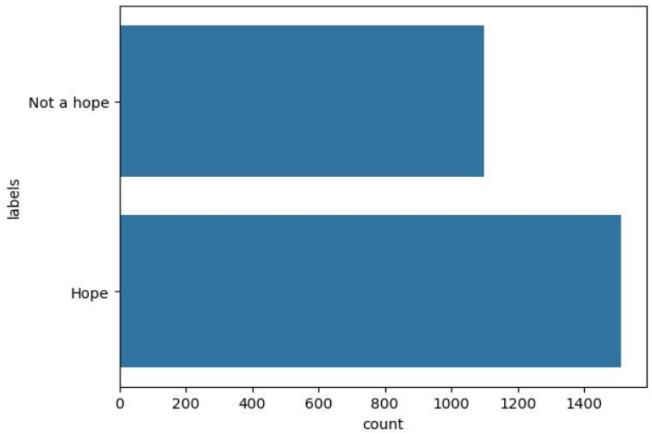

Chart-5.3: Data distribution for the Generated data.

The new dataset prepared with 1,098 Hope_speech and 1512 Non_hope_speech out of the 2,610 generated data.

5.1 Methods Employed

Many ML and NLP Methods might be utilized to effectively identify hope speech. We focused on the execution of various cutting-edge prototypes and algorithms, including:

- **Logistic Regression (LR):** The statistical approach employed in the analysis of binary classification is known as logistic regression. It computes the likelihood of an outcome being binary by considering one or more predictor factors. Based on characteristics taken from the text or voice data, Logistic Regression can categorize speech samples in order to determine whether or not the speech content is hopeful.

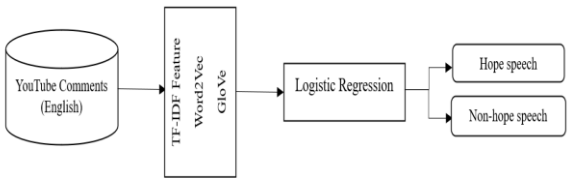

Fig 5.1: LR Architecture

1. Input Features: Text data is turned into a numerical feature vector using TF-IDF or word embeddings like Word2Vec and GloVe.
2. Logistic Regression Model: The model calculates a weighted sum of the input data to create a linear decision boundary in the feature space.
3. Sigmoid Function: The linear output is converted into a probability score using the sigmoid function.
   The sigmoid function for a LR can be expressed as: $1/(1 + e^{(-z)})$.
4. Output: The final classification is determined by using a decision threshold.

This architecture offers an easy technique to recognizing hope speech, using the linear decision boundary to distinguish hopeful messages from others based on textual properties.

- **Support vector machines (SVM's):** SVM are effective supervised learning prototypes that are applied to problems with classification and regression both. SVMs are known for being flexible in high-dimensional spaces and are especially useful when working with smaller datasets. By collecting relevant information from the spoken text, such as tone, pitch, and specific word usage, SVMs can be utilized in the context to categorize speech data into categories like "hopeful" or "non-hopeful".

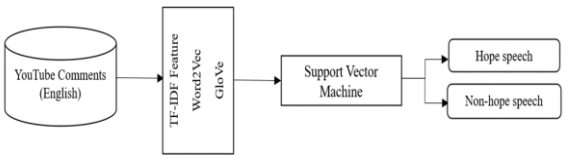

Fig 5.2: SVM Architecture

1. Input Features: Text data is turned into a numerical feature vector using TF-IDF or word embeddings such as Word2Vec and GloVe.
2. SVM Model: SVM determines the best hyperplane that maximizes the margin between the two classes.
3. Decision Function: The input text's class is determined by the linear combination of its features and learning weights.
   The decision function for a linear SVM can be expressed as: $f(x)=w \cdot x+b$.
4. Support vectors: These crucial data points determine the ideal hyperplane and thus the decision boundary.
5. Output: The SVM classifies the input according to the sign of the decision function. If f(x) is greater than zero, the input is labeled as hope speech; otherwise, it is classified as non-hope.

This design makes SVM an excellent alternative for detecting hope speech, especially if the feature space is well-defined and separable.

- **Recurrent Neural Networks (RNN):** RNNs are good at comprehending the context of hope speech because they are especially well-suited for sequential data and can capture temporal connections in text. In natural language processing, recurrent neural networks (RNNs) are crucial, particularly for categorized text applications. Unlike typical feedforward networks, RNNs have the unique ability to capture sequential dependencies in input, which makes them perfect for processing and understanding sequential information.

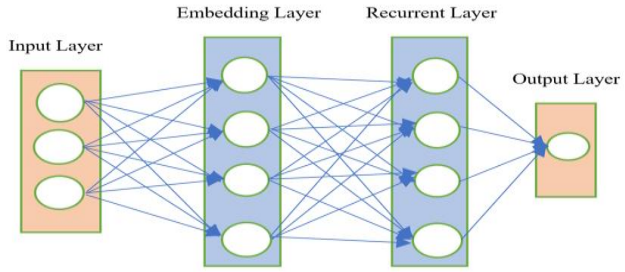

Fig 5.3: RNN Architecture

1. Input Sequence: The text data is input into the model word by word. The Embedding Layer transforms each word into a dense vector.
2. Recurrent Layer: The RNN processes the sequence, updating its hidden state with each of the words in order to capture sequential context.
3. Output Layer: The final hidden state is utilized to determine if the text shows hope.

This architecture enables the RNN to accurately capture the temporal connections and variations in the text, which is critical for tasks such as hope speech detection.

- **BERT (Bidirectional Encoder Representations from Transformer):** This language representation prototype is revolutionizing NLP by utilizing the strength of transformer architecture to produce contextualized embeddings. BERT uses a bidirectional approach to evaluate input sequences in forward as well as backward directions. This allows it to identify minute linguistic nuances, contextual dependencies, and complicated semantic linkages.

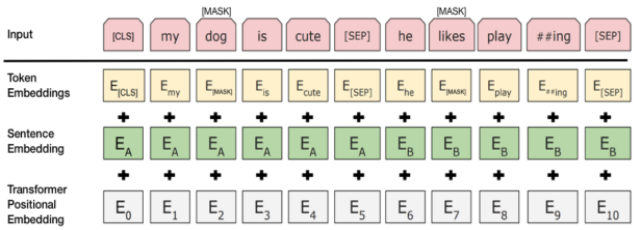

Fig 5.4: BERT Architecture

1. Input Representation: The input text is tokenized and integrated with additional relative and categorize data.
2. Transformer Encoder: The embedded tokens are passed through various layers of self-attention and feed-forward networks to capture the complex relationships between tokens in the sequence.
3. [CLS] Token Representation: The vector corresponding to the [CLS] token captures the entire meaning of the input and is used for classification.
4. Output Layer: This representation is mapped to the target classes (hope speech or not) using a fully connected layer followed by SoftMax.

This design allows BERT to successfully interpret and classify text depending on the context provided by the complete sentence or statement, making it highly effective at recognizing hope speech.

6. Prototype Evaluation

Metrics: Precision, recall, and the F1 score

- Precision: Precision assesses the accuracy of positive predictions.
  Formula:

$$\text{Precision} = \frac{\text{True Positives (TP).}}{\text{True Positives (TP)+False Positives (FP).}}$$

- Recall (Sensitivity): Recall assesses the ability to identify all positive instances.
  Formula:

$$\text{Recall} = \frac{\text{True Positives (TP).}}{\text{True Positives (TP) + False Negatives (FN).}}$$

- F1-Score: The F1-Score, which is the harmonic average of Precision and Recall and is useful for unbalanced classes [1].
  Formula:

$$\text{F1-Score} = 2 * \frac{\text{Precision x Recall.}}{\text{Precision + Recall}}$$

- Accuracy: The proportion of correctly predicted instances to total instances. It Offers a quick snapshot of prototype performance, particularly when classes are balanced.
  Formula:

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total instances}}$$

7. RESULTS AND DISCUSSION

During this task, we employed four different prototypes to detect hope speech: Logistic Regression (LR), Support Vector Machine (SVM), BERT, and Recurrent Neural Networks. The primary purpose was to analyze and compare the prototypes' effectiveness in locating hope speech in text data. The dataset was divided between training and testing sets using an 80:20 split. The labels were encoded with Label Encoder, which converted categorical labels into numerical values. Traditional machine learning prototypes (LR and SVM) had features extracted via TF-IDF vectorization. For deep learning prototypes (BERT and RNN), text data was tokenized and padded as needed.

Evaluation Metrics

- Accuracy: The proportion of correctly predicted instances.
- Precision, Recall, F1-Score: Metrics evaluating classification performance.

Prototype Performance

The unbalanced data, balanced data and generated data is checked and verified by using feature extraction methods such as TFIDF, Word2Vec and Glove, BERT embeddings with Classifiers such as LR, SVM, RNN, and Transformer prototype (BERT) to predict Hope Speech classification. Traditional Machine Learning Prototypes (Logistic Regression, Support Vector Machine (SVM)) and DL neural network type (RNN), Transformer prototype (BERT) was trained on the dataset, and the following results were obtained.

1. Logistic Regression (TFIDF +LR)

Table -7.1: Results Obtained for (TFIDF+LR) Prototype

Unbalanced data	92%
Balanced data	80%
Generated data	95%

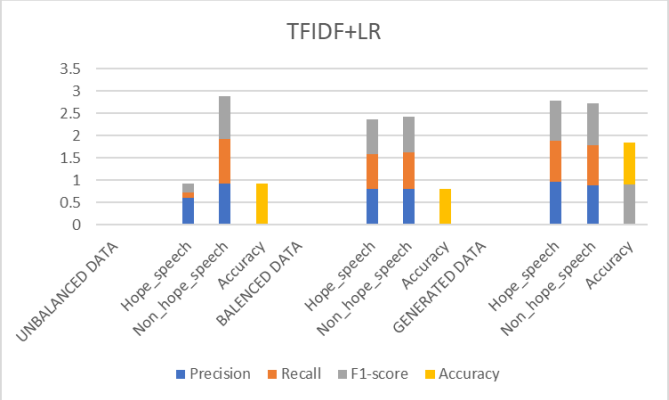

Fig 7.1: Comparison of evaluation metrics of (TFIDF+LR) prototype

2. Logistic Regression (W2V +LR)

Table-7.2: Results Obtained for (W2V+LR) Prototype

Unbalanced data	92%
Balanced data	75%
Generated data	89%

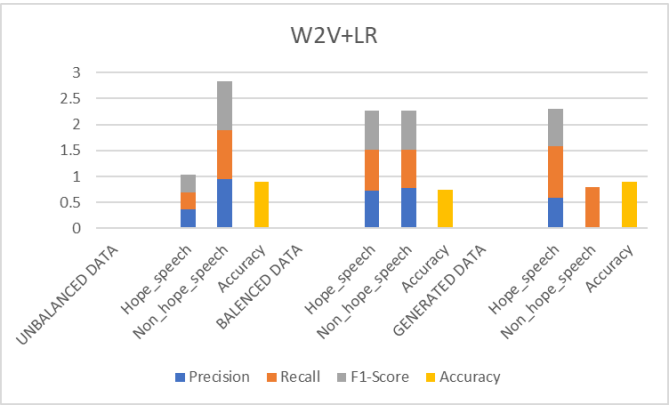

Fig 7.2: Comparison of evaluation metrics of (W2V+LR) prototype

3. Logistic Regression (GloVe +LR)

Table-7.3: Results Obtained for (GloVe+LR) Prototype

Unbalanced data	91%
Balanced data	54%
Generated data	58%

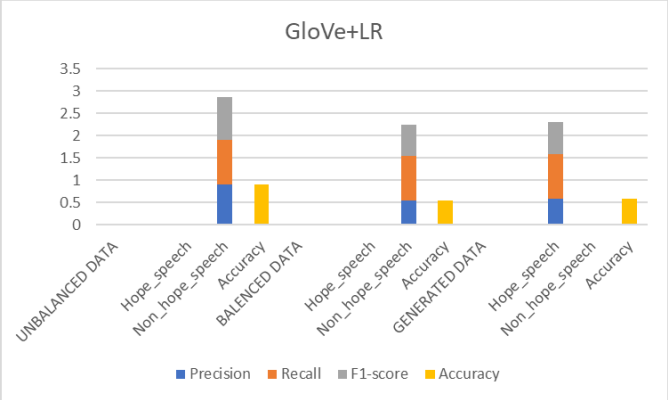

Fig 7.3: Comparison of evaluation metrics of (GloVe+LR) prototype

Discussion: Logistic Regression, a simple and interpretable prototype, performed well on the challenge. The prototype generalized well, but it struggled to capture complicated patterns in the text, which is understandable given its linear character.

4. Support Vector Machine (TFIDF+SVM)

Table-7.4: Results Obtained for (TFIDF+SVM) Prototype

Unbalanced data	76%
Balanced data	76%
Generated data	95%

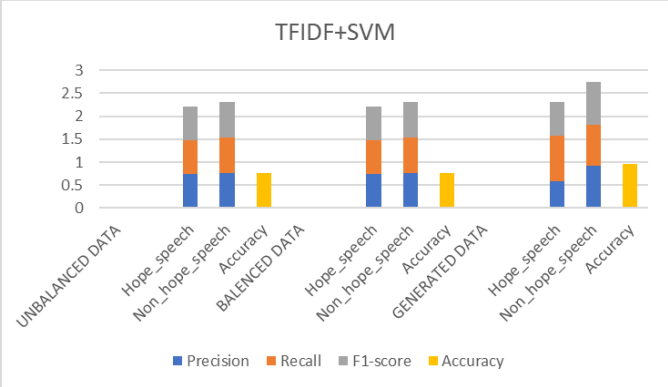

Fig 7.4: Comparison of evaluation metrics of (TFIDF+SVM) prototype

5. Support Vector Machine (W2V+SVM)

Table-7.5: Results Obtained for (W2V+SVM) Prototype

Unbalanced data	57%
Balanced data	59%
Generated data	73%

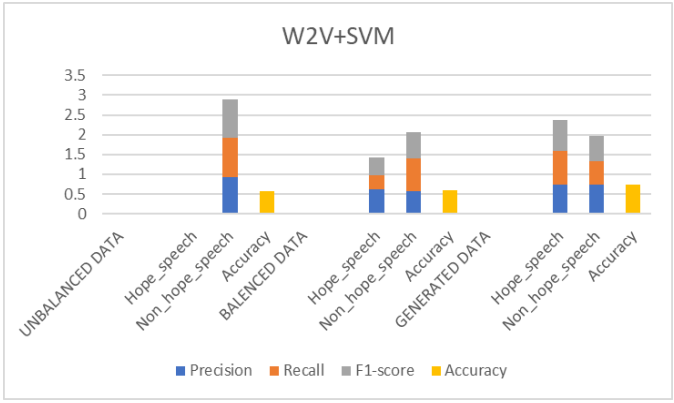

Fig 7.5: Comparison of evaluation metrics of (W2V+SVM) prototype

6. Support Vector Machine (GloVe+SVM)

Table-7.6: Results Obtained for (GloVe+SVM) Prototype

Unbalanced data	91%
Balanced data	54%
Generated data	58%

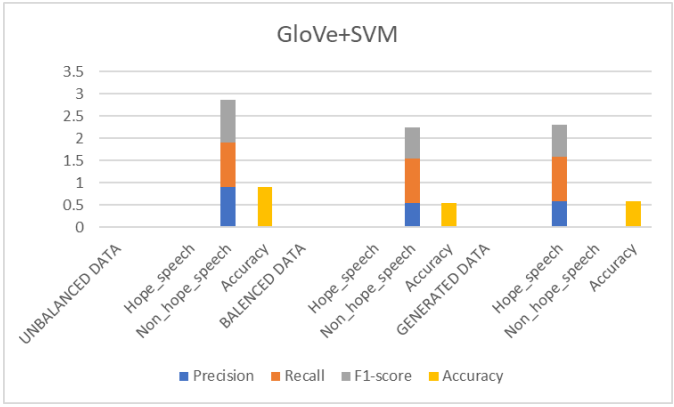

Fig 7.6: Comparison of evaluation metrics of (GloVe+SVM) prototype

Discussion: The SVM prototype outperformed Logistic Regression by a small margin. Its ability to handle high-dimensional data made it slightly better at distinguishing between hope speech and other types of speech. However, it still had limitations in understanding the contextual nuances of the text.

7. Recurrent Neural Network (RNN)

Table-7.7: Results Obtained for RNN Prototype

Unbalanced data	90%
Balanced data	75%
Generated data	89%

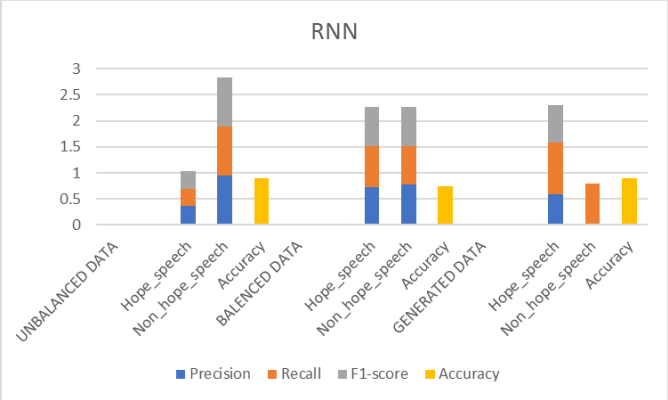

Fig 7.7: Comparison of evaluation metrics of RNN prototype

Discussion: The RNN prototype also showed strong performance, although it was slightly lower than BERT. RNNs are designed to capture sequential dependencies in text, which helped in understanding the flow of information. However, RNNs may struggle with long-term dependencies compared to transformer-based prototypes like BERT.

8. BERT (Bidirectional Encoder Representations from Transformers)

Table-7.8: Results Obtained for BERT Prototype

Unbalanced data	92%
Balanced data	52%
Generated data	57%

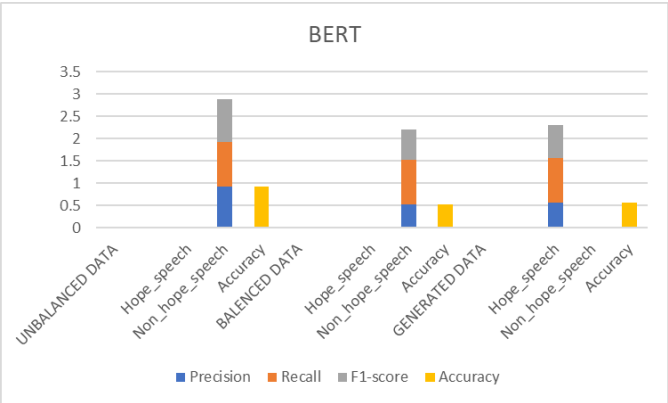

Fig 7.8: Comparison of evaluation metrics of BERT prototype

9. BERT+SVM

Table-7.9: Results Obtained for (BERT+SVM) Prototype

Unbalanced data	92%
Balanced data	79%
Generated data	94%

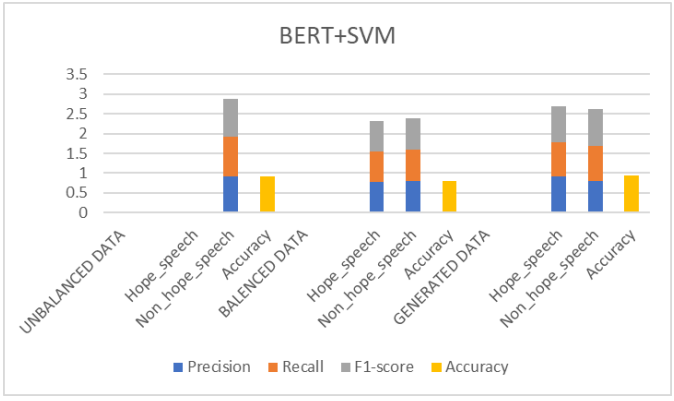

Fig 7.9: Comparison of evaluation metrics of (BERT+SVM) prototype

10. BERT+LSTM

Table-7.10: Results Obtained for (BERT+LSTM) Prototype

Balanced data	79%
Generated data	99%

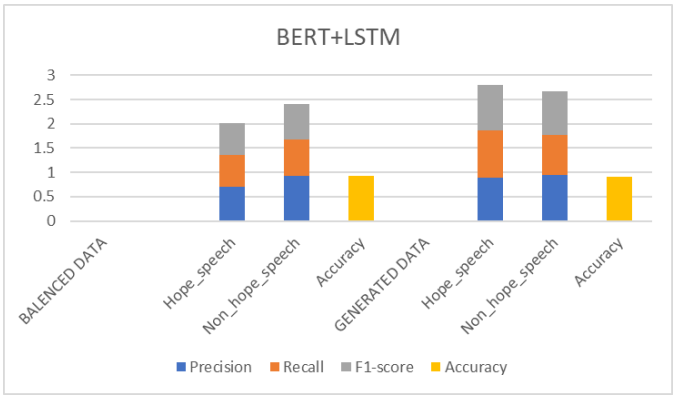

Fig 7.10: Comparison of evaluation metrics of (BERT+LSTM) prototype

Discussion: BERT, a transformer-based prototype, fared much better than both LR and SVM. Its deep bidirectional transformers enabled it to comprehend the contextual and semantic meaning of words in the text. The prototype excelled in capturing the language's complicated patterns and dependencies, resulting in good performance across all measures.

Comparative Analysis

Among the four prototypes, BERT had the best accuracy, precision, recall, and F1-score. This suggests that transformer-based prototypes are more effective at detecting hope speech because they can understand contextual information and semantic complexities. Traditional machine learning prototypes, such as LR and

SVM, performed well but were constrained by their linear character and inability to grasp complicated correlations in data. RNNs achieved a reasonable combination of performance and computational economy, but BERT outperformed them marginally.

BERT consistently outperformed other methods due to its deep contextual understanding. It is highly effective in grasping nuances of hope speech. RNN's showed good performance, particularly with longer sequences where context is important. SVM and LR performed well with simpler data representations but struggled with more complex patterns. Word2Vec, GloVe and TF-IDF, provided valuable insights, but their effectiveness was limited compared to BERT.

8. CONCLUSIONS

The literature survey highlights various approaches to predicting hopeful speech in text sentences. Traditional machine learning methods like SVMs and Logistic Regression, along with modern techniques like Word2Vec, TF-IDF, RNNs, and BERT, offer diverse tools for analysing and classifying text based on emotional content. Each method brings unique strengths to the task of predicting hopefulness. The methodology for predicting hopeful speech in text sentences encompasses a comprehensive approach from data collection to deployment. By employing various techniques and advanced machine learning prototypes, the system aims to accurately identify and predict hopeful sentiments in text. Continuous evaluation and updates will ensure the system remains effective and relevant. The study demonstrated that BERT is the most effective technique for predicting hope speech due to its deep contextual capabilities. While traditional methods like SVM and LR are useful, modern NLP techniques such as BERT provide significant improvements. Future work may involve exploring hybrid prototypes and fine-tuning pre-trained prototypes on specialized datasets.

REFERENCES

[1] P. Aggarwal (2022). Hope Speech Detection on Social Media Platforms.

[2] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7785056/

[3] https://www.indeed.com/career-advice/career-development/types-of-speeches

[4] Sharma, N., Pandey, R., & Singh, S. (2022). Detecting hope and motivation in online forums using logistic regression and sentiment analysis. Journal of Information Science, 48(3), 456-468.

[5] Jones, K. S. (2004). A Statistical Interpretation of Term Specificity and its Application in Retrieval. Journal of Documentation, 60(5), 493-502.

[6] Jurafsky, D., & Martin, J. H. (2020). Speech and Language Processing (3rd ed.). Prentice Hall.

[7] Ng, A. Y., & Jordan, M. I. (2002). On Discriminative vs. Generative classifiers: A comparison of logistic regression and naive Bayes. In Advances in Neural Information Processing Systems.

[8] https://www.deeplearning.ai/resources/natural-language-processing/

[9] Joachims, T. (1998). Text categorization with Support Vector Machines: Learning with many relevant features. In European Conference on Machine Learning.

[10] Liu et al. (2019). Transcriptome profiling of periwinkle infected with Huanglongbing.

[11] Le, Q. V., & Mikolov, T. (2014). Distributed Representations of Sentences and Documents. In Proceedings of the 31st International Conference on Machine Learning (ICML-14).

[12] https://www.geeksforgeeks.org/ml-machine-learning/

[13] Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery.

[14] Hochreiter, S., & Schmid Huber, J. (1997). Long short-term memory. Neural Computation.

[15] Chakravarthi, B. R. (2022). HopeEDI: A Multilingual Hope Speech Detection Dataset for Equality, Diversity, and Inclusion. Proceedings of the 13th Language Resources and Evaluation Conference (LREC 2022), European Language Resources Association (ELRA).

[16] https://www.analyticsvidhya.com/blog/2020/02/cnn-vs-rnn-vs-mlp-analyzing-3-types-of-neural-networks-in-deep-learning/

[17] Santos, C. N. d. S., Barbosa, L., Boghrati, R., Braga, D., & Carvalho, R. (2017).

[18] Convolutional Neural Networks for Sentiment Analysis of Short Texts.

[19] https://en.wikipedia.org/wiki/BERT_(language_model)

[20] Gers, F. A., Schmid Huber, J., & Cummins, F. (2002). Learning to Forget: Continual Prediction with LSTM. Neural Computation.

[21] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding.

[22] Huang, B., Li, Z., & Zhan, J. (2020). Identification of Hope Speech in social media: A BERT-based Approach. Journal of Digital and Social Media Marketing.