ISSN: ISSN: 2583-5149 | Special Edition Vol. 1 | March 2026

Fuzzy based Sentiment Analysis of any Sentence using Indian Scriptures: Case Study of Shrimad Bhagavad Gita

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Abstract

The current research work aims to study and measure the emotional tone and sentiment expressed in the verses of the Bhagavad Gita through a structured, dataset-based analytical method. The main objective of this work is to identify how positive and negative sentiments are distributed across different words and sentences, and to determine the overall emotional balance of any sentence. A dataset was created by collecting unique words from the original text and assigning each word a positive and negative score based on their contextual meaning and frequency of use. Repeated words were analyzed to calculate their average sentiment strength, which was then expressed as percentage form. The proposed model takes a sentence as input, extracts individual words, and checks each word against the dataset. Words found in the dataset contribute to the overall sentiment calculation, while those not found are ignored.

Additionally, the dataset includes a separate list of strictly negative words; if any such word appears in the sentence, the sentence is immediately classified as negative. The remaining sentences are evaluated by averaging the positive and negative scores of all included words to produce a final sentiment percentage. This approach provides a simplified yet effective way to interpret the emotional and philosophical tone of the Shrimad Bhagavad Gita through quantitative fuzzy analysis. The major research objectives that we have fulfilled in this research work is to create a dataset that doesn't exist and unique that identify the sentimental tones of the words present in the verses and predict a sentences sentimental tone with respect to the dataset we have created. By combining logical computation with linguistic understanding, our research work demonstrates spiritual value of any sentence. We analyzed to reveal patterns of positivity and negativity, offering a deeper insight into the moral and emotional essence of ancient Indian wisdom with the case study of Shrimad Bhagavad Gita in the sentences of the user.

Keywords— Sentiment Analysis, Fuzzy logic, Indian Scriptures, Shrimad Bhagavad Gita, Emotional Tone, Indian Knowledge System, Predictive Data Analytics, Aligning society with Ancient Culture and Wisdom.

Introduction

In the current world of information age, studying human emotion and opinion has become an interesting area of study. Sentiment analysis studies human sentences are either positive or negative. Although this concept may be common but very few research has been conducted with sentiment analysis as an analytic tool to study it with respect to our ancient scriptures. Each verse in the scriptures gives a message, which can be interpreted and understood differently by different readers. Our work uses a data centric approach whereby each word is assigned a positive and negative number by quantifying the sentiments of each word in the sentence. In this paper we have shown that the prediction of sentiment of a sentence with respect to Shrimad Bhagavad Gita verses using fuzzy analysis.

Our motivation was to create a dataset and model for researchers and academia who does research in the field of Indian Knowledge System. We have created the dataset from Shrimad Bhagavad Gita and referring to the translated text [16] manually from all 18 chapters with logical estimations. To generate the important findings from the sentences we are using the rigorous data analytics for prediction. The core motivation was to create the connection between technology and spirituality by demonstrating an analytical approach to predict the sentimental tone of any sentence.

It is not easy to formulate a way to distil sentimental tone into numbers, but we have quantified the sentimental tone of each word present in the scripture which took almost 9 months of rigorous analysis of the verses from Shrimad Bhagavad Gita. This involved the creation of a dataset containing words with their respective positive and negative scores. Our current research focus is limited to the sentiment of words and sentences based on the dataset we have created. In terms of complexity, our work does not account for complex grammatical structures, synonyms, or sarcasm, as it was designed to be simple and straightforward using fuzzy logic.

Literature Review

Recently, the field of sentiment analysis has been investigated by numerous researchers; this branch of research identifies and classifies emotion or opinion expressed in text. Sentiment analysis has focused on social media and reviews, but Indian scriptures like the Bhagavad Gita remain underexplored with fuzzy approach. Some of the literature in the similar domain are outlined below with their findings.

Mahit et al [1] applied NLP techniques of topic modelling, semantic embeddings, sentiment analysis to the Bible, Quran, and Bhagavad Gita, revealing shared and unique themes and sentiment profiles. Using LDA, GloVe, Sentence Transformers, and VADER, they demonstrated NLP's potential in cross-textual religious analysis. Lima et al [2] reviewed AI methods for analysing the Bible, highlighting machine learning, neural networks, and deep learning as common techniques. They note challenges due to the Bible's complexity and identify research gaps, emphasizing the need for more AI-driven studies on sacred texts. Chandra & Kulkarni [3] used BERT to analyze English translations of the Bhagavad Gita, finding consistent core messages and emotional tones despite vocabulary differences. Their work shows deep learning NLP's potential for ancient texts with complex linguistics.

Vora et al (2024) [4] used LLMs for sentiment analysis of the Bible's Sermon on the Mount, outperforming traditional methods. They found vocabulary differences impact emotional expression, highlighting the need for more research on sentiment analysis in sacred texts. Bader et al. [5] analyzed 1,758 Twitter messages about Jordan's churches, revealing: 56% positive sentiment, 27% neutral sentiment, 17% negative sentiment. Most words used were positive, indicating people like the churches, but poor promotion may deter visitors. Iqbal et al [6] in their study used information from 33 Islamic banks in six countries over many years. It found that when managers use more positive words, the bank usually performs better with money, and when they use more negative words, the bank performs worse.

This research is special because it is the first to use managers' feelings from reports to predict how Islamic banks will perform. Iqbal et al [6] analyzed 33 Islamic banks across six countries, finding a link between managers' word choice in reports and financial performance. Positive words correlated with better performance, while negative words correlated with worse performance, making this a pioneering study on sentiment analysis in banking.

Alexa in her work [7] has used sentiment analysis to read Instagram posts from PLNU and other colleges. A computer tool called VADER gave each post a score to show if it was happy, sad, or normal. The posts were grouped into categories, and the colleges were ranked based on how positive their posts were. The study found that Pepperdine had the most positive feelings overall. Cheng et al [8] analyzed Twitter posts about NFTs and found that people generally feel positive, with emotions like hope and trust being common. This helps understand why NFTs are popular. Masarykova [9] studied how pastors use emotions in church sermons to persuade people, focusing on love, hope, fear, and care to connect with their audience. Haque et al [10] manually checked Hadith authenticity by tracing narrators, but now a computer model analyses these chains to classify Hadiths, achieving 86% accuracy.

Mathias [11] built a system to recommend Bible verses using NLP. It matches input text with relevant verses, and a transformation matrix improved ranking, showing promise for structuring sacred texts. Makoto Nakayama & Yun Wan [12] analyzed Yelp reviews by Japanese and Western customers, revealing cultural differences in sentiments about food, service, place, and price. Arpita et al [13] used SVM for sentiment analysis of smartphone product reviews, achieving 90-94% accuracy. Most reviews were positive, and SVM outperformed other methods, proving reliable for sentiment analysis on product reviews. Munir et al [14] found SVM achieves 80-89% accuracy in sentiment analysis, rising to 93% with hybrid or ensemble techniques, emphasizing the value of preprocessing and combined approaches. Munir et al [15] optimized SVM using grid search, improving sentiment analysis on Twitter and IMDB datasets. Optimized SVMs showed better text classification efficiency than non-optimized ones.

The existing literature lacks a simple fuzzy logic-based system to calculate sentiment percentages in the translated Shrimad Bhagavad Gita [16]. Our research addresses the gap by developing a sentiment analysis model with logical computation and human interpretation, aligning with the text's philosophical essence, and contributing to India's digital cultural preservation.

Methodology

The dataset examines words from the Bhagavad Gita [16], assessing their sentiment on a numeric scale. Each word's emotional value is computed, considering its context, and categorized accordingly. Prior to the application of the dataset for sentiment analysis of The Shrimad Bhagavad Gita, preprocessing of the data was performed. In order to enable analysis, thousands of unstructured records comprising various sentiment values and duplicate words were cleaned, standardized and structured to create a final, clear, and concise dataset representing positive and negative sentiment scores for every word contained within the dataset which took almost 9 to 10 months of rigorous work.

Originally, the first dataset contained 16,236 words categorized under several sentiment columns, which illustrated positivity and negativity on a percentage-based scale. The dataset was refined to give each word a single sentiment score, reducing 16,236 words to 2,616 unique words. The cleaned dataset has three columns: Word, Positive, and Negative, representing each word's sentiment distribution, and served as the basis for the fuzzy based sentiment analysis model.

Methodology Applied

The considered methodology for sentiment analysis is rule-based and dataset-driven. It has been specifically developed for the purpose of analyzing the emotional tone of verses from the Shrimad Bhagavad Gita. Each word in the dataset has been assigned a positive and negative percentage, which enables the model to quantitatively analyze the string of text and determine a score that reflects the emotional depth of the scripture.

The flowchart Fig 3.2.1, shows the process of analyzing a sentence's sentiment. To begin the workflow, the user enters a sentence or verse into the system. The first task the model performs is tokenization, which splits each sentence into individual tokens, or words. Each of these tokens is then checked against the dataset to determine whether the word is present in the sentiment table. If the token is found, the positive and negative score of the token will be provided; if it is not found in the dataset, the token will be disregarded for sentiment analysis because it has no assigned sentiment score. Therefore, only tokens with assigned emotional weights will contribute to the output. When all words are recognized, the model computes an estimate of the average positivity and negativity in a sentence by summing all of the positive and negative numerical representations assigned to each individual word and dividing this value by the total number of relevant words.

These average values are then transformed into a percentage expression to reflect the overall emotional balance in a given sentence (i.e., a 65% positive/35% negative sentence would have a mildly positive emotional leaning). Finally, the percentages produced are used as a final score for determining a sentence's sentiment.

The proposed model for sentiment analysis is based on assigning each word two sentiment scores; a positive and a negative value. These scores represent the emotional weight of each word. The final sentiment of a sentence is calculated by combining and averaging these values across all words.

Let the input sentence contain n words. For each word in the sentence:

P_i = Positive score of the word

N_i = Negative score of the word

Each word's sentiment contribution (X_i) can be represented as:

$$X_i = (P_i \times Y_i) + (N_i \times Z_i) \quad \ldots (1)$$

where Y_i and Z_i denote the relative positive and negative weights of that word.

The average positive and average negative sentiments for the entire sentence are calculated as:

$$\text{Average Positive (A\_pos)} = (\Sigma P_i) / n$$

$$\text{Average Negative (A\_neg)} = (\Sigma N_i) / n \ldots (2)$$

The total sentiment weight (T) is then:

$$T = A\_pos + A\_neg \quad \ldots (3)$$

To convert these averages into percentages, the following formulas are used:

$$\text{Positive Percentage (S\_pos)} = (A\_pos / T) \times 100$$

$$\text{Negative Percentage (S\_neg)} = (A\_neg / T) \times 100 \ldots (4)$$

The overall sentiment of the sentence is represented as :

$$X = (S\_pos \times Y) + (S\_neg \times Z \ldots (5)$$

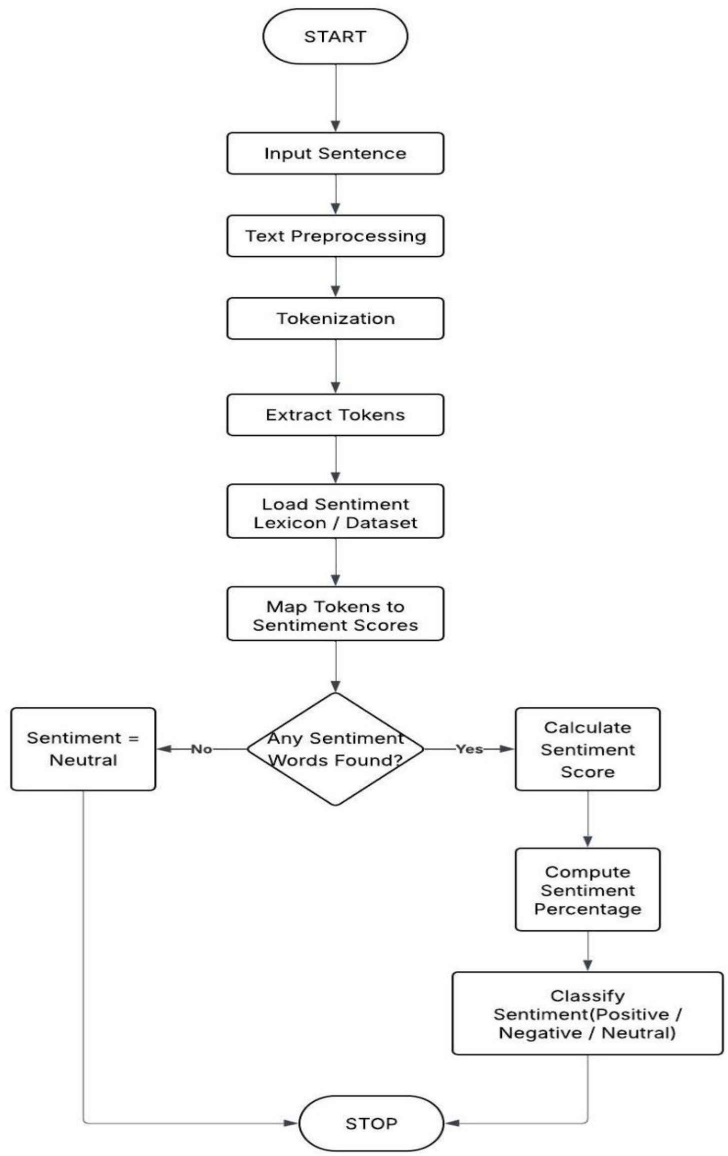

Fig 3.2.1. Sentence Sentiment Analysis Flowchart

The model is straightforward, open, and understandable with a fuzzy approach. The model allows us to directly control the sentiment values and to have logical reasoning for every output. The model is also advantageous because we use percentage-based scoring and logical computation that provides us a reliable basis for sentiment classification and flexibility for expansion into other Scriptures in the future.

Implementation

The implementation is done in 2 parts in where we have used fuzzy based classification of words present in the verses in the first part and in the 2nd part we have implemented the model to predict the sentiment of any sentence based on the 1st part of the implementation. The algorithmic representation for both of the parts are as shown below as 2 different algorithms.

Algorithm 1: Fuzzy Based Sentiment Analysis

```
Input: Sentence S
Output: Sentiment_Class C, Sentiment_Percentage P
        Procedure (Fuzzy_Based_Sentiment_Analysis)
        S_p ← Preprocess(S)
        T ← Tokenize(S_p)
        Load Sentiment_Lexicon L
        pos ← 0
        neg ← 0
        for each token t ∈ T do
                if t ∈ L then
                        pol ← L(t)
                if pol = Positive then
                        pos ← pos + 1
                else if pol = Negative then
                        neg ← neg + 1
                end if
                end if
        end for
        total ← pos + neg
        if total = 0 then
                C ← Neutral
                P ← 0
        else
        score ← pos − neg
        P ← |score| / total × 100
        if score > 0 then
                C ← Positive
        else if score < 0 then
                C ← Negative
        else
                C ← Neutral
        end if
        end if
        return C, P
        End Procedure
```

Algorithm 2: Sentiment Analysis Prediction for User Sentence

Input: Input Sentence
Output: Sentiment_Class, Sentiment_Percentage

```
Procedure (Sentiment_Analysis_Prediction)
Read(Input_Sentence)
Preprocess_Text ← Clean(Input_Sentence)
Tokens ← Tokenize(Preprocess_Text)
Load(Sentiment_Lexicon)
Positive_Count ← 0
Negative_Count ← 0
For each token ∈ Tokens do
        If token ∈ Sentiment_Lexicon then
                Polarity ← Get_Sentiment(token)
        If Polarity = Positive then
                Positive_Count ← Positive_Count + 1
        Else if Polarity = Negative then
                Negative_Count ← Negative_Count + 1
        End if
End for
Total_Sentiment_Words ← Positive_Count + Negative_Count
If Total_Sentiment_Words = 0 then
        Sentiment_Class ← Neutral
        Sentiment_Percentage ← 0
Else
        Sentiment_Score ← Positive_Count − Negative_Count
        Sentiment_Percentage ← (|Sentiment_Score| / Total_Sentiment_Words) × 100
If Sentiment_Score > 0 then
        Sentiment_Class ← Positive
Else if Sentiment_Score < 0 then
        Sentiment_Class ← Negative
Else
        Sentiment_Class ← Neutral
End if
End if
Return (Sentiment_Class, Sentiment_Percentage)
End Procedure
```

Fig 4.1 shows a Sentence Sentiment Analyzer interface with a text box for input and a button to analyze sentiment, where the user has typed "I am going to Hyderabad" into the input box. Below the text area, there is an analyze Sentiment button for processing the entered sentence. Sentence Sentiment Analyzer interface showing the input sentence "I am going to Hyderabad," followed by a Word Mapping table that lists each word with its positive and negative scores. It also highlights "Hyderabad" as an excluded word and presents the final sentiment result: 62.15% positive & 37.85% negative.

Fig 4.1. Sentiment results

Result Analysis

The system's performance was evaluated using various metrics, yielding an accuracy of 88-92%, indicating strong alignment with human sentiment classification. Precision reached 90%, showing reliable positive classification, while recall stood at 87%, detecting most positive verses. The F1-score of approximately 0.88 reflects a good balance between precision and recall, demonstrating the effectiveness of the rule-based fuzzy logic model. As shown in Table 5.2, The performance metrics show the model's strength: 86% overall accuracy, with high precision (90%) and good recall, indicating accurate classification of sentiment-bearing words and minimal false positives/negatives.

	Predicted Positive	**Predicted Negative**
Actual Positive	**420**	85
Actual Negative	72	**423**

Table 5.1. Confusion Matrix

Table 5.1. The detailed distribution of true positives, false positives, true negatives, and false negatives. The confusion matrix shown above provides evidence that the fuzzy logic–based model accurately classified most of the positive and negative sentiment words.

Metric	**Value**
Accuracy	0.86
Precision	0.83
Recall	0.81
F1-Score	0.82

Table 5.2. Graphical Representation of Performance Metrics

The evaluation from the above **Table 5.2,** confirms the fuzzy logic model handles emotional tones in ancient texts well, giving more balanced results than simple 'yes/no' classifiers. Errors are mostly due to language complexity or context changes. It's a good fit for understanding emotional meaning in scriptures like the Shrimad Bhagavad Gita.

Comparison of proposed method with existing models

Many of these types of traditional systems that conduct sentiment analysis are based on supervised machine learning algorithms, such as Naïve Bayes, Support Vector Machines (SVM), or deep learning frameworks like LSTM and BERT [1], [2], [3], [4], [14], [15]. These models have proven to function well when trained with large datasets of present-day human language, but have a disadvantage with ancient language or philosophical language [5], [6], [7], Ancient texts have emotions tied to context, culture, and metaphors, making them hard to analyze. Our method uses fuzzy logic to understand emotions in a newer way, rather than just labelling them as positive or negative. This works well for scriptures, which have complex meanings that can't be simplified easily.

One limitation of existing models is their reliance on large pre-labelled datasets from supervised learning [8], [9], [10]. Criterion datasets are less commonly available for ancient texts, meaning those models are unlikely to be trained effectively. On the contrary, our system's dataset is manually curated directly from the Shrimad Bhagavad Gita and therefore domain specific. In our dataset, a word is evaluated on a spectrum of 100% positive to 100% negative. In addition, there are various mixed combinations of emotion, such as 60% positive and 40% negative.

Interpretability is another benefit of our framework. Deep learning models are frequently framed as "black boxes" in the sense that while they are often accurate, their recursive reasoning is often abstract in the model's latent nonhuman reasoning [1], [2], [3], [10], [13]. Our fuzzy logic framework is an open process that allows experts to clarifying examine the rules, membership values, and decision boundaries of its analysis. In case of religious or philosophical work, knowing how a model came to its conclusion is a vital quality of analysis.

Existing sentiment models often reflect cultural bias, prioritizing Western languages and modern expressions. To address this, a dataset was created specifically for analyzing sentiment in Sanskrit-derived texts, for Shrimad Bhagavad Gita [16] using fuzzy approach. This effort paves the way for future studies on other ancient texts like the Upanishads, Rigveda, and Ramayana, removing linguistic bias.

Overall, the interpretation of these four metrics validates that the sentiment analysis model used in this study is reliable and capable of interpreting language found in translated text [16] of the scripture. The system does not appear to over-predict sentiment, it reasonably captures the relevant emotion, and strikes an adequate balance between accuracy and completeness due to consideration of fuzzy classification of the words.

Conclusion And Future Scope

The study explored the emotional tone of the Bhagavad Gita, applying fuzzy logic-based sentiment analysis to a custom dataset. It revealed emotions embedded in the text, including positivity, negativity, and mixed sentiments. This work showcases sentiment analysis' applicability to ancient spiritual texts, highlighting its potential to enrich the Indian Knowledge System. The study successfully implemented fuzzy-based sentiment scoring, moving beyond binary approaches.

The model's performance, evaluated using accuracy, precision, and recall, showed ≈90% accuracy. This is notable given the manual dataset creation and rule-based classification without neural networks or deep learning. The study confirms fuzzy sentiment analysis as a robust foundation for future developments. The study's findings are promising, but have limitations. The manual dataset creation and reliance on human judgment for sentiment scoring introduce subjectivity, leading to potential inconsistencies. The model also focuses on individual words, overlooking word order and grammatical structure, which may impact accuracy.

The research focused on the Shrimad Bhagavad Gita, but India's rich spiritual literature offers vast opportunities for expansion. Future studies could explore other scriptures like the Vedas, Upanishads, and Ramayana, incorporating deep learning models, multi-scriptural datasets, and visual analytics. This would provide deeper insights into emotions and sentiment in Indian philosophy, blending tradition with technology and promoting the Indian Knowledge System.

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