Development of Hybrid Model for **Sentimental Classification** for review comments in **Bengali** language

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PROBLEM STATEMENT

PROBLEM

As online businesses continue to flourish, customer satisfaction in the digital marketplace has become a focal point for success. A significant challenge in this context is the precise prediction of sentiment in Bengali text. The Bengali language, rich in nuances and cultural context, requires specialized machine learning algorithms for accurate sentiment analysis. Misinterpretation can lead to incorrect market strategies and consumer engagement efforts, making it critical to develop robust methods for understanding the emotional tone of Bengali customer feedback.

SOLUTION

This study utilizes a Bengali dataset to train and evaluate pre-existing machine learning models, aiming to precisely predict sentiment in Bengali text. The research is not just academically significant but also has practical implications. The results could serve as a foundation for future scholarly research and practical applications, offering guidance on how to improve sentiment analysis algorithms for the Bengali language. The successful implementation of these models could revolutionize customer engagement strategies and market research

SIGNIFICANCE OF THE STUDY

EMOTION KEY

Understanding public emotion is essential for business success, whether the context is a political, social, or sports event, or a product like a service or e-commerce offering.

BENGALI FOCUS

Bengali is one of the most widely spoken languages, and native speakers are more comfortable expressing their feelings in it.

LANGUAGE BARRIER

People often prefer to express their opinions in their mother tongue, which necessitates sentiment analysis in various languages for authentic insights.

BUSNESS IMPACT

Investing in Bengali-specific sentiment analysis can significantly improve customer satisfaction, foster positive business growth, and enable more effective decision-making across industries.

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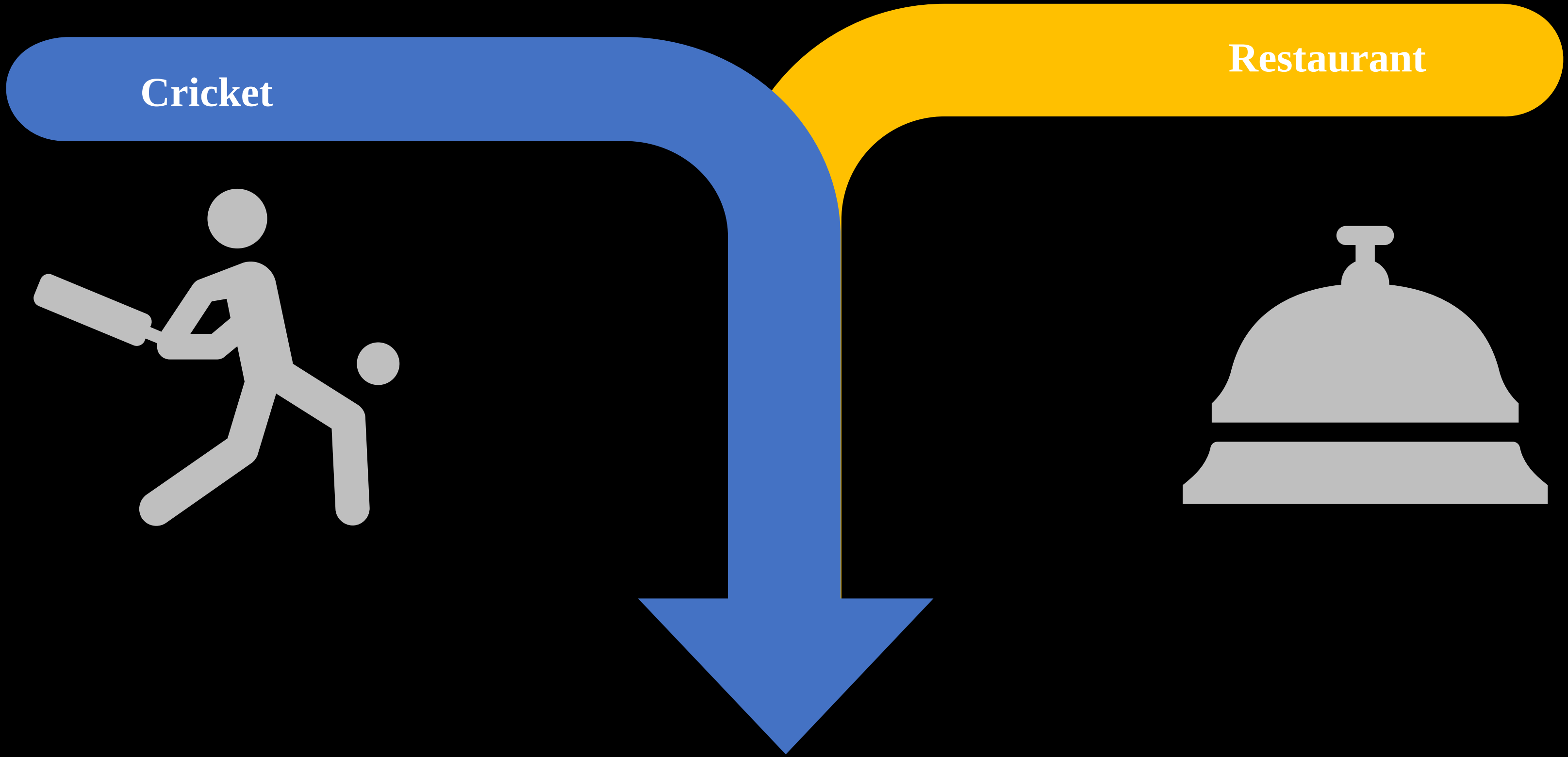
DATA GATHERING

2720 Data point

Negative - 1978
Positive - 505
Neutral – 237



1714 Data point

Negative - 386
Positive - 992
Neutral – 236
Conflict - 100

4434 Data point
negative 2364
positive 1497
neutral 473
conflict 100

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RESEARCH METHODOLOGY

Data Collection

Step 1

Two datasets, one covering cricket and restaurants and another focusing on balanced sentiments, provide a comprehensive foundation for Bengali sentiment analysis

EDA

Step 2

The dataset explores text length and word frequency in Bengali sentiment analysis, revealing linguistic complexity and offering key NLP insights.

Data Processing

Step 3

The study employs a three-step pre-processing pipeline—cleaning, tokenizing, and filtering Bengali text—to improve sentiment analysis using BERT and GPT-2.

RESEARCH METHODOLOGY

BERT –
2 Epochs

Step 4

Utilizing BERT with just two epoch provides a quick but potentially less accurate sentiment classification in Bengali.

BERT –
3 Epochs

Step 5

Running BERT for three epochs improves accuracy and generalization, making it more reliable for Bengali sentiment analysis.

GPT – 2
Epochs

Step 6

Using GPT-2 for two epochs offers a balance between speed and accuracy but may still require further optimization for Bengali text.

GPT – 3
Epochs

Step 7

Extending GPT-2 training to three epochs enhances performance, but it might still lag behind BERT in Bengali sentiment classification.

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RESEARCH METHODOLOGY

Result

Final Step

Assessing the model outcomes through performance metrics like F1 scores provides critical insights into the model's efficacy in tasks like sentiment analysis.

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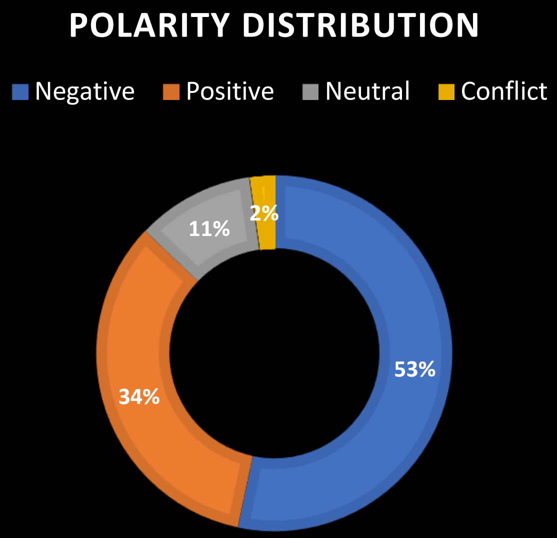
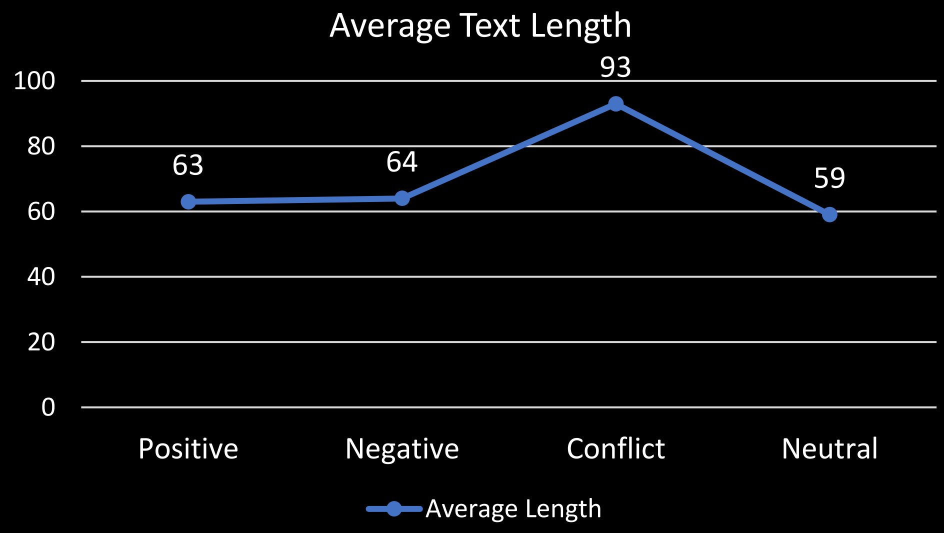
EXPLORING THE DATA





Word cloud for Neutral sentiment words

Word cloud for Negative sentiment words

Word cloud for Positive sentiment words

Word cloud for conflict Sentiment words

Upon examining the dataset, it becomes evident that the distribution of classes is 53% negative, 34% positive, 11% neutral, and 2% conflict. The average word lengths for these classes are 63 for positive, 64 for negative, 93 for conflict, and 59 for neutral. Word clouds for each class effectively highlight the pertinent vocabulary.

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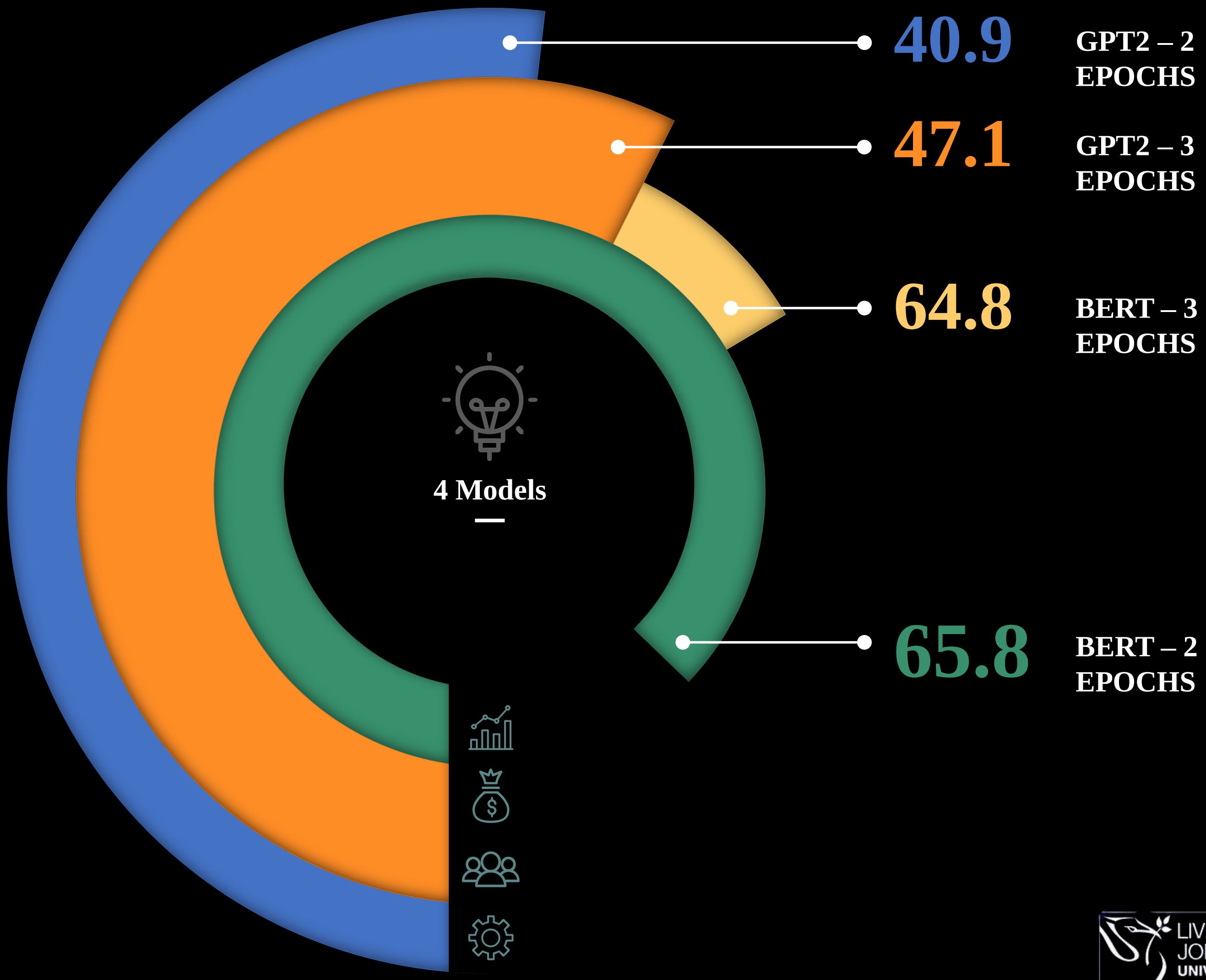
RESULTS & EVALUATIONS

Result Summary

BERT quickly grasped Bengali sentiment, reaching an F1 score of 65.83% after two epochs but slightly declined with further training. GPT-2 started slower, improving from 40.94% to 47.13% after three epochs, but lagged behind BERT.



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CONCLUSION

Research Importance

The study addresses the crucial need for research in sentiment analysis of Bengali review comments, emphasizing its importance in the digital marketplace.

Model Efficacy

The use of BERT and GPT-2 demonstrated robust and nuanced sentiment classification, underscoring the effectiveness of these models when applied to well-prepared Bengali data.

BERT's Superiority

In head-to-head performance, BERT surpassed GPT-2, achieving an impressive F1 score of 65.83% after just two epochs.

GPT-2 Potential

Although GPT-2 lagged behind BERT, it showed promise by improving its performance to reach an F1 score of 47.13% in the third epoch, indicating potential for future optimization.

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FUTURE SCOPE

Deployment Options

04

BERT is ideal for quick deployment and limited resources, while GPT-2 may benefit from extended training. Caution is advised to avoid overfitting during long training periods.

Performance Tuning

03

Tweaking learning rates and other hyperparameters can fine-tune the model. Data augmentation methods like back translation can diversify the dataset and potentially improve outcomes.

Robust Analysis

02

Leveraging predictions from multiple models can yield a more robust sentiment analysis. Contextual embeddings excel in capturing the intricacies of the Bengali language.

Niche Adaptation

01

Customizing models for various Bengali dialects or specific areas like literature and online reviews can greatly improve accuracy and performance in specialized applications.

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