Context-Aware Sentiment Analysis Framework Using Decision-Based Recurrent Neural networks

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Abstract
Sentiment analysis, a key area within opinion mining, focuses on extracting subjective information from textual data such as reviews, social media posts, and user comments. This project introduces Deep-Sentiment, a robust deep learning framework that integrates multiple components to enhance sentiment classification accuracy. The proposed system combines the pre-trained BERT-large-cased (BLC) model with Stochastic Gradient Descent (SGD) optimization to improve contextual understanding and convergence efficiency. Additionally, the model incorporates Aspect-Based and Priority-Based Sentiment Analysis to capture nuanced sentiment signals related to specific features and their importance. A Decision-Based Recurrent Neural Network (D-RNN) is employed for final sentiment classification, enabling the model to make informed decisions based on contextual cues and sentiment priority. The framework is evaluated on benchmark datasets including Twitter sentiment data, restaurant reviews, and laptop review datasets. Results, supported by confusion matrix analysis, demonstrate that Deep-Sentiment outperforms conventional models in terms of accuracy and contextual relevance. The model is implemented using Python libraries such as Keras and Pandas, offering a scalable and effective solution for real-world sentiment analysis applications
Keywords: Sentiment analysis, RNN, BLC, D-RNN, SGD

Introduction

Sentiment Analysis is a critical task in Natural Language Processing that focuses on identifying and interpreting the emotional tone within textual data. With the increasing volume of user-generated content on platforms like Twitter, review websites, and online forums, understanding public sentiment has become essential for businesses, researchers, and policymakers. This project aims to enhance sentiment analysis by leveraging advanced machine learning techniques, particularly using a Decision-based Recurrent Neural Network combined with pre-trained BERT models and various optimization algorithms. This project is designed to accurately classify sentiment polarity (positive, negative, or neutral) from textual data across multiple domains such as social media, restaurant reviews, and laptop feedback. By integrating techniques like Aspect-Based Sentiment Analysis and Priority-Based Sentiment Analysis , along with feature extraction methods such as Bag of Words and Word2Vec, this model can capture both contextual and semantic nuances in language. In the following sections, we will explore how Decision-Based Recurrent Neural Network works, how it processes and classifies text, and the impact it can have in real world sentiment-driven applications. The motivation behind this project arises from the growing complexity and importance of interpreting sentiments in digital communication. As more people express their opinions online, understanding these sentiments becomes vital for decision-making, brand management, and public opinion monitoring. However, traditional sentiment analysis methods often fall short when dealing with nuanced language, mixed sentiments, or domain specific jargon.

This project aims to overcome those limitations by developing a more intelligent and context-aware sentiment analysis system. By fine-tuning pre-trained deep learning models like BERT-Large and incorporating Stochastic Gradient Descent (SGD) for optimization, the system is designed to adapt to diverse data sources and deliver high accuracy in sentiment classification. A robust sentiment analysis tool has immense value across multiple sectors. Businesses can gain deeper insights into customer feedback, researchers can analyze social trends more effectively, and news platforms can better understand public opinion. Ultimately, this work contributes to building a more emotionally aware and responsive digital environment.

Literature Review

In this chapter will review some papers to get knowledge and understanding on the techniques had been proposed. All those techniques have the same aim which is to analyse the Sentiments. As Archimedes once said, "Man has always learned from the past. After all, you can't learn history in reverse!" it is essential for man to learn from history. Thus, considering all past researches, the most relevant research glimpses have been picked to be explained in detail. The overview shall discuss relevant aspects contributing to our research.

Sentiment Classification Using BERT-based Transformer: "B. Smith et al "

This study presents a sentiment classification approach using a BERT-based model applied to the IMDb movie reviews dataset. The model achieved 91.23% accuracy by leveraging transformer based contextual embeddings, which capture word dependencies bidirectionally. This significantly enhanced sentiment analysis compared to traditional methods, enabling a deeper understanding of context and emotion in reviews.

Emotion Detection with Transformer Models on Twitter Data:
"C. Lee et al"

This research introduces a transformer-based model for emotion detection, trained on the Twitter Sentiment Dataset. Achieving 89.75% accuracy, the model outperformed recurrent neural networks by effectively managing long-range dependencies and context in tweets. The results demonstrated the transformer's strength in emotion classification in short, informal text formats.

Sentiment Analysis Using Graph Neural Networks:
"E. Kumar et al"

A GNN-based sentiment analysis model is proposed in this study, applied to Amazon Product Reviews. The model, which achieved 87.45% accuracy, captured structural relationships between words by representing text as graphs. This allowed for more contextual understanding and improved sentiment classification in complex review data.

Aspect-Based Sentiment Analysis on Hotel Reviews:
"G. Rao et al"

The authors propose an aspect-based sentiment analysis (ABSA) model using the Trip Advisor hotel reviews dataset. The model reached 86.92% accuracy by classifying sentiment on specific aspects such as cleanliness, service, and location. This fine-grained approach allows for more actionable insights into customer feedback.

Deep Neural Networks for Complex Sentiment Detection:
"H. Singh et al"

This study uses a deep neural network (DNN) with multiple dense layers for sentiment classification on Rotten Tomatoes reviews. Achieving 90.12% accuracy, the model effectively identified complex sentiment patterns by learning high-level abstract features, improving classification over simpler architectures.

Proposed Model

The proposed sentiment analysis system introduces several improvements over traditional models by incorporating advanced preprocessing, feature extraction, and deep learning techniques to achieve higher accuracy and better contextual understanding.

Text Preprocessing

To ensure cleaner input for the model, the system begins with comprehensive text preprocessing:

Removal of special characters helps eliminate noise and irrelevant symbols that do not contribute to sentiment. Tokenization breaks down text into individual words or tokens, which is essential for further linguistic analysis and embedding.

2

Advanced Deep Learning Model

The core of the system utilizes the BERT-large-cased model. This version of BERT is particularly powerful because:

It is case-sensitive, meaning it distinguishes between words like "Apple" (the company) and "apple" (the fruit), preserving semantic meaning. As a deep contextual language model, BERT considers both left and right contexts of each word, enabling a much richer understanding of nuanced text and sentiment.

Feature Extraction Techniques

To transform text into numerical form suitable for machine learning models, the system uses: Word2Vec, which learns vector representations of words based on their contexts, capturing semantic similarities.

BERT embeddings, which provide contextualized word vectors that adapt depending on the surrounding words, making them more accurate for sentiment detection.

Model Optimization with SGD

For training and optimization, the system employs Stochastic Gradient Descent (SGD): SGD is a widely used optimization algorithm that helps minimize the loss function by updating model weights iteratively.

It improves the model's learning efficiency and generalization, leading to better accuracy on sentiment classification tasks.

Aspect-Based Sentiment Analysis (ABSA)

One of the key enhancements in the proposed system is the inclusion of Aspect- Sentiment Analysis Based: ABSA enables the system to identify sentiments towards specific aspects or entities within a single sentence or document. For instance, in the sentence *"The screen is amazing but the battery life is poor,"* the system can distinguish that the sentiment toward *"screen"* is positive, while for *"battery life"* it is negative.

This granular sentiment detection is especially valuable in product reviews, surveys, And customer feedback.

Priority-Based Sentiment Analysis (PBSA)

An enhancement in the proposed system is the use of Priority-Based Sentiment Analysis:

PBSA not only detects sentiment towards specific aspects but also considers how important each aspect is.

For example, in "The screen is amazing but the battery life is poor," if battery life has higher priority, the overall sentiment leans negative.

This approach helps focus on what matters most to users or businesses.

PBSA assigns priority levels to aspects and combines them with sentiment polarity for better decision-making.

It is especially useful in product reviews, customer feedback, and personalized recommendations.

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Architecture

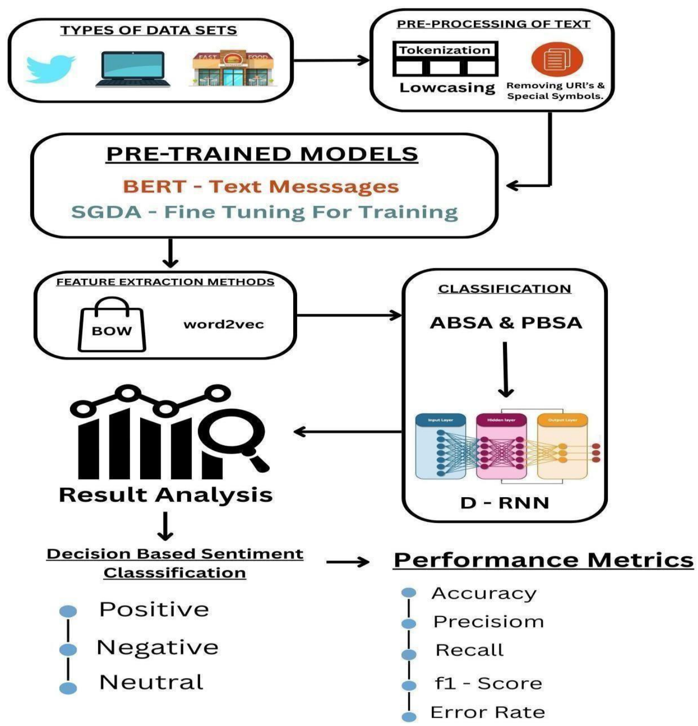

Fig.1. System Architecture

Types of Datasets

The system starts by collecting various text data from different sources:
Twitter (social media)
Computer-based platforms (web apps, forums)
Retail/Food reviews (customer feedback)

These diverse datasets contain opinions, reviews, or messages that will be analyzed for sentiment.

Pre-Processing of Text

Before feeding the text into models, it undergoes cleaning and preparation:

Tokenization:

Splits the text into individual words or phrases (tokens).

Lowercasing:

Converts all text to lowercase to maintain consistency.

Removing URIs & Special Symbols:

Cleans the data by removing URLs, emojis,
special characters, etc., which might not contribute meaningfully to sentiment detection.

Pre-Trained Models

The processed text is passed into powerful pre-trained models, which are already trained on large datasets:

BERT (Bidirectional Encoder Representations from Transformers):

Used for understanding deep contextual relationships in text.

SGDA (Stochastic Gradient Descent Algorithm):

Used for fine-tuning the pre trained model to adapt it to the specific sentiment classification task.

Feature Extraction Methods

Before classification, the text is converted into a numerical format**:**

BoW (Bag of Words):

Converts text into vectors based on word frequency.

Word2Vec

Represents words in dense vector space based on context. These help the model understand semantic meaning and structure of sentences.

Classification

The feature vectors are passed to the classification module:

Aspect-Based Sentiment Analysis:

Identifies specific sentiments related to different aspects (e.g., "service" = good, "food" = bad).

Priority-Based Sentiment Analysis

weighs sentiments based on the importance of each aspect to provide a more meaningful overall sentiment

Decision Based Recurrent Neural Network:

This neural network captures dependencies in text and helps in accurate sentiment classification, especially in sequential data like sentences.

Result Analysis

After classification, the system evaluates results:

The sentiment is labeled as:

✓

Positive

✕

Negative

−

Neutral

This step allows the decision-making engine to interpret and display sentiment outcomes.

Performance Metrics

To assess how well the system is performing, several metrics are used:

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform.

The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).

Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$= \frac{+}{+ \quad + \quad +} \quad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$= \frac{}{+} \quad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$= \frac{}{+} \quad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

$$1 = \frac{2 * Pcso * ca}{+} \quad (4)$$

Error Rate : Percentage of incorrect predictions.

DECISION BASED RECURRENT NEURAL NETWORK(D-RNN)

A Decision Based Recurrent Neural Network (D-RNN) in sentiment analysis refers to a neural model that processes sequences of text (like reviews or tweets) to determine the overall sentiment positive, negative, or neutral. It uses an RNN layer to read the input text word by word, capturing the context and dependencies between words across the sequence. The final hidden state from the RNN acts as a summary of the entire text. This state is then passed to a fully connected (decision) layer that outputs a sentiment label. Essentially, the model “decides” the sentiment based on the learned representation of the whole sentence or document. The decision RNN is trained using labeled sentiment data to learn which patterns correspond to which sentiments. It is simple yet powerful for handling varying input lengths and capturing sequence information effectively.

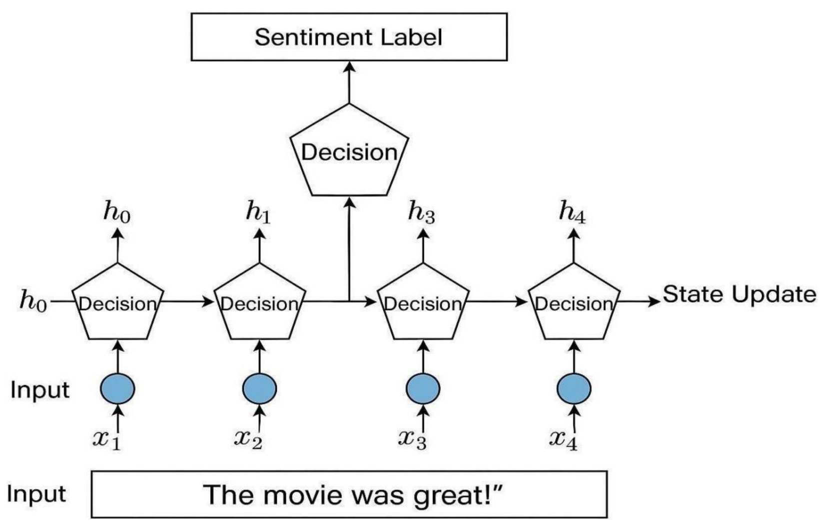

Fig.2. working of D-RNN in sentiment analysis

DATA FLOW DIAGRAM :

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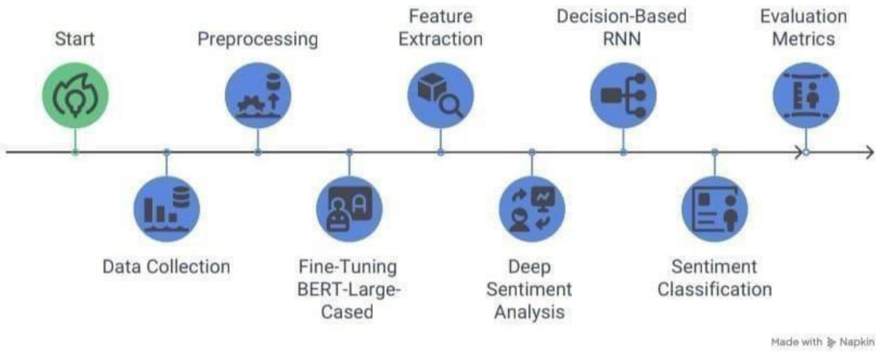


Fig.3. Data Flow Diagram

SYSTEM IMPLEMENTATION
SYSTEM MODULES

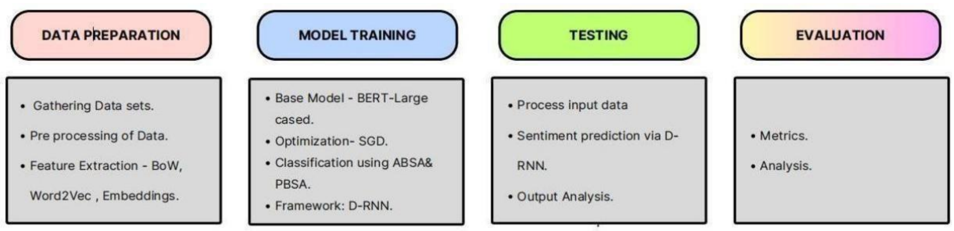


Fig.4. System Modules

Data Preparation:

Gather Data

Collect labeled sentiment datasets from domains like Twitter, Restaurant, and Laptop reviews. Ensure variety in content and writing style.

Preprocess Data

Clean the text by removing punctuation, special characters, stop words, and convert all text to lowercase. Use tokenization to prepare input for the model.

Feature Extraction:

BoW & Word2Vec

Apply Bag of Words to count term frequency and Word2Vec to capture semantic meaning of words.

BERT Embeddings

Use BERT-large-cased to extract deep contextual features from text input for accurate representation.

Model Training:

Load BERT-large-cased

Acts as the base model to understand word context. Original output layer is removed.

Add D-RNN Layer

Attach a Decision-based Recurrent Neural Network (D-RNN) as the classifier for sentiment analysis.

Fine-tune

Train the model with labeled data using Stochastic Gradient Descent (SGD) to improve prediction accuracy.

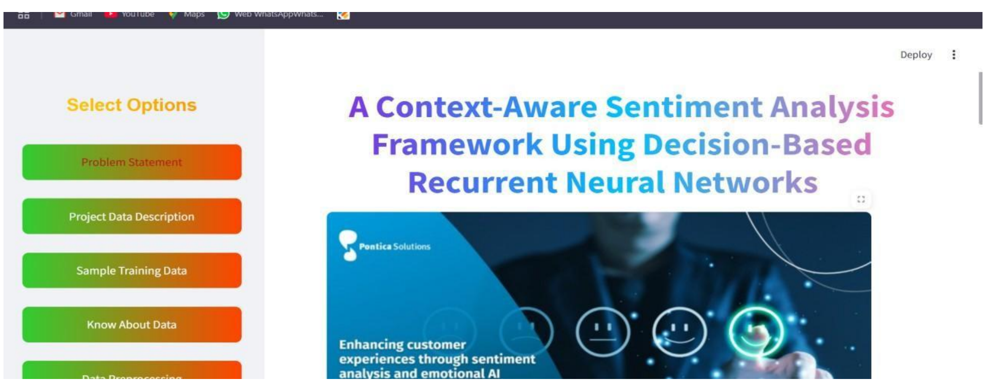
Testing:

Feed Test Data
Provide new review texts to the trained model for evaluation.
Obtain Predictions
The model outputs probabilities for each sentiment class (positive, neutral, negative).
Label Assignment
Assign sentiment based on the highest probability or predefined thresholding logic.
Evaluation:
Metrics
Calculate accuracy, precision, recall, and F1-score to evaluate performance on unseen reviews.
Analysis
Study misclassified samples (false positives and false negatives) to identify model weaknesses and areas for improvement.

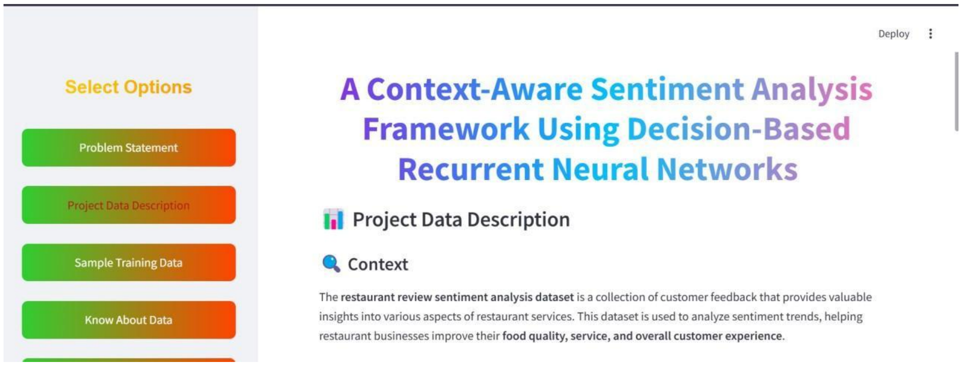
Results & Analysis

The execution of the process will be explained clearly with the help of continuous screenshots.
Step 1: Run Streamlit

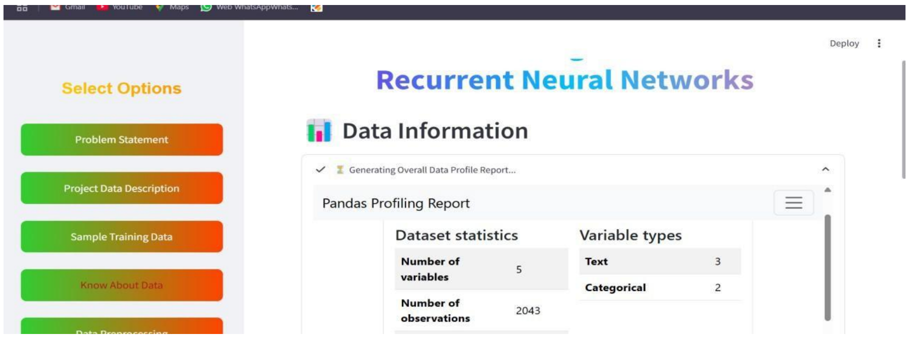
Step 2: Application Interface



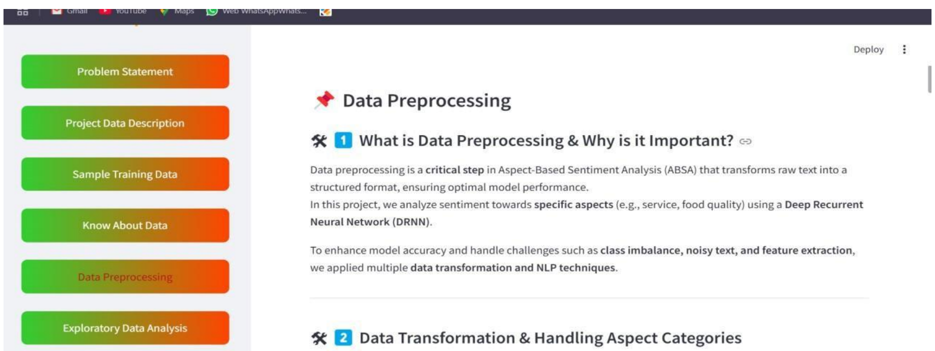
Step 3: Project Data Description



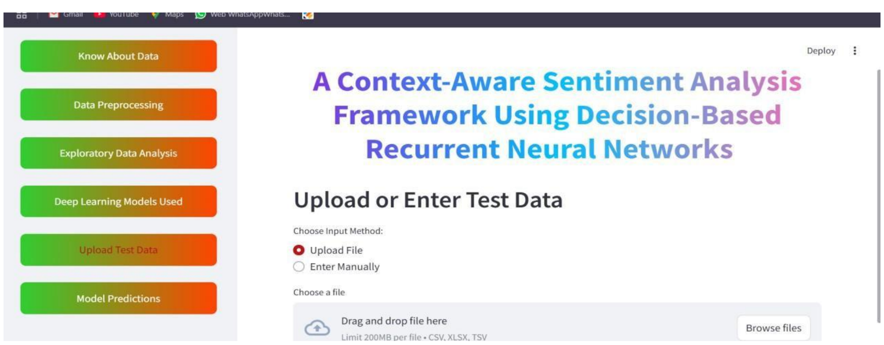
Step 4: Dat information



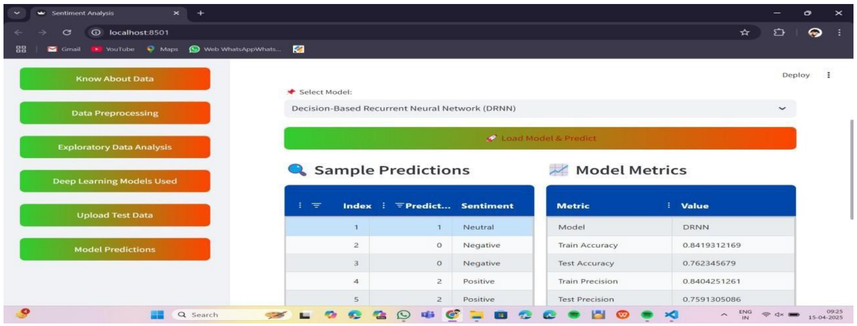
Data Processing



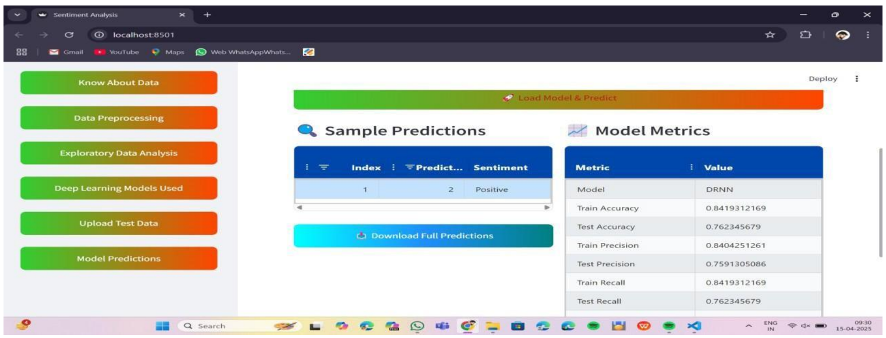
Upload data



Step 12: Final Result for Dataset Upload



Step 15: Final Result of Manually Entered Data



Conclusion

This project explored the application of Decision-Based Recurrent Neural Networks (D-RNN) for effective sentiment analysis using the Deep-Sentiment framework. We developed a system that begins with pre-processing input text data, including tokenization, lemmatization, and vectorization using Bag of Words and Word2Vec techniques. The processed text is then passed into a BERT-Large Cased (BLC) model for feature extraction, followed by classification using the D-RNN architecture. The model assigns sentiment labels such as positive, negative, or neutral based on learned patterns. Optimization was achieved using the Stochastic Gradient Descent (SGD) algorithm to enhance prediction accuracy. By combining deep learning with aspect and priority-based classification, the system effectively captures complex linguistic features and emotional tones from the text. The results from various datasets confirm the model's robustness and its capability to deliver high-performance sentiment classification. This project highlights the strength of advanced neural networks in understanding human emotions through natural language.

FUTURE SCOPE

This project lays the foundation for more advanced sentiment analysis techniques across varied text data. In the future, the system can be extended to support multiple languages, deeper emotional classifications, and improved contextual understanding. Enhancing the model by integrating transformer-based architectures like BERT alongside the Decision-based RNN can significantly boost accuracy and adaptability. domain transfer learning can allow the model to adjust to new sectors like healthcare or finance. Real-time sentiment trend analysis can also help businesses track user opinions over time. Moreover, developing personalized sentiment models can further refine predictions based on individual behaviors and preferences Additionally, expanding the framework to include multi-modal sentiment extraction—such as from images and videos opens new research possibilities. These advancements will contribute to building a more scalable and intelligent sentiment analysis model capable of handling real time and domain-diverse data

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