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Cortext
A Machine Learning System For Emotion Recognition and Mood Detection from Text

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Abstract

Cortex is a machine learning-based system designed for emotion recognition and mood detection from textual data. Leveraging advanced natural language processing techniques, it analyzes input text to identify emotional states with high accuracy. The system integrates a robust pipeline, including data preprocessing, feature extraction, and the application of supervised learning algorithm, to classify emotions effectively, such as sadness, joy, love, anger and fear. With an intuitive user interface, it ensures accessibility for users across diverse applications, ranging from mental health monitoring to customer sentiment analysis. This project highlights the potential of machine learning in automating emotion detection, demonstrating its capability to manage complex linguistic and contextual variations. While the current implementation focuses on classifying a defined set of emotions, Cortex establishes a scalable framework for future enhancements. Prospective improvements include expanding the emotion taxonomy, optimizing model performance, and integrating deep learning approaches to achieve greater contextual understanding and adaptability.

Contents

Chapter 1

Introduction

1.1 Background and Motivation

Emotion recognition from text has become a critical area of research due to its potential to revolutionize various industries, such as mental health, customer service, and human-computer interaction. Emotions play a fundamental role in human communication, and the ability to automatically detect emotions from text can enhance decision-making processes, improve user experiences, and support personalized services. However, accurately identifying emotions is a challenging task due to the inherent complexity of language, cultural differences, and the subtle nature of emotional cues. Advances in natural language processing and machine learning have opened new opportunities to address these challenges. By leveraging data-driven approaches, emotion recognition systems can process large datasets, identify intricate patterns, and achieve high accuracy. This project, Cortext, is motivated by the growing demand for intelligent systems capable of understanding human emotions in textual communication and aims to contribute a robust solution to this field.

1.2 Problem Statement

The detection of emotions from textual data is a multifaceted problem influenced by the ambiguity and diversity of human expression. Current systems often rely on rigid rule-based methods or limited datasets, which result in poor generalization across real-world applications. Furthermore, many existing models fail to consider the contextual nuances of language, leading to inaccurate predictions in emotionally ambiguous situations. These limitations are further compounded by the lack of user-friendly interfaces that enable non-technical users to access and benefit from such systems. The absence of an efficient, scalable, and adaptable solution for emotion recognition presents a significant obstacle to its widespread adoption in practical applications. Therefore, there is a pressing need to develop a machine learning-based system that combines advanced modeling techniques with an accessible interface to provide accurate and actionable emotion insights from text.

1.3 Objectives

The Cortext project seeks to address the identified gaps in emotion recognition by developing a comprehensive system that integrates machine learning with natural language processing. The primary objective is to design and implement a solution capable of analyzing text data and accurately identifying emotions, such as joy, sadness, anger, fear, and love. This involves building a robust pipeline that includes data preprocessing, feature engineering, and model training to ensure high performance and reliability. Additionally, the project aims to create an intuitive and interactive interface that simplifies user engagement and enhances accessibility. By evaluating the system against standardized metrics, the project will provide insights into its effectiveness and identify areas for future improvement. Ultimately, Cortext aspires to serve as a scalable foundation for more advanced emotion recognition systems in various domains.

1.4 Scope

Cortext is designed to focus on the analysis of textual data in English, with the ability to recognize a predefined set of emotions. While the current implementation addresses a limited number of emotional categories, the system is developed with scalability in mind, allowing for the future inclusion of additional languages and a more comprehensive range of emotions. The project emphasizes real-world applicability, targeting scenarios such as mental health monitoring, customer sentiment analysis, and interactive AI applications. Although the scope is currently constrained by computational and dataset limitations, future iterations aim to incorporate deep learning techniques, contextual language models, and larger datasets to improve accuracy and adaptability. By establishing a strong foundation, Cortext positions itself as a versatile tool with the potential to evolve into a more sophisticated and inclusive emotion recognition platform.

Chapter 2

State of art

2.1 Emotion Recognition in Text Analysis

Emotion recognition from text is a growing field that intersects natural language processing (NLP) and machine learning. The ability to automatically identify emotions in written communication has applications in sentiment analysis, mental health monitoring, and customer interaction systems. Traditional approaches to emotion recognition relied on lexicon-based methods, which use predefined dictionaries of emotion-related words to detect sentiments. While these methods are simple and interpretable, they often fail to capture the context and nuanced expressions of emotions. Recent advancements in machine learning, particularly in supervised learning and deep learning, have significantly improved the accuracy and reliability of emotion recognition systems. Models such as Support Vector Machines (SVMs), Decision Trees, and Neural Networks are widely used for classifying emotions, as they can learn complex patterns from large datasets.

2.2 Machine Learning in Emotion Recognition

The application of machine learning to emotion recognition has led to notable advancements in understanding and interpreting human emotions in text. Supervised learning methods are the cornerstone of most emotion classification systems, requiring labeled datasets for training and evaluation. Data preprocessing, such as tokenization, stop-word removal, and stemming, plays a crucial role in preparing text for analysis. Feature extraction techniques, including Bag-of-Words (BoW), TF-IDF, and word embeddings, are commonly used to convert textual data into numerical representations that machine learning algorithms can process. Recently, transformer-based models like BERT and RoBERTa have revolutionized NLP tasks, including emotion recognition, by leveraging self-attention mechanisms to capture contextual relationships in text. These models, combined with fine-tuning techniques, have demonstrated state-of-the-art performance in emotion classification. However, challenges such as handling ambiguous emotions, imbalanced datasets, and computational efficiency remain areas of active research.

2.3 Related Work

Several studies and projects have explored the potential of machine learning for emotion recognition from text. For instance, researchers have developed systems that classify emotions into categories such as happiness, sadness, anger, fear, and surprise using traditional machine learning models like Naïve Bayes and SVMs. Recent efforts have focused on leveraging deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to improve accuracy by learning hierarchical and sequential features from text. Advanced architectures, such as attention mechanisms and transformers, have further enhanced the capability of emotion recognition systems. Projects like Google's Natural Language API and IBM Watson's Tone Analyzer are practical implementations of emotion analysis, offering real-world applications in customer service and sentiment analysis. Despite these advancements, many existing systems struggle to generalize across diverse datasets and fail to capture subtle emotional cues in complex linguistic contexts. CORTEX builds upon these efforts by integrating a comprehensive pipeline of machine learning techniques and a user-friendly interface to address these challenges, aiming for a more robust and scalable emotion recognition solution.

Chapter 3

Methodology

3.1 Model Architecture

The model architecture is built upon a Support Vector Machine (SVM) classifier, implemented using the sklearn library. The model utilizes a pipeline that integrates two key components: a TF-IDF Vectorizer and the SVM classifier. The TF-IDF Vectorizer transforms the input text data into numerical features by converting the text into a term-frequency inverse document frequency (TF-IDF) representation. This helps in capturing the importance of words within the context of the dataset. The SVM classifier, with a linear kernel, is used for sentiment classification based on the extracted features. Hyperparameter tuning is performed using GridSearchCV to find the best value for the regularization parameter C, which controls the trade-off between achieving a low error on the training data and minimizing model complexity. This ensures that the model is not overfitting while maintaining strong generalization performance.

3.2 Data Exploration and Preprocessing

The data preprocessing process begins with loading the datasets from CSV files into Pandas DataFrames. The data consists of text entries paired with corresponding emotion labels. The text data is extracted from the "Text" column, while the associated labels are stored as target variables. For the feature extraction, a TF-IDF Vectorizer is used, which converts the raw text data into numerical representations by calculating the term frequency-inverse document frequency for each word. Common English stop words are ignored during this process to ensure that the features used for training are more meaningful. The datasets are divided into three distinct sets: training, validation, and test. This division allows the model to be trained on one set of data, fine-tuned and validated on another, and finally evaluated on a third set of unseen data, ensuring the model's ability to generalize and perform well on new inputs.

3.3 Model Evaluation Metrics

The model's performance is assessed through a combination of cross-validation and separate evaluations on training, validation, and test datasets. GridSearchCV is used to identify the optimal regularization parameter C for the SVM, which is found to be 1, leading to a cross-validation score of 87.8%. This score indicates how well the model performs when evaluated on different subsets of the training data. The model is further evaluated on the training, validation, and test datasets, providing additional insights into its effectiveness. The training accuracy reaches 96.04%, suggesting that the model performs excellently on the data it has been trained on. On the validation dataset, the accuracy is 89%, demonstrating the model's good generalization capability. Finally, the model achieves an accuracy of 88.3% on the test dataset, confirming its robustness and ability to predict sentiment accurately on unseen data. These evaluation results demonstrate that the model strikes a balance between training accuracy and generalization, indicating its effectiveness for sentiment analysis tasks.

3.4 User Interface Design

3.4.1 Technologies Used

The Cortex system utilizes a range of technologies to provide an efficient and responsive user experience. The frontend is developed using HTML and CSS for structure and styling, while JavaScript is employed for interactivity and dynamic content handling. The core model of the system is built using Python, which processes text inputs and performs sentiment analysis. To ensure seamless communication between the frontend and the model, an additional Python file serves as a bridge, facilitating the interaction between the user interface and the backend logic. This combination of frontend and backend technologies ensures a smooth and effective operation of the Cortex system.

3.4.2 UML Diagrams

Usecase Diagram

The use case diagram for the Cortex interface illustrates the system's interactions with various users and their roles within the platform. Key actors such as the "User" and "System" are identified, with the User being responsible for uploading various types of data—text, audio, images, and videos for emotion analysis. The diagram also showcases the core functionality available to the User, including the ability to analyze data and clear inputs. Additionally, the use case diagram highlights the "Emotion Analysis" feature, which processes the uploaded media and provides insights based on emotional context. Supporting use cases, such as "Data Upload" and "Data Interpretation," are also represented, showcasing the different pathways through which the user interacts with the system to derive actionable insights. This diagram serves as a visual representation of the main interactions within the Cortex system and its capabilities for data analysis.

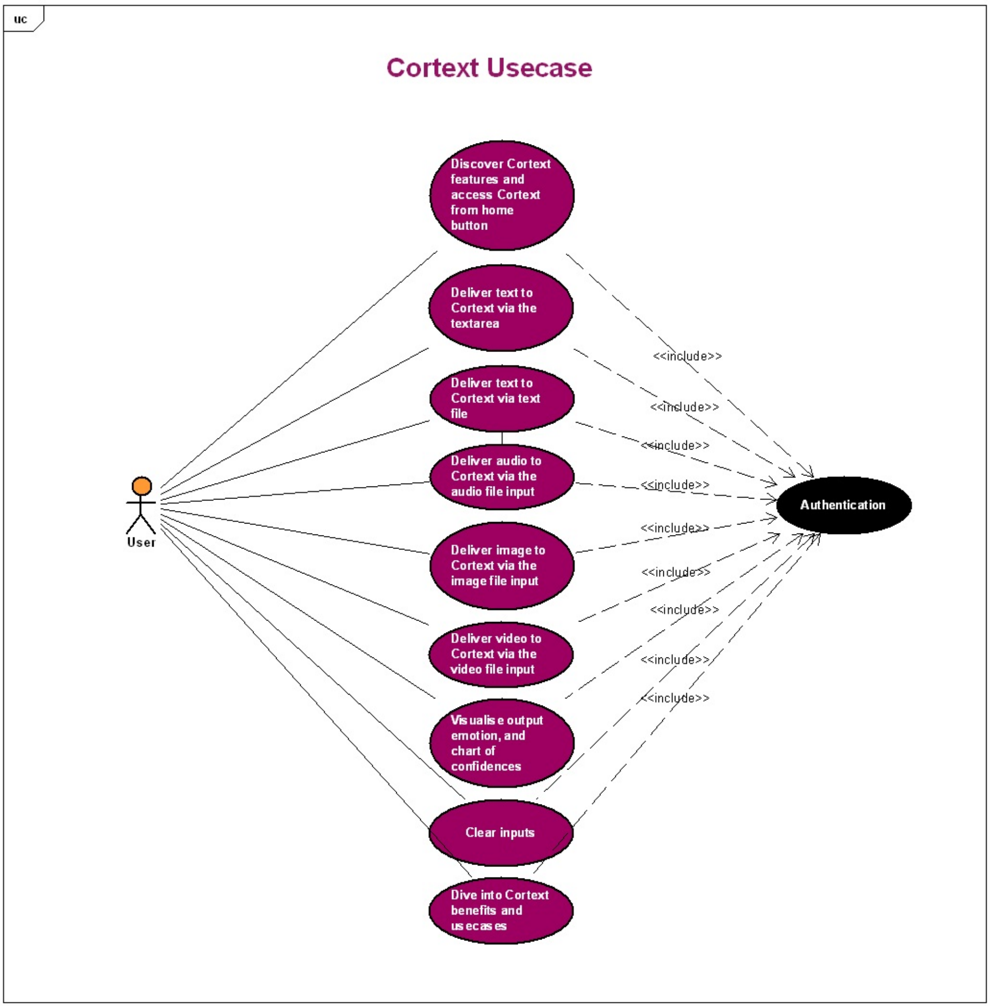

Figure 3.1: Usecase Diagram

Deployement Diagram

The deployment diagram for the Cortex system illustrates the hardware and software components involved in delivering the system's functionality. The diagram showcases how the user interface (UI) interacts with the backend through a bridge that connects the frontend (built with HTML, CSS, and JavaScript) to the Python-based model for emotion analysis. The user interacts with the system through a web application that runs on a client machine, which then communicates with a server that handles the analysis process. The server is responsible for processing the uploaded data, running emotion analysis algorithms, and returning the results to the frontend. The system also includes file storage for managing user-uploaded media (text, audio, images, and videos). This diagram provides a high-level view of the system architecture, detailing the relationship between the user, the frontend, backend, and server components to ensure seamless deployment and functionality.

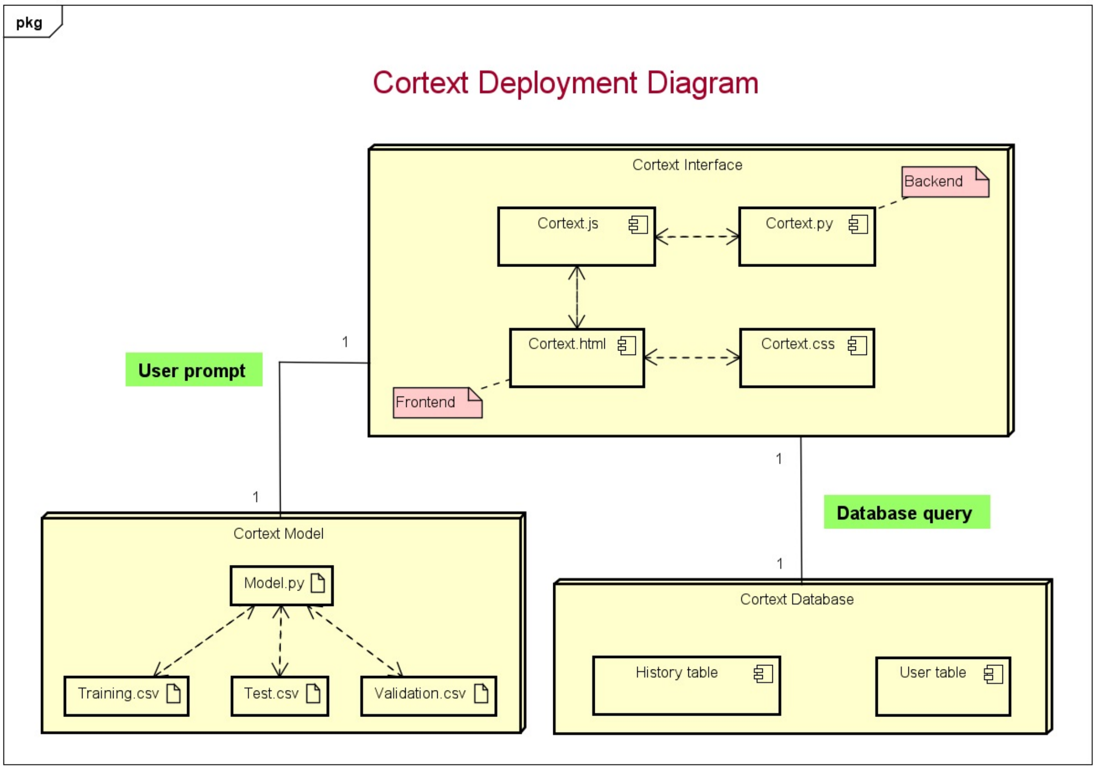

Figure 3.2: Deployment Diagram

3.4.3 Home

The Home section of the Cortex interface introduces users to the core capabilities of the system, focusing on its advanced text emotion analysis features. The section highlights the power of Cortext's AI-driven solutions with a catchy tagline, "Unlock the Power of Text Emotion Analysis with Cortext," paired with a call-to-action button that invites users to analyze text emotions. The content emphasizes Cortext's ability to provide actionable insights through data analysis and machine learning algorithms. A set of images further illustrates key aspects of the system, such as data-driven insights, machine learning precision, and real-time analytics, positioning Cortext as a comprehensive tool for empowering AI journeys and driving innovation in decision-making processes.

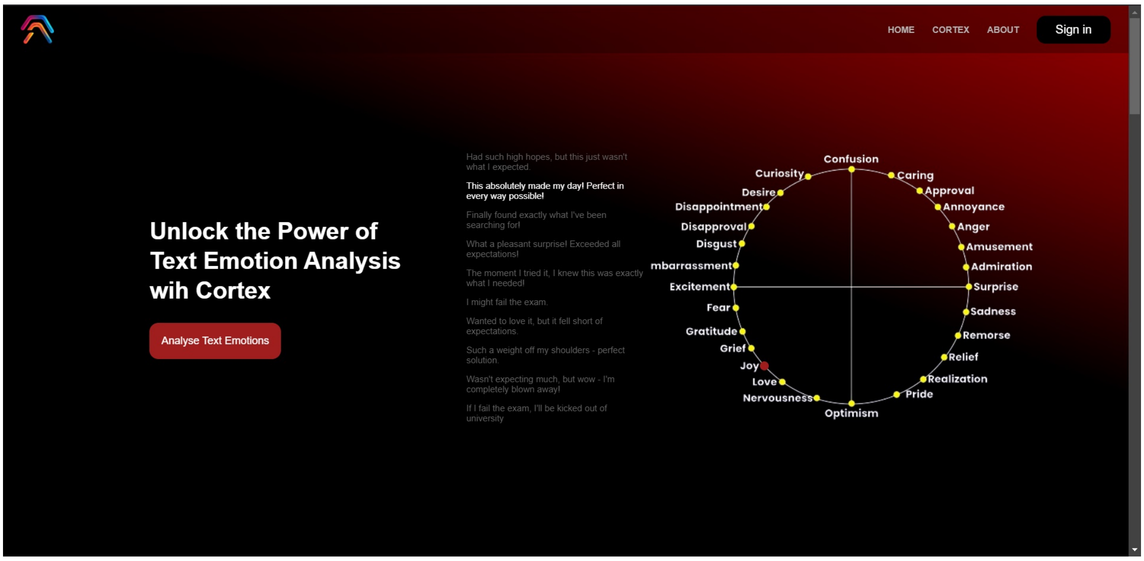

Figure 3.3: Home Section

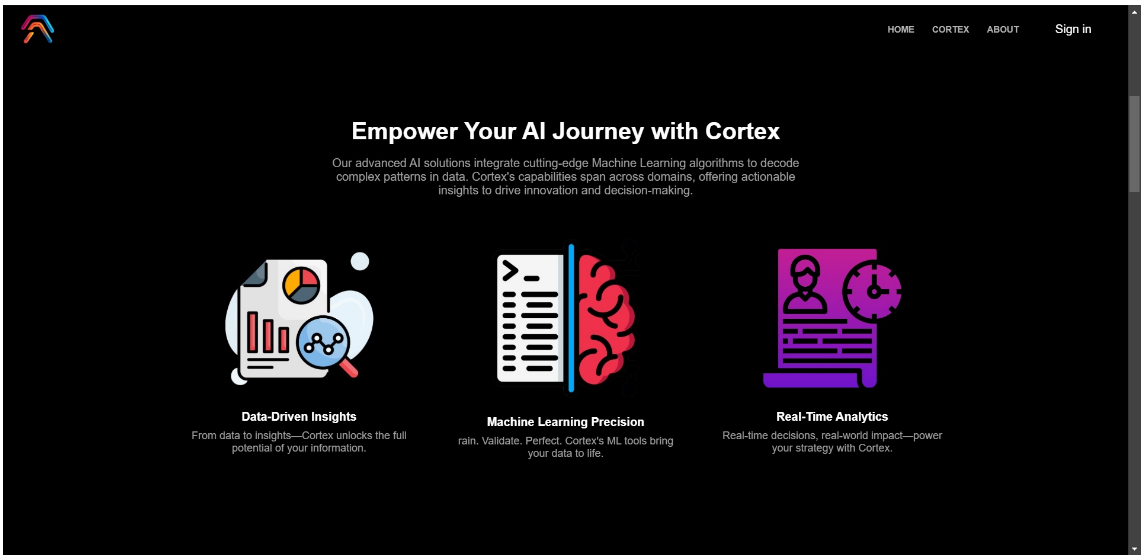

Figure 3.4: Home Section

3.4.4 Cortex

The Cortex section allows users to upload various types of media, including text, audio, images, and videos, for emotion analysis. The interface provides clear options for users to upload files through intuitive input fields for each media type, with icons representing text, audio, image, and video files. A large text area enables users to input data directly for analysis. Once the data is uploaded, users can click on the "Analyze" button to process the files and analyze the emotions within the content. A "Clear" button is also available to reset the inputs. The section is designed to be user-friendly, offering a streamlined way to interact with the system and receive valuable emotional insights from multiple types of media.

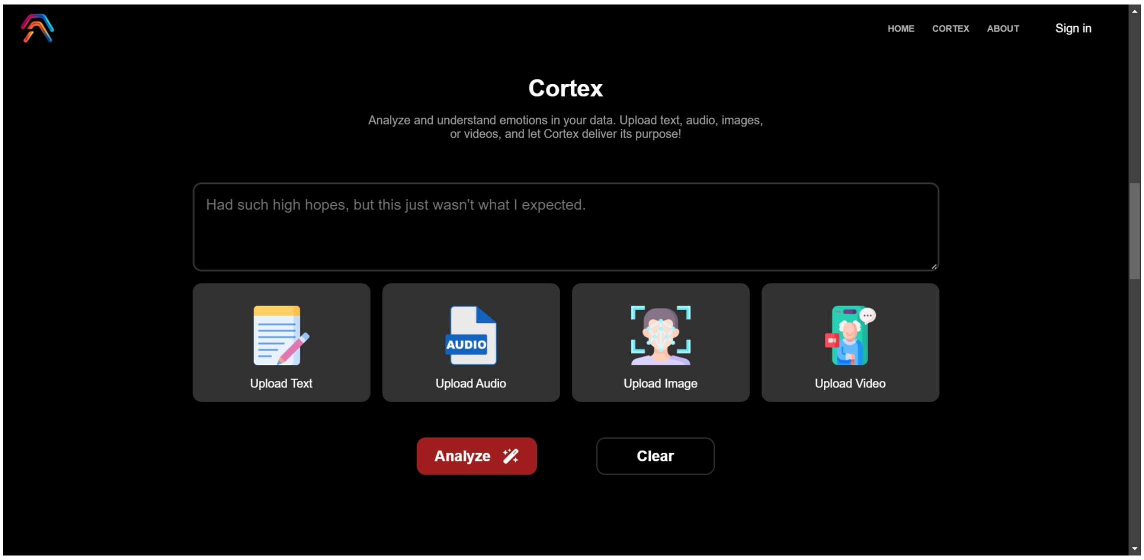

Figure 3.5: Cortext Section

3.4.5 About

The About section of the Cortex interface provides detailed information about the benefits and practical applications of the system. It highlights how Cortext's emotion analysis capabilities enable users to gain deeper insights into the emotional context of their data, fostering data-driven decision-making and tailored strategies for greater impact. The section also emphasizes the ease of data optimization and the intuitive interface Cortext offers. Additionally, the use cases area explores various industries and scenarios where Cortext can be applied, such as user reviews, filmmaking, social media, sales webinars, product feedback, ad analysis, and mental health. This section illustrates the versatile impact of Cortext across different sectors, showcasing how its emotion analysis can refine strategies, enhance engagement, and drive meaningful change.

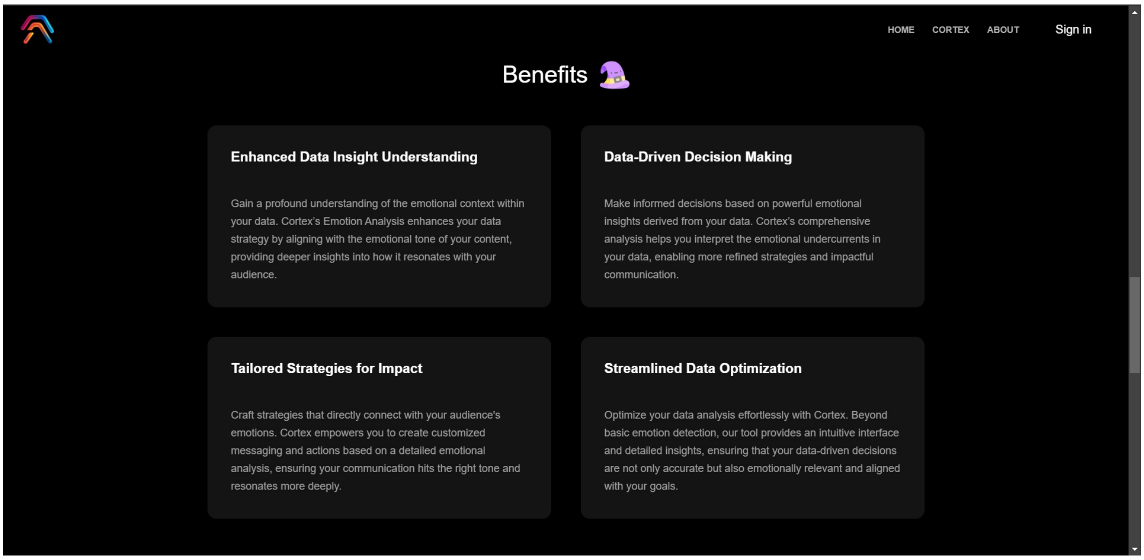

Figure 3.6: About Section

Figure 3.7: About Section

Chapter 4

Results and Discussion

4.1 Performance Metrics

In evaluating Cortext's performance, the primary metric used is accuracy, which measures the proportion of correct predictions out of all predictions made. The model's performance was assessed on multiple datasets, including training, validation, and test sets, to ensure reliable results. The cross-validation score and test set performance were key indicators of how well Cortext generalizes to unseen data. These metrics demonstrated the model's consistency and effectiveness in delivering accurate sentiment analysis.

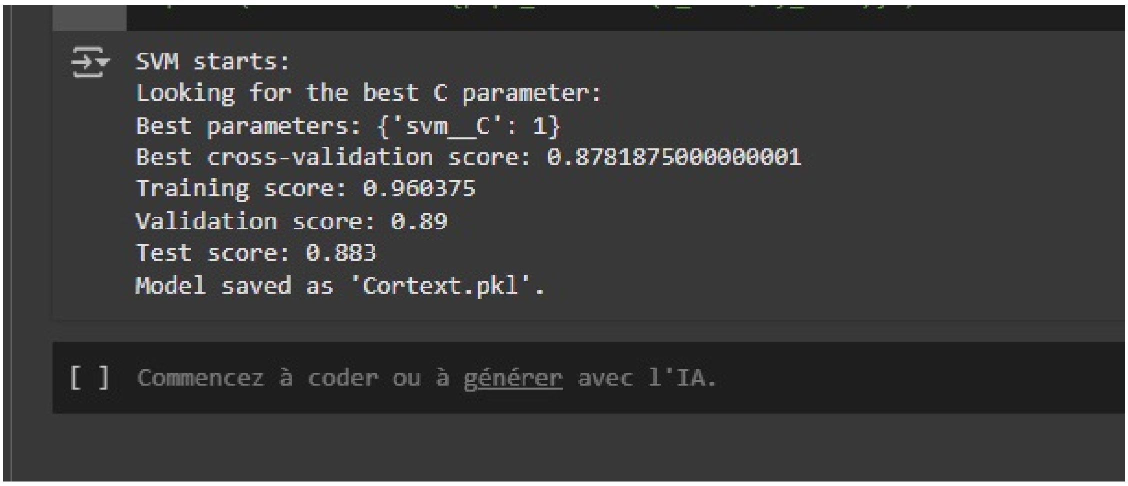

Figure 4.1: Cortext model accuracy

4.2 Testing and Evaluation

Cortext has undergone rigorous testing and evaluation using separate training, validation, and test datasets. The model consistently demonstrated strong performance across different sets, accurately predicting emotions in text data. Through extensive testing with diverse inputs, Cortext was able to generalize well and produce reliable results. The predictions, as shown in the screenshots, highlight the model's ability to categorize emotions accurately, with minimal error rates. This performance was achieved through a well-tuned pipeline and the use of a robust machine learning model, providing users with dependable sentiment analysis.

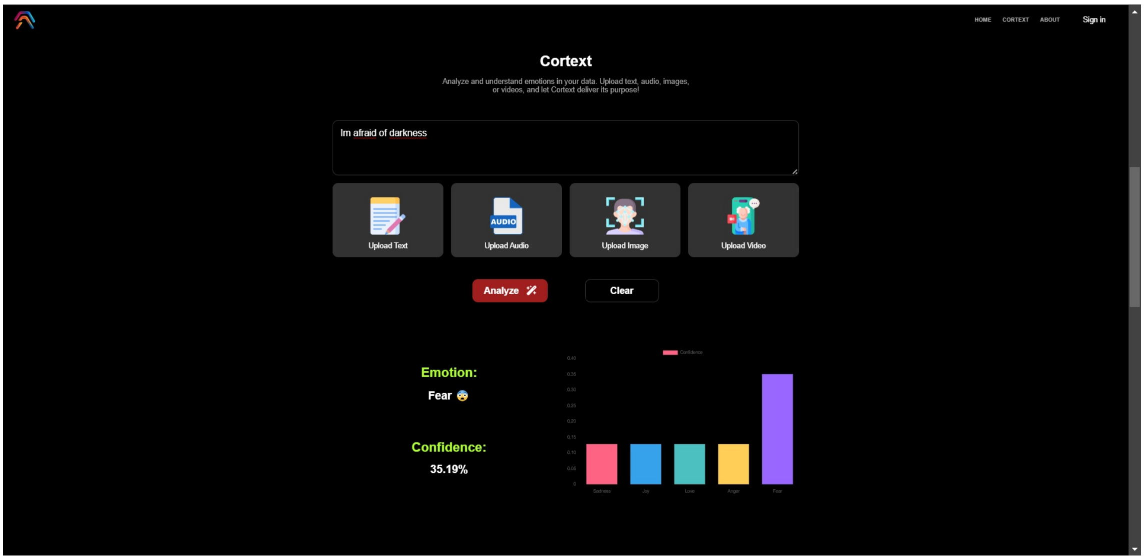

Figure 4.2: Short text content with fear emotion

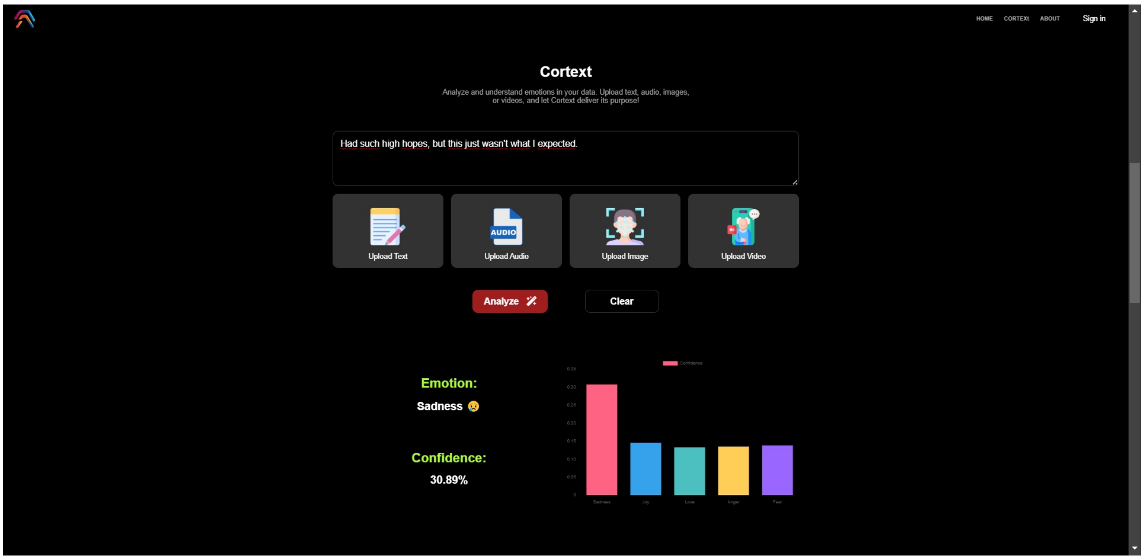

Figure 4.3: Short text content with sad emotion

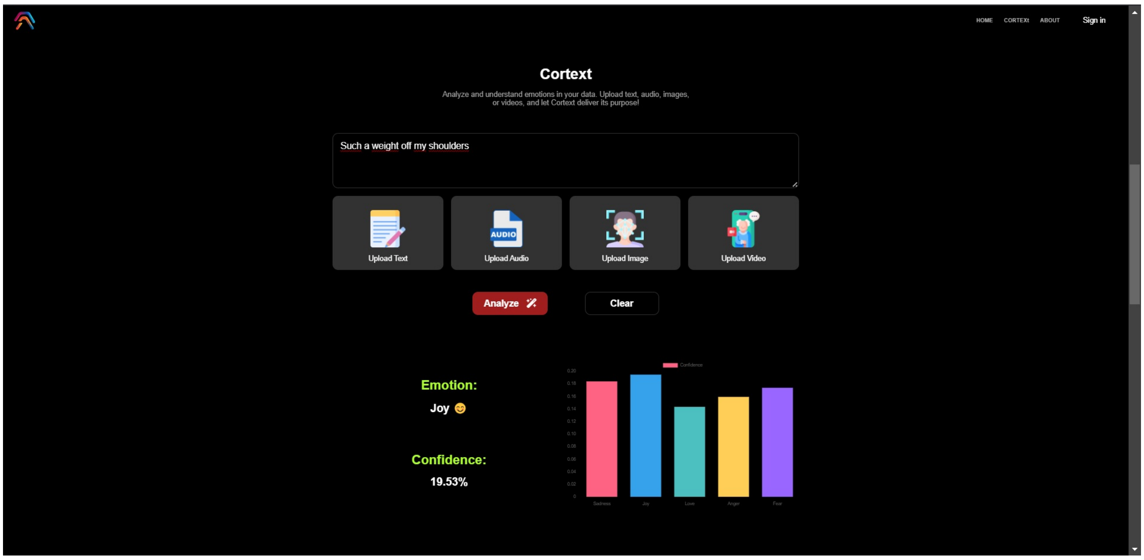

Figure 4.4: Short text content with joy emotion

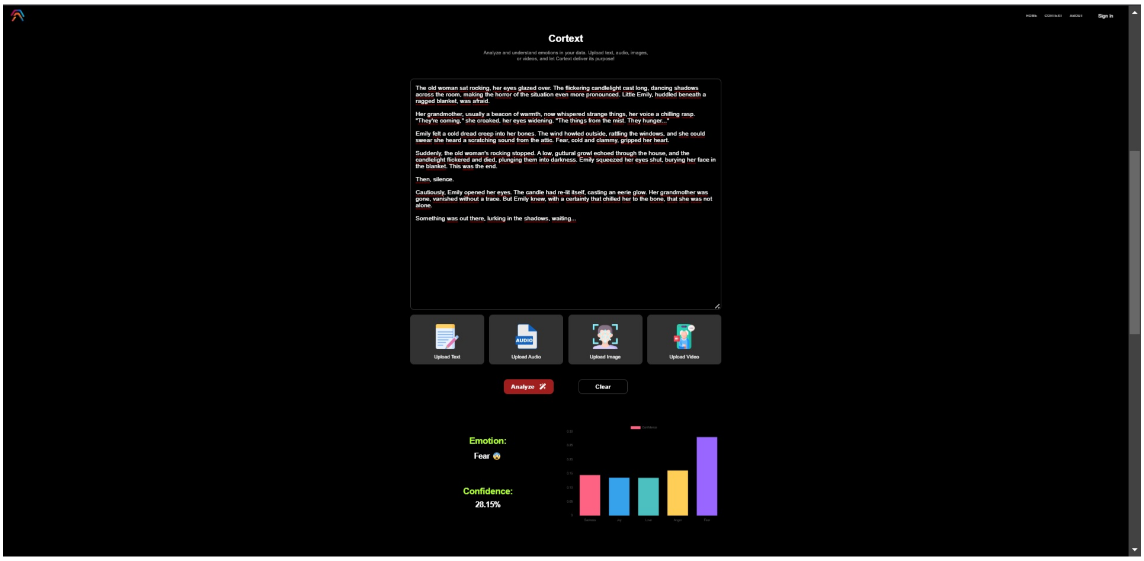

Figure 4.5: Long text content with fear emotion

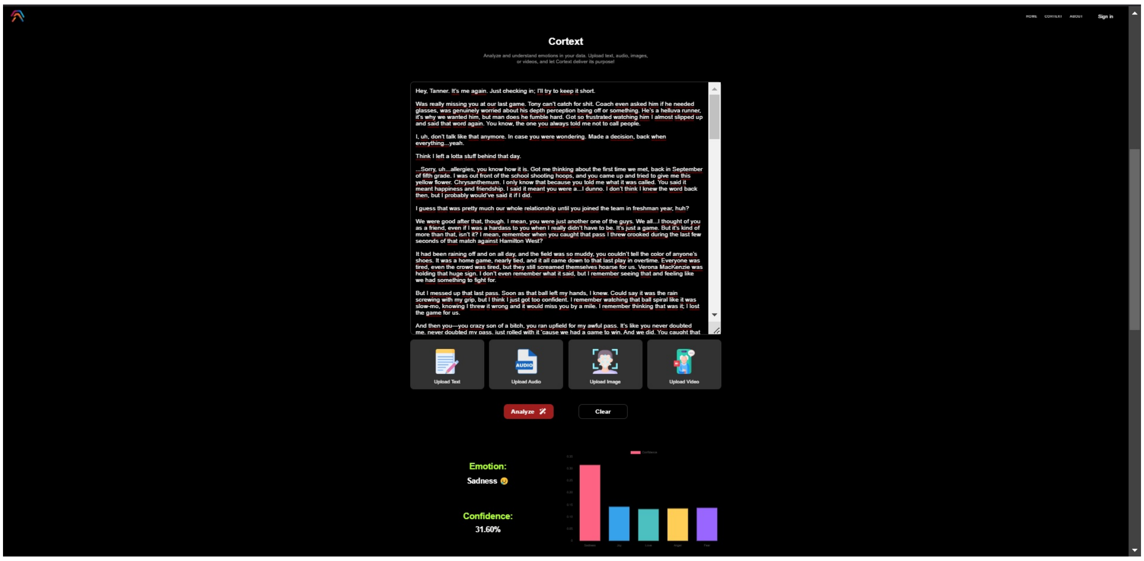

Figure 4.6: Long text content with sad emotion

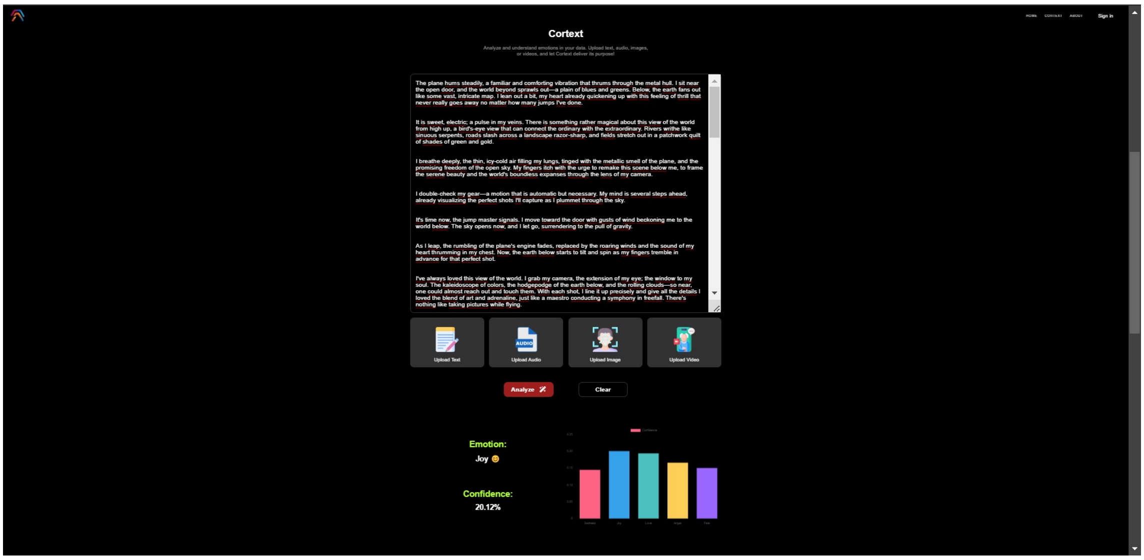

Figure 4.7: Long text content with joy emotion

Chapter 5

Conclusions and Perspective

5.1 Summary

The Cortext project presents a sentiment analysis tool that leverages machine learning to analyze and classify text data based on emotional tone. The model employs a Support Vector Machine (SVM) classifier, supported by a TF-IDF vectorizer to transform text into meaningful features. Through extensive data exploration and preprocessing, the system ensures that the text data is processed efficiently, and the model is optimized using GridSearchCV to identify the best parameters. The project demonstrates the potential of machine learning in understanding the emotional context within text, and its architecture provides a robust solution for various applications such as content analysis, customer feedback, and social media monitoring. Overall, the Cortext model has shown strong performance in terms of accuracy and generalization, achieving satisfactory results on both training and unseen data.

5.2 Limitations

Despite the promising results of the Cortext model, several limitations exist that could affect its overall performance and scope. One of the primary challenges is the relatively limited size of the dataset, which may not fully represent the diverse linguistic expressions and emotions found in broader real-world data. The model's performance could benefit from access to a larger, more diverse dataset to better capture nuances in emotional context across different domains. Additionally, the reliance on a linear kernel for the SVM classifier may limit its ability to capture more complex relationships in data, particularly when dealing with non-linear emotional patterns. Performance-wise, while the model achieves strong accuracy metrics, its ability to process large datasets in real-time could be enhanced. Moreover, the current implementation focuses solely on text analysis, leaving out other rich sources of data, such as images or videos, that could provide additional context for emotion detection.

5.3 Future Improvements

To address the limitations and broaden the scope of the Cortext project, several improvements and future enhancements can be considered. First and foremost, expanding the dataset with more diverse and comprehensive text data would enhance the model's ability to generalize and improve performance across various domains. Additionally, exploring non-linear models, such as kernelized SVMs or deep learning approaches, could improve the model's ability to capture more intricate emotional patterns in text. To further enhance the tool's functionality, future work should focus on integrating additional types of data for analysis, including images and videos, which can provide richer insights into emotional context. Though these features have been implemented in the interface, they are not yet functional and would be a crucial area of development. By incorporating multimodal analysis, the model could analyze emotional tone not only from text but also from visual and auditory data, making it more versatile and applicable across a wider range of industries and use cases. Moreover, optimizing the model for real-time performance and scaling it to handle larger datasets would greatly increase its practical utility. These improvements would ensure Cortext continues to evolve as a powerful and comprehensive tool for emotional analysis.

References