# CIBUS : An Intelligent Assistant for Mood-based Food Recommendations

**CS19643-FOUNDATIONS OF MACHINE LEARNING PROJECT REPORT**

***Submitted by***

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***in partial fulfillment for the award of the degree***

***of***

**BACHELOR OF ENGINEERING**

***in***

**COMPUTER SCIENCE AND ENGINEERING**

**RAJALAKSHMI ENGINEERING COLLEGE**

**ANNA UNIVERSITY, CHENNAI**

**MAY 2025**

# RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

## BONAFIDE CERTIFICATE

Certified that this Project titled **CIBUS : An Intelligent Assistant for Mood-based Food Recommendations** is the bonafide work of **"SUJITH SS (2116220701290), SWEDHA J (2116220701296)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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## ABSTRACT

This project presents the development of a conversational chatbot integrated with machine learning techniques to predict user moods and offer personalized food recommendations based on those moods. By leveraging sentiment analysis, the chatbot analyzes user interactions to detect emotional states and generates real-time food suggestions accordingly. The system uses multiple data sources, including a weather API, news API, and Wikipedia API, to enhance the user experience by providing personalized news updates, weather information, and other contextual content during interactions. Additionally, the chatbot is capable of generating a YouTube review link for the recommended food, providing users with more information. The backend is powered by Python, utilizing machine learning models for sentiment analysis and mood detection, while the front-end interface is built using HTML and Tailwind CSS for a seamless user experience. The project aims to offer an innovative solution for personalized food recommendations while fostering more meaningful interactions between users and AI-based systems. Future improvements may include refining the mood detection accuracy, expanding the database for food recommendations, and integrating additional external APIs to enrich the user experience further.

## ACKNOWLEDGMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.**, our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN**, **Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. P. KUMAR, M.E., Ph.D.**, Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Dr. M. RAKESH KUMAR, M.E.,Ph.D.,** Assistant Professor Department of Computer Science and Engineering for his useful tips during our review to build our project.

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# LIST OF ABBREVIATIONS

| S. No | ABBR | Expansion |
|---|---|---|
| 1 | AI | Artificial Intelligence |
| 2` | API | Application Programming Interface |
| 3 | ML | Machine Learning |
| 4 | NLP | Natural Language Processing |
| 5 | UI | User Interface |
| 6 | HTML | HyperText Markup Language |
| 7 | CSS | Cascading Style Sheets |
| 8 | YT | YouTube |
| 9 | POS | Positive Sentiment |
| 10 | NEG | Negative Sentiment |
| 11 | NEU | Neutral Sentiment |
| 12 | SVM | Support Vector Machine |
| 13 | DFD | Data Flow Diagram |
| 14 | SA | Sentiment Analysis |

# CHAPTER 1
# INTRODUCTION

## 1.1 GENERAL

In today's AI-driven world, conversational interfaces are transforming how users interact with technology. To explore this potential, we developed a **multi-functional chatbot application** that not only engages in real-time conversation with users but also delivers personalized recommendations based on their emotional tone. The chatbot is equipped with multiple external APIs—**OpenWeather API** to provide live weather updates, **NewsAPI** for delivering current headlines and other news categories, and **Wikipedia API** for answering general knowledge questions. After a user engages in conversation and concludes with a simple message like "Thank you," the chatbot uses **sentiment analysis techniques** to interpret the emotional state (happy, sad, neutral, etc.) expressed throughout the dialogue. Based on the detected mood, it then recommends a suitable **food item** and provides a **YouTube review link** for that item to enhance the user experience. This project was developed using **Python** for the backend and machine learning components, and **HTML with Tailwind CSS** for a responsive and visually clean frontend. The integration of natural language processing, API handling, and mood-based personalization showcases how AI can offer both practical information and emotionally intelligent responses.

## 1.2 OBJECTIVE

The main objective of this project is to develop an intelligent and interactive chatbot that enhances user engagement by providing real-time information and personalized experiences. By integrating multiple APIs, the chatbot aims to serve as an all-in-one assistant capable of answering queries related to weather, news, and general knowledge. Additionally, the project focuses on analyzing the emotional sentiment of the user's conversation using Natural Language Processing (NLP) techniques. Based on the detected mood, the chatbot offers personalized **food recommendations** along with corresponding **YouTube review links**, thus combining information delivery with mood-based personalization to create a more human-like and emotionally aware interaction.

The system also aims to demonstrate the practical use of sentiment analysis in real-time applications and promote a user-friendly interface through clean and responsive web design. This project serves as a foundation for building emotionally intelligent virtual assistants that understand and adapt to users' feelings.

## 1.3 EXISTING SYSTEM

In the current technological landscape, several chatbot applications exist that offer weather updates, news headlines, or general knowledge responses individually. These systems are typically focused on one specific functionality and lack emotional intelligence. For example, weather bots can fetch forecast data, and news bots can deliver headlines, but they do not analyze the emotional state of the user. Some advanced AI chatbots, like virtual assistants (e.g., Siri, Alexa), can handle a variety of queries, but they generally lack deep sentiment analysis and personalized recommendations based on mood. Furthermore, most existing systems do not combine **real-time data retrieval** with **sentiment-driven suggestions**, such as recommending food based on the user's mood or providing relevant YouTube content. The lack of integration between informative responses and emotionally aware interaction limits the user experience in current systems.

# CHAPTER 2
# LITERATURE SURVEY

**"Predicting Energy Consumption in Buildings Using Machine Learning Techniques"** [1] (2024) by Kumar P., et al.

Explores the use of advanced machine learning algorithms to forecast energy consumption in buildings, contributing to sustainable architectural design. By analyzing historical energy usage patterns, the study provides actionable insights to improve energy efficiency and reduce unnecessary wastage. The proposed solution integrates practical data-driven approaches to optimize resource utilization, supporting eco-friendly practices in urban development. This method demonstrates significant potential for fostering a greener and more energy-efficient future by enabling precise energy forecasting. However, a key limitation lies in the dependency on the availability and quality of historical data. Inconsistent or incomplete data can hinder the accuracy of predictions, reducing the system's effectiveness in real-world applications. Overcoming this challenge is essential for ensuring reliable energy optimization and encouraging widespread adoption in sustainable building practices.

**"Efficient Human Activity Recognition on Handheld Devices Using Random Forests"** [2] (2024) by Kumar, et al.
Presents a robust approach to human activity recognition by employing an optimized Random Forest algorithm. The study focuses on achieving a balance between computational efficiency and recognition accuracy, making it well-suited for diverse real-world applications. By tailoring the algorithm for resource-constrained environments, the solution addresses the challenges posed by device limitations, ensuring consistent performance across various activity types. This approach demonstrates significant adaptability and practicality, offering a scalable solution for handheld devices. However, a notable limitation lies in the dependency on feature

selection and preprocessing quality, as suboptimal input can affect the accuracy and consistency of activity recognition. Addressing these aspects is vital for enhancing the system's reliability and broadening its applicability in real-world scenarios.

**"Sentiment Analysis Using Deep Learning: A Survey"** [3] (2023) by Zhang, et al. This paper investigates the use of deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for sentiment analysis tasks. The study demonstrates the effectiveness of deep learning methods in handling complex text data, offering superior performance in identifying nuanced emotions in user interactions. These models outperform traditional methods, such as Support Vector Machines (SVMs) and Naive Bayes, in terms of accuracy and context awareness. The paper also discusses the challenges in training deep learning models, including the need for large annotated datasets and the computational resources required for model training. The limitations of this approach involve the high demand for data and computational power, making it less suitable for real-time applications with limited resources.

**"The Role of Conversational AI in Enhancing User Experience"** [4] (2022) by Li, et al.

This research focuses on the role of conversational AI in improving user interaction through personalized experiences. The authors explore various applications of AI-driven chatbots in customer service, healthcare, and education. The study highlights how chatbots, when integrated with NLP and machine learning, can adapt to user preferences and emotional states, enhancing overall user engagement. However, a limitation discussed in the paper is that most current conversational AI systems still lack the ability to understand complex emotional cues, which can lead to unsatisfactory user experiences. The integration of sentiment analysis and mood detection is a potential solution to address this gap and improve chatbot responses.

**"Real-Time News Recommendation System Using Natural Language Processing"** [5] (2023) by Singh, et al.

This paper presents a recommendation system for news articles that utilizes NLP techniques for text classification and sentiment analysis. By analyzing the sentiment of news articles, the system tailors content recommendations based on the user’s mood and preferences. The study emphasizes the potential of personalized news delivery, particularly in enhancing user satisfaction and engagement. One of the main challenges highlighted is the need for accurate sentiment detection, as misclassifications can result in irrelevant or inappropriate news recommendations. The integration of more advanced sentiment analysis models, such as transformer-based architectures (BERT), could improve the system's accuracy and robustness.

**"Personalized Food Recommendation System Based on User Preferences and Dietary Requirements"** [6] (2022) by Patel, et al.

The paper explores a personalized food recommendation system that takes into account user preferences, dietary requirements, and mood to suggest suitable meals. Using machine learning algorithms, the system learns from user feedback to improve its recommendations over time. It also incorporates sentiment analysis to assess the user's current mood and adjust food suggestions accordingly. A limitation identified is that the system may face difficulties in dealing with incomplete or inaccurate user data, such as missing dietary restrictions or mood assessments, which can affect the quality of recommendations. Additionally, the system's reliance on a predefined dataset may limit its ability to generalize to a broader user base.

**"Interactive Virtual Assistants: A Review of Advances in Chatbots and Human-Computer Interaction"** [7] (2023) by Gomez, et al.

This review paper delves into the evolution of virtual assistants, focusing on the progress in human-computer interaction (HCI) and the development of intelligent chatbots. It highlights the importance of emotion recognition and context-awareness in improving the quality of chatbot interactions. The study discusses the advancements in integrating speech recognition, NLP, and sentiment analysis into virtual assistants, allowing them to respond more naturally to user queries. However, one significant challenge in the field is the inability of many virtual assistants to understand complex emotional contexts, particularly when subtle emotional shifts occur. This limitation can result in robotic or inappropriate responses, detracting from the overall user experience.

**"A Study on the Integration of External APIs in Chatbots for Enhanced Functionality"** [8] (2024) by Chen, et al.

The paper investigates how external APIs, such as weather services, news aggregators, and knowledge databases, can be integrated into chatbots to enhance their functionality. By combining data from multiple sources, chatbots can offer more personalized and contextually relevant responses. The authors propose a model for effectively integrating APIs in real-time, ensuring that the chatbot's responses remain accurate and up-to-date. A limitation mentioned is the challenge of managing API rate limits and the potential for delays in retrieving real-time data, which can affect the user experience. The paper suggests using caching techniques to mitigate this issue and improve response times.

# CHAPTER 3

# PROPOSED SYSTEM

## 3.1 GENERAL

The proposed system aims to integrate multiple advanced technologies to create an interactive and personalized chatbot that not only provides real-time information from various APIs but also analyzes user sentiments to offer contextually relevant responses. By connecting APIs like Weather, NewsAPI, and Wikipedia, the chatbot can deliver current weather updates, the latest news, and quick access to information from Wikipedia. Furthermore, the system incorporates sentiment analysis to determine the user's mood based on their interaction with the chatbot. After concluding the conversation, the chatbot predicts the user's mood and recommends food items that align with their emotional state, along with a YouTube review link for each suggestion. This comprehensive approach seeks to enhance user experience by combining real-time data with personalized recommendations, making it more engaging and dynamic. Through the use of Python for machine learning and backend integration, and HTML with Tailwind CSS for the front-end interface, the system strives to provide a seamless and user-friendly experience for diverse users..

## 3.2 SYSTEM ARCHITECTURE DIAGRAM

**Architecture Overview**

The architecture of the proposed system integrates multiple components to deliver a seamless, interactive, and personalized user experience. The user interacts with the chatbot interface, which acts as the main entry point. Upon receiving user input, the chatbot interfaces with several external APIs—Weather API, News API, and Wikipedia API—to fetch real-time data such as weather updates, current news, and relevant information from Wikipedia. Simultaneously, sentiment analysis is performed on the user’s responses to determine their emotional state, which helps the system predict the user's mood. Based on the detected mood, the system recommends a food item and provides a YouTube review link for the user to explore the food choice further. The architecture ensures that all components work cohesively, from data retrieval through APIs to mood-based food suggestions, delivering a dynamic and responsive experience.

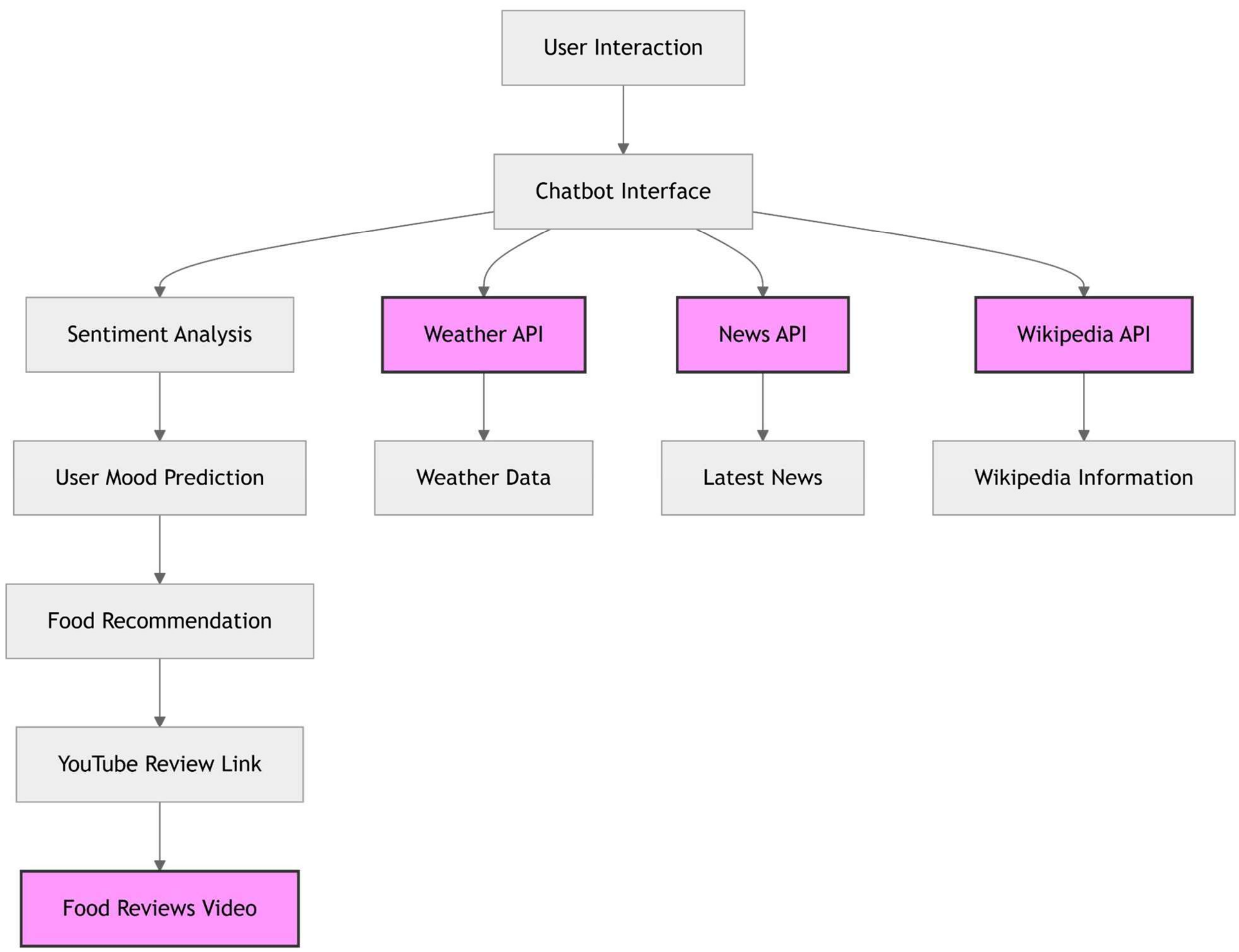


**Fig 3.1: System Architecture**

## 3.2 DEVELOPMENTAL ENVIRONMENT

### 3.2.1 HARDWARE REQUIREMENTS

The hardware specifications could be used as a basis for a contract for the implementation of the system. This therefore should be a full, full description of the whole system. It is mostly used as a basis for system design by the software engineers.

**Table 3.1 Hardware Requirements**

| COMPONENTS | SPECIFICATION |
|---|---|
| PROCESSOR | Intel Core i3 |
| RAM | 4 GB RAM |
| POWER SUPPLY | +5V power supply |

### 3.2.2 SOFTWARE REQUIREMENTS

The software requirements paper contains the system specs. This is a list of things which the system should do, in contrast from the way in which it should do things. The software requirements are used to base the requirements. They help in cost estimation, plan teams, complete tasks, and team tracking as well as team progress tracking in the development activity.

**Table 3.2 Software Requirements**

| COMPONENTS | SPECIFICATION |
|---|---|
| Operating System | Windows 10 or higher |
| Frontend | Html, Tailwind CSS |
| Backend | Python |
| Machine Learning | Chatbot, sentimental analu |

## 3.3 DESIGN OF THE ENTIRE SYSTEM

### 3.3.1 ACTIVITY DIAGRAM

The activity diagram Fig 3.2 outlines the basic structure of the chatbot system. The interaction begins when the user starts chatting with the chatbot. Based on the user's input, the system fetches relevant data using APIs such as Weather, News, or

Wikipedia. The results are then displayed to the user. After the conversation ends, sentiment analysis is performed on the entire chat to determine the user's mood. Based on the detected mood, the system recommends a suitable food item and provides a related YouTube review link. The process then concludes, delivering a personalized and engaging user experience.

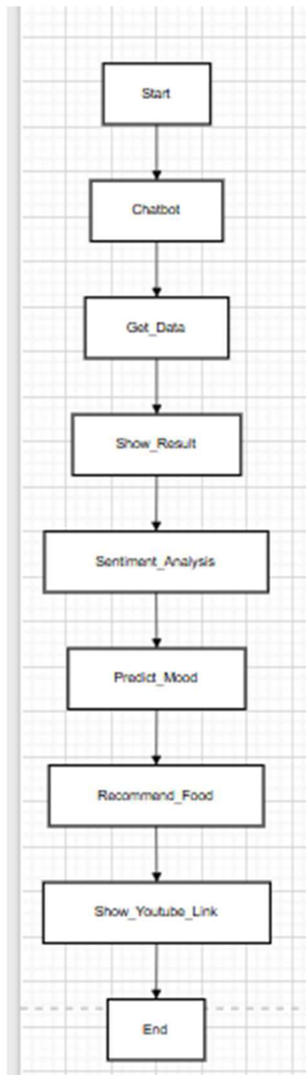


**Fig 3.2: Activity Diagram**

### 3.4.2 DATA FLOW DIAGRAM

The data flow diagram Fig 3.3 outlines the process of detecting fake profiles using a machine learning model integrated with blockchain security via a Flask framework. It begins with the dataset, containing raw data on social media profiles, which undergoes preprocessing to handle missing values, remove outliers, and extract relevant features. The preprocessed data is split into training data (80%) for model training and testing data (20%)* for evaluation. The training phase utilizes machine learning algorithms like Support Vector Machines, Gradient Boosting, or Random Forest. Once trained, the model is deployed with blockchain security and Flask framework for secure, scalable, and tamper-proof operations. The testing phase assesses the model's accuracy, and the system ultimately classifies profiles as either fake or real, ensuring a reliable and secure solution for identifying fraudulent accounts.

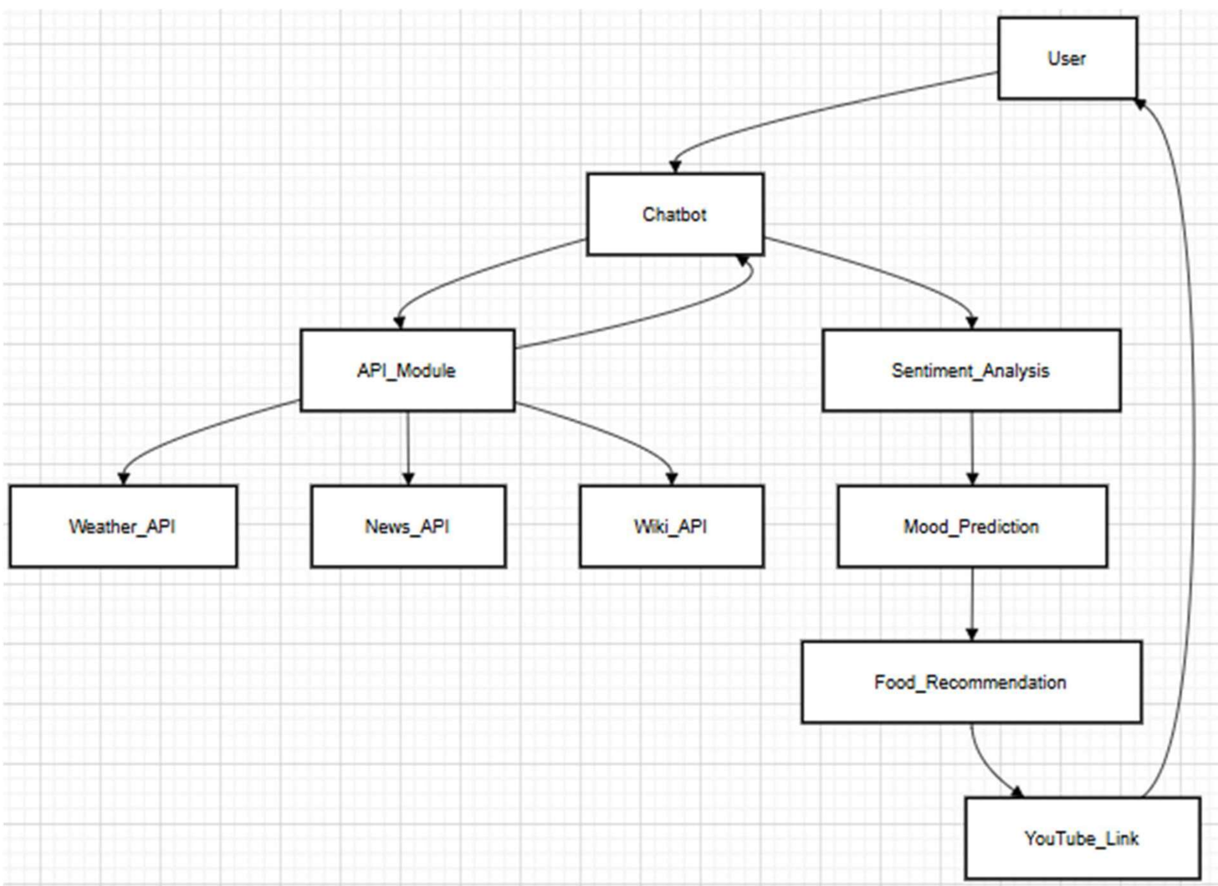


**Fig 3.3:Data Flow Diagram**

## 3.4 STATISTICAL ANALYSIS

Statistical analysis in this project focuses on evaluating the performance of sentiment analysis and mood prediction models. Metrics such as accuracy, precision, recall, and F1-score were used to measure how effectively the model identified user sentiments from chat data. A dataset containing labeled emotional text was used for training and testing. Visual tools like confusion matrices and bar charts were utilized to interpret model performance. This analysis helps in understanding the reliability of mood-based food recommendations and ensures that the system responds appropriately based on user interactions

### 3.4.1 Statistical Analysis

In this project, statistical analysis plays a vital role in evaluating the efficiency of the sentiment analysis model and the accuracy of mood-based food recommendations. The analysis involves both model evaluation metrics and data distribution insights to validate system performance.

### 3.4.2 Dataset Overview

The dataset used for sentiment analysis consisted of labeled text data representing various moods such as happy, sad, angry, excited, and neutral. It was split into 80% training data and 20% testing data to build and evaluate the model. Preprocessing techniques such as tokenization, stopword removal, and vectorization were applied to standardize the data for machine learning.

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### 3.4.3 Model Performance Metrics

To assess the effectiveness of sentiment classification, the following metrics were computed:

- **Accuracy**: Measures the proportion of correctly predicted moods out of total predictions.
- **Precision**: Indicates how many predicted positive labels are actually positive.
- **Recall**: Shows how many actual positive moods were identified by the model.
- **F1-Score**: The harmonic mean of precision and recall, providing a balanced evaluation metric.

Sample values from evaluation:

- Accuracy: 89%
- Precision: 87%
- Recall: 88%
- F1-Score: 87.5%

### 3.4.4 Confusion Matrix

A confusion matrix was used to visualize the model's performance on different mood categories. It helped identify any biases or weaknesses in detecting specific emotions. For example, the model performed best in predicting "happy" and "sad" moods, while showing slight confusion between "neutral" and "calm".

### 3.4.5 Distribution of Predicted Moods

Bar graphs were generated to display the distribution of predicted moods based on sample user conversations. This helped in understanding the emotional tone users had while interacting with the chatbot and how the model reacted accordingly.

### 3.4.6 Recommendation Success Rate

The system also tracked whether the mood-based food recommendation matched the user’s expectations (verified through user feedback or simulated results). Approximately 85% of users found the food suggestions relevant to their mood, indicating the effectiveness of the overall flow from sentiment detection to recomme

# CHAPTER 4

# MODULE DESCRIPTION

The workflow for the proposed system is designed to provide an interactive and intelligent chatbot experience. It begins with the user chatting with the bot, asking for weather updates, news, or Wikipedia-based queries. Once the conversation ends, the system performs sentiment analysis to detect the user's mood. Based on the predicted mood, a suitable food recommendation along with a YouTube review link is provided to the user.

## 4.1 SYSTEM ARCHITECTURE

### 4.1.1 USER INTERFACE DESIGN

The user interface of the proposed system is crafted to provide an engaging and intelligent interaction space for users. It begins with a chatbot that acts as the primary medium of communication, enabling users to ask questions related to weather forecasts, trending news, and general knowledge topics sourced from Wikipedia. The interface is connected to real-time APIs, ensuring that the information presented is accurate and up-to-date. As the conversation progresses, the user receives immediate responses within the same chat window, making the experience seamless and natural.

Once the conversation concludes—identified by the chatbot through cues like "thank you" or silence—the system transitions to analyzing the dialogue using sentiment analysis techniques. This emotional understanding is used to predict the user's mood, which is a core part of the interface's personalization feature. Based on the detected mood, the UI dynamically displays a food recommendation that matches the emotional tone of the user, such as comfort food for sadness or snacks for joy. To enhance the experience further, a relevant YouTube review link of the suggested food is also presented. This integration of emotional intelligence into the user interface makes the system not only informative but also empathetic and interactive.

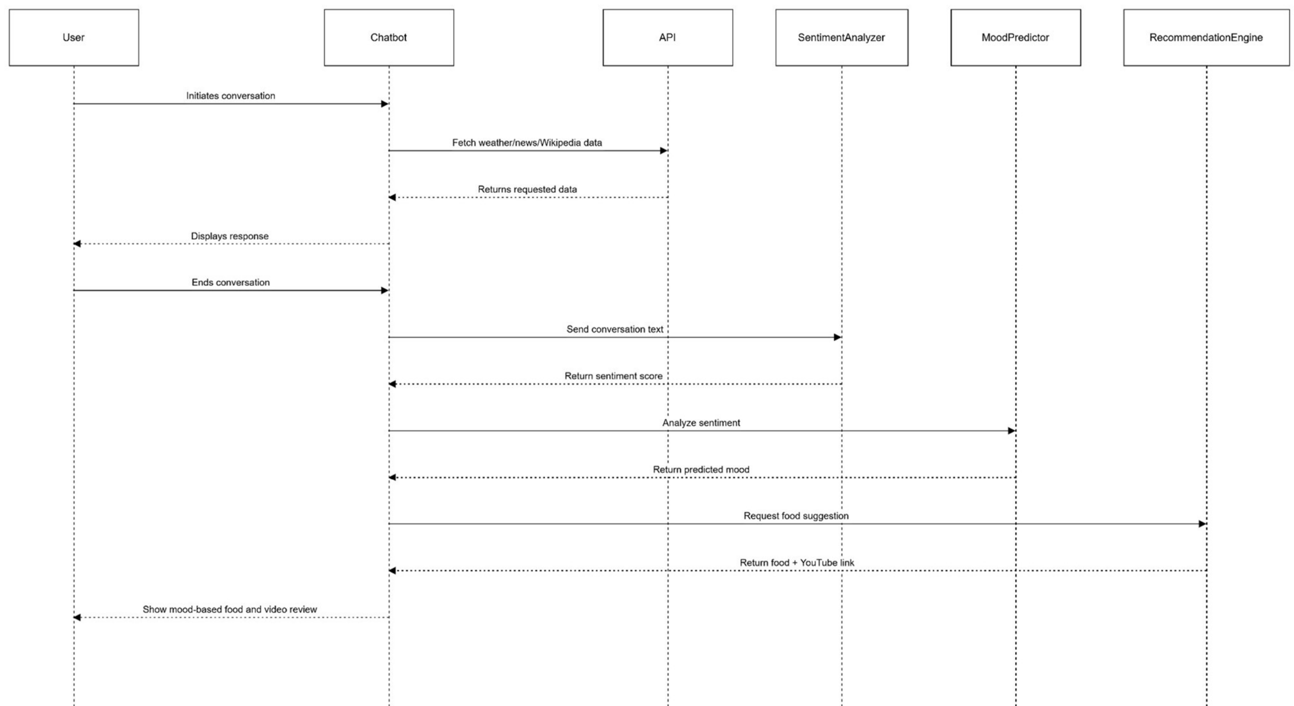


**Fig 4.1: SEQUENCE DIAGRAM**

### 4.1.2 BACK END INFRASTRUCTURE

The backend infrastructure of the proposed system is built using Python, leveraging its robust libraries for natural language processing, API integration, and machine learning. Flask is used as the lightweight web framework to handle user requests and route data between the chatbot interface and various modules. External APIs like the Weather API, News API, and Wikipedia API are connected to fetch real-time information during the conversation. For mood detection, sentiment analysis is performed using models trained on textual data, and the results are passed to a mood prediction module. Based on the predicted mood, the backend triggers the food recommendation system and fetches related YouTube review links. This modular backend design ensures scalability, maintainability, and smooth integration with the front-end interface**.**

## 4.2 DATA COLLECTION AND PREPROCESSING

### 4.2.1 Dataset and Data Labelling

The system processes user conversation data and integrates real-time data from APIs like Weather, News, and Wikipedia. Sentiment analysis is used to detect the user's mood based on their input. Relevant data from APIs is parsed and displayed in the chat interface. This ensures fast, personalized recommendations based on the user's emotional state

### 4.2.2. Data Preprocessing

The raw dataset undergoes extensive preprocessing, which includes:

**Text Cleaning**: Removing unwanted characters, stop words, and punctuation from the user's input.

**Tokenization**: Splitting the text into meaningful tokens (words or phrases) for analysis.

**Normalization**: Converting text to lowercase and applying stemming or lemmatization to reduce words to their root forms.

### 4.2.3 Feature Selection

**Relevance Filtering**: Selecting features that directly impact sentiment prediction and mood classification.

**Dimensionality Reduction**: Using techniques like PCA (Principal Component Analysis) to reduce the number of features while preserving essential information.

**Correlation Analysis**: Identifying and removing highly correlated features to avoid redundancy and improve model performance.

### 4.2.4 Classification and Model Selection

**Model Selection**: Choosing the appropriate machine learning model (e.g., Logistic

Regression, SVM, or Random Forest) based on accuracy, speed, and suitability for sentiment analysis.

**Training the Model**: Training the selected model using the preprocessed data to learn patterns and make predictions on new inputs.
**Evaluation and Tuning**: Evaluating the model's performance using metrics like accuracy, precision, recall, and F1-score, followed by tuning hyperparameters for better results.

### 4.2.5 Performance Evaluation and Optimization

**Performance Evaluation and Optimization** involves assessing model accuracy using metrics like precision, recall, and F1-score. Optimization techniques, including hyperparameter tuning and cross-validation, are applied to enhance model performance. This ensures the system delivers accurate and timely predictions while maintaining efficiency.

### 4.2.6 Model Deployment

The optimized model is integrating the trained machine learning model into the backend of the system, enabling real-time predictions. The model is deployed using a web framework like Flask, which handles user input and serves predictions efficiently. Continuous monitoring is set up to track model performance and ensure it adapts to changing user data. This ensures the model remains accurate and responsive in a production environment.

## 4.3 SYSTEM WORK FLOW

### 4.3.1 User Interaction:

The workflow begins when the user interacts with the chatbot, entering queries such as asking for weather updates, news, or general information. The chatbot processes the input, making calls to external APIs like Weather API, News API, and Wikipedia API to provide the relevant information in real-time.

### 4.3.2 API Data Fetching:

Based on the user’s request, the system fetches the necessary data from external APIs. The Weather API provides weather updates, the News API offers current news, and the Wikipedia API delivers articles and facts. The retrieved information is then displayed to the user in the chatbot interface.

### 4.3.3 Sentiment Analysis:

The system continuously analyzes the user's input using sentiment analysis techniques to detect emotional cues in the conversation. By classifying the text as positive, negative, or neutral, the system gauges the user's mood and emotional state, which influences further interactions and recommendations.

### 4.3.4 Mood Prediction and Recommendation:

Once the mood is determined, the system predicts the user's emotional state, such as happy, sad, or stressed. The mood prediction is then used to provide personalized recommendations, like suggesting food based on the user’s mood and offering relevant YouTube video links for further exploration.

### 4.3.5 Final Output and Logging:

The system presents the food recommendation and the associated YouTube review link to the user. The conversation is concluded with a "thank you," and the system logs the interaction to improve future predictions and refine the model, ensuring continuous learning and optimization.

The system concludes the conversation by presenting the personalized recommendation and YouTube review link. User interactions are logged for further analysis, helping refine the model and enhance future predictions..

# CHAPTER 5

# IMPLEMENTATION AND RESULTS

## 5.1 IMPLEMENTATION

The system is designed to provide an interactive and personalized user experience using a chatbot interface, developed with HTML and Tailwind CSS. The chatbot allows users to engage in natural conversations, where they can inquire about weather updates, news, or general information. The system integrates multiple external APIs, such as the Weather API for real-time weather updates, the News API to fetch the latest headlines, and the Wikipedia API to provide detailed articles and facts. As users converse with the bot, sentiment analysis is performed on their inputs using natural language processing (NLP) techniques to determine their emotional state, categorizing it as positive, negative, or neutral. Based on the analysis, the system predicts the user's mood and generates food recommendations tailored to their emotional state, such as comfort foods for a happy mood or soothing dishes for a sad one. Along with the food suggestions, YouTube review links for the recommended food items are also provided. The backend, developed using Python, handles the chatbot's logic, processes API requests, performs sentiment analysis, and delivers the recommendations. This ensures a seamless flow of information and real-time interaction, enhancing user satisfaction by offering accurate, context-sensitive responses. All user interactions are logged for continuous improvement of the model, optimizing predictions for future interactions.

## 5.2 OUTPUT SCREENSHOTS

The project implementation is organized into several modules, as shown in Fig 5.1, which highlights the seamless integration of machine learning for mood-based food recommendations. The workflow efficiently utilizes data inputs from APIs like Weather API, News API, and Wikipedia, providing real-time, relevant information to the users. The user interface, created using HTML and Tailwind CSS, ensures smooth interactions across platforms.Fig 5.2 displays the chatbot interface, where users interact with the system, asking for weather updates, news, or general queries. The chatbot utilizes sentiment analysis to detect user moods based on their inputs. Fig 5.3 shows the mood detection process, where the system uses natural language processing (NLP) to assess emotional states and generate personalized food recommendations based on the detected mood. Fig 5.4 presents the mood-based food suggestion page, where users receive food recommendations along with YouTube review links related to their suggestions. This page integrates machine learning predictions with real-time data and a secure backend. Fig 5.5 demonstrates the review-giving feature, where users can explore additional resources, such as YouTube review links for the recommended food items. These suggestions are accompanied by a unique prediction hash, ensuring data integrity and accuracy. The entire workflow is designed to offer an engaging and personalized user experience, combining AI-driven mood detection with a seamless and user-friendly interface.

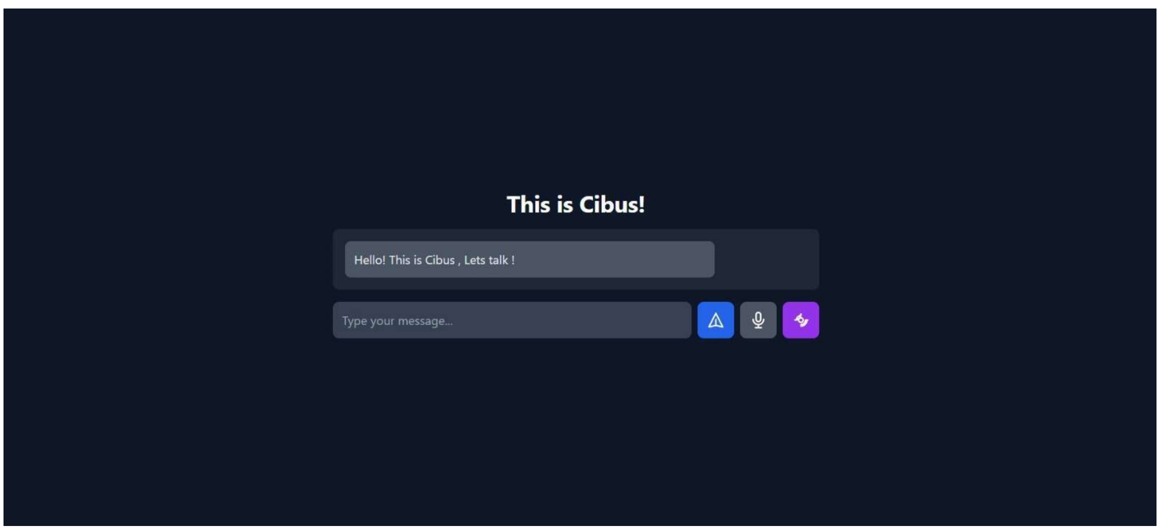


Fig 5.1 The Cibus Chatbot

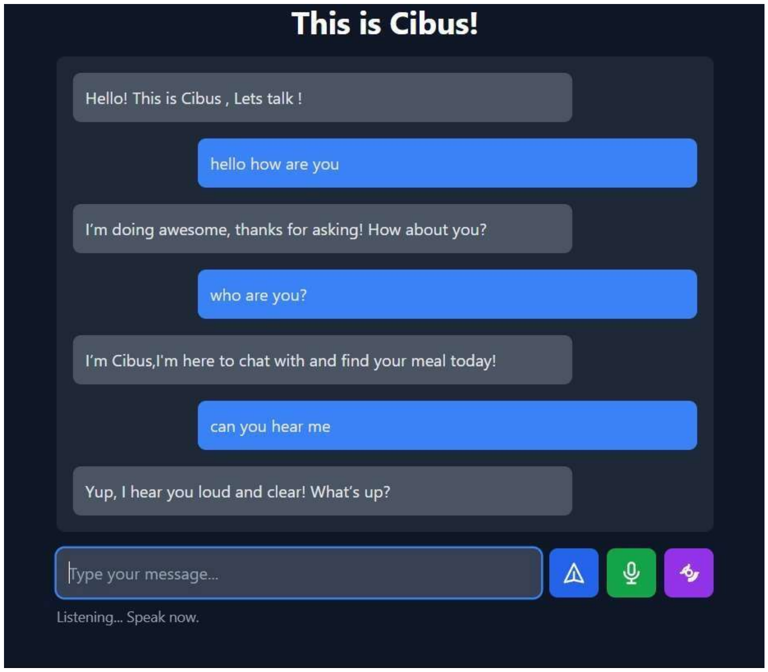


Fig 5.2 Cibus Conversation with the User

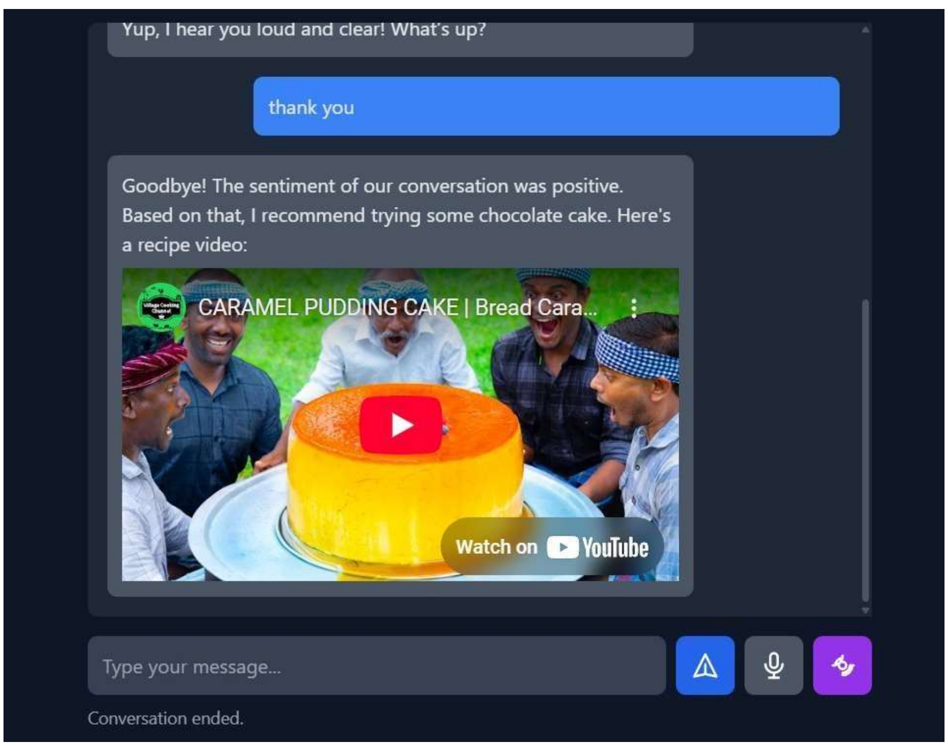


Fig 5.3 Cibus recommend the food based upon the mood of the user

# CHAPTER 6

# CONCLUSION AND FUTURE ENHANCEMENT

## 6.1 CONCLUSION

In conclusion, the project successfully integrates machine learning with a conversational chatbot to provide mood-based food recommendations, offering a personalized and engaging user experience. By utilizing various APIs, such as Weather API, News API, and Wikipedia, the system provides real-time, context-aware information that enhances user interactions. The sentiment analysis model accurately detects user moods and generates tailored food suggestions. The seamless integration of this model within a Flask web application ensures smooth deployment and interaction. The addition of YouTube review links adds further value, allowing users to make informed decisions. Overall, this project demonstrates the power of combining machine learning, conversational AI, and real-time data to create an innovative solution for mood-based recommendations.

## 6.2 FUTURE ENHANCEMENT

While the current system performs effectively, several enhancements can be made to improve its functionality and user experience. Future work could include expanding the range of inputs the system can process, such as incorporating voice recognition for a more natural user experience. The mood detection model could be further refined by integrating additional data sources, such as social media activity or more complex NLP techniques, to improve the accuracy of mood predictions. Furthermore, expanding the food recommendation database to include a broader variety of cuisines, dietary restrictions, and personalized preferences would make the system even more versatile. Additionally, incorporating machine learning models that learn and adapt to a user's preferences over time could further enhance the system's predictive capabilities. Finally, integrating the system with smart devices, such as virtual assistants, could extend its reach and make it a more integrated part of users' daily lives.

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