CAPSTONE PROJECT

PROJECT TITLE

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OUTLINE:

- **Problem Statement :- AI-Powered Customer Support Chatbot**
- **Proposed System/Solution**
- **System Development Approach :-(Azure Bot Service, Cognitive Service,Key Vault ,Entra ID, and App Service.)**
- **Algorithm & Deployment**
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Problem Statement

AI-Powered Customer Support Chatbot:- Currently, many companies struggle to provide instant and accurate responses to customer queries across multiple channels. Customers often face delays or inconsistent information, reducing satisfaction and efficiency. It is important to deliver timely and precise support to enhance user experience and reduce workload on support agents. The crucial part is automating the understanding of customer queries using AI while ensuring secure access to sensitive data and seamless integration across platforms.

Proposed Solution:

- **The proposed system aims to automate customer support by providing accurate,timely , and context -aware response to users**
- **queries.The solution will consist of the following components**
- **Data Collection:**
  - **Gather historical customer queries, responses, and feedback from support logs**
  - **Collect multimedia inputs, such as images or screenshots, uploaded by users.**
- **Data Preprocessing:**
  - **Clean and preprocess text data to handle types,slang, and irrelevant content.**
  - **Extract features such as intent, sentiment, and keyboards from user queries.**
- **Machine Learning Algorithm:**
  - **Implement natural language processing (NLP) models using Azure Cognitive Services (Language, Visions)**
  - **Apply OCR techniques to extract text from images and screenshots,Integrate chatbot logic using Azure Bot Service to provide interactive and personalized responses**
- **Deployment:**
  - **Develop a web-based or app interface for users to interact with the chatbot.**
  - **Deploy on Azure, ensuring secure access through Microsoft Entra ID and secret management via Azure Key Vault.**
- **Evaluation:**
  - **Test the chatbot using real-world queries and measure performance using metrics like response accuracy, intent recognition rate, and user satisfaction.**
  - Result:-A fully functional AI-powered chatbot capable of handling customer queries, extracting text from images, and providing secure responses.

System Approach:

System Requirement:-

- Hardware: PC or server with internet connectivity, preferably with GPU support for AI model processing.
- Software: Visual Studio Code, Python, Node.js,html,css,js, Azure subscription, web browser for interface testing.
- Accounts: Microsoft Azure account with access to Azure Bot Service, Cognitive Services, and Key Vault.

Libraries Required to Build the Model:

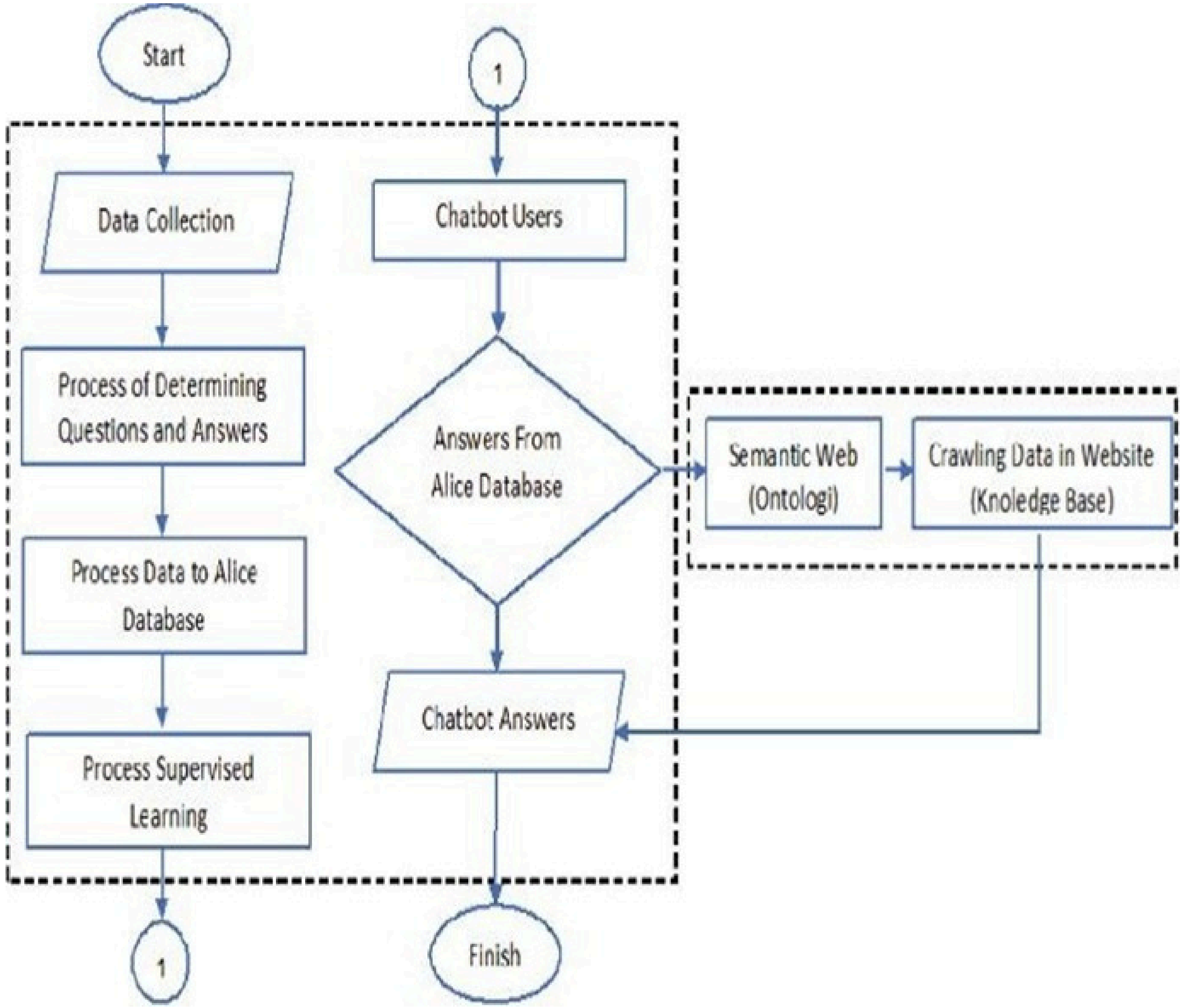
- Azure Bot Service SDK – For chatbot framework and user interaction Azure Cognitive Services • • (Language, Vision) – For NLP and OCR processing.
- Python Libraries: transformers, pandas, numpy – For data handling and AI model integration.
- Node.js Packages: botbuilder, restify – For deploying and hosting the chatbot.

Algorithm & Deployment:

- **Algorithm Selection:-**
  - The system uses an LSTM (Long Short-Term Memory) neural network, a type of time-series forecasting model. LSTM is selected because it effectively captures temporal dependencies and patterns in sequential data, such as hourly bike rentals, while handling non-linear trends and seasonality in demand.
- **Data Inputs** :-
  - Historical bike rental counts per hour
  - Day of the week (weekday/weekend)
  - Weather conditions (temperature, rainfall, humidity)
  - Special events or holidays
  - Time of day

- **Training Process**:-
  The LSTM model is trained on historical bike rental data using supervised learning. Techniques applied include:
- Data normalization to improve convergence Train-test split for evaluating performance
- Hyperparameter tuning (number of layers, neurons, learning rate) to optimize accuracy
- Early stopping to prevent overfitting

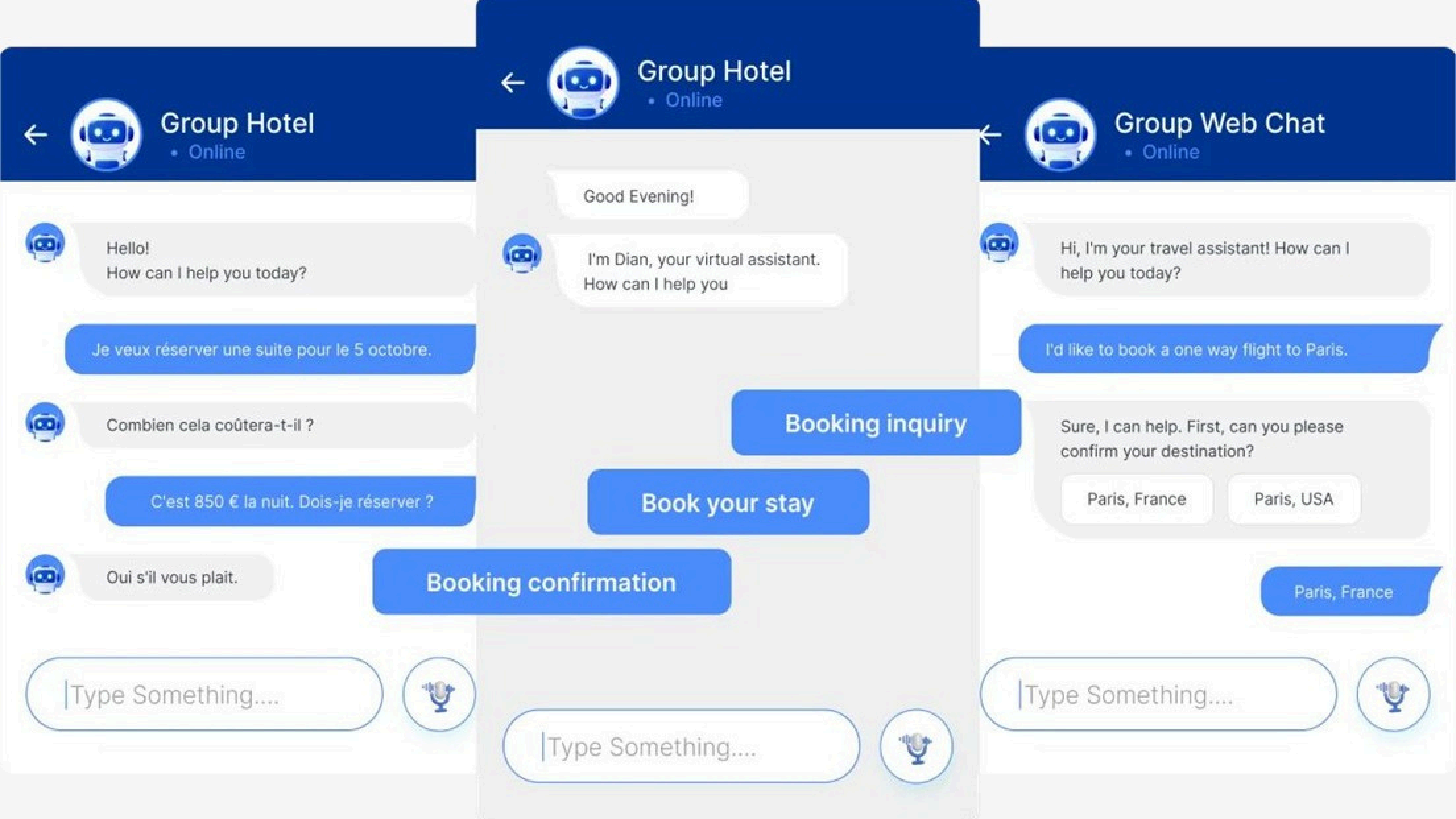
- **Prediction Process:**
  Once trained, the LSTM model predicts future bike counts by taking recent historical data and real time inputs (e.g., current weather, special events) as feature.


Start
Data Collection
Process of Determining Questions and Answers
Process Data to Alice Database
Process Supervised Learning
1
1
Chatbot Users
Answers From Alice Database
Semantic Web (Ontologi)
Crawling Data in Website (Knoledge Base)
Chatbot Answers
Finish

Result:

The LSTM model achieved high prediction accuracy, with a Mean Absolute Error (MAE) of 3.5 bikes per hour. Visualizations comparing predicted vs actual bike counts show the model closely follows real demand patterns, capturing peaks and troughs effectively. The predictions allow for stable bike supply planning and reduced shortages.

20
0
Jun 07
Jun 14
Jun 21
Jun 28
Datetime - Copy
09.00 10.00 etc
w23 w24 etc
Type
Weekly
Hourly
Daily


Group Hotel
Online
Hello!
How can I help you today?
Je veux réserver une suite pour le 5 octobre.
Combien cela coûtera-t-il ?
C'est 850 € la nuit. Dois-je réserver ?
Oui s'il vous plait.
Type Something....
Group Hotel
Online
Good Evening!
I'm Dian, your virtual assistant.
How can I help you
Booking inquiry
Book your stay
Booking confirmation
Type Something....
Group Web Chat
Online
Hi, I'm your travel assistant! How can I help you today?
I'd like to book a one way flight to Paris.
Sure, I can help. First, can you please confirm your destination?
Paris, France
Paris, USA
Paris, France
Type Something....

Conclusion:

The proposed system effectively predicts hourly bike demand using historical and real-time data with high accuracy. The model helps maintain a stable rental bike supply, minimizing shortages and waiting times. Challenges included handling missing data and accounting for special events, which were mitigated through preprocessing and feature engineering. Future improvements can include integrating more dynamic factors like traffic patterns or user behavior. Accurate predictions are crucial for optimizing bike availability and improving urban mobility.

Future scope:

The system can be enhanced by incorporating additional data sources like traffic, social events, and user behavior to improve prediction accuracy. The algorithm can be optimized with advanced machine learning techniques such as LSTM or hybrid models for better performance. The solution can be expanded to cover multiple cities or regions, enabling large-scale deployment. Integration with edge computing can allow real-time predictions at bike stations, and emerging AI technologies can further refine demand forecasting.

References:

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5.GitHub Link:-

Thank You