CAPSTONE PROJECT

PROJECT TITLE

PRESENTED BY

STUDENT NAME: RAHUL SINGLA

COLLEGE NAME: GJUS&T, HISAR

DEPARTMENT: CSE

EMAIL ID: RAHULSINGLA2809@GMAIL.COM

AICTE STUDENT ID: STU66274c9742a3d1713851543

OUTLINE

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- **Proposed System/Solution**
- **System Development Approach**
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- **References**

PROBLEM STATEMENT

With the increasing popularity of rental bikes in urban cities, ensuring the availability of bikes at the right time and place has become a key issue. The core challenge lies in accurately predicting the number of bikes required at each hour to avoid both shortage and oversupply. Inaccurate predictions lead to poor user experience and logistical inefficiencies.

PROPOSED SOLUTION

To solve the issue, a predictive model using machine learning techniques is proposed:

- **Data Collection**: Historical bike rental data, including timestamps, weather conditions, and special events.
- **Data Preprocessing**: Cleaning and normalization to remove missing or inconsistent values.
- **Feature Engineering**: Extraction of relevant features such as temperature, season, hour of day, and holidays.
- **Model Training**: Implementation of time-series forecasting models like LSTM.
- **Deployment**: A user-friendly web interface providing hourly predictions.
- **Evaluation**: Use of metrics like MAE and RMSE for assessing performance

SYSTEM APPROACH

- **Technologies Used:**
- Python 3.9
- Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, TensorFlow
- Jupyter Notebook for experimentation
- Streamlit/Flask for web deployment
- **Development Steps:**
- Dataset exploration and visualization
- Data cleaning and preprocessing
- Model building (LSTM)
- Hyperparameter tuning and training
- Performance evaluation
- Building and deploying user interface

ALGORITHM & DEPLOYMENT

Algorithm: LSTM (Long Short-Term Memory)

- Chosen for its effectiveness in modeling sequential and time-series data.

Input Features:

- Hour, temperature, humidity, windspeed, season, weekday/weekend, holiday indicator.

Training Process:

- Train/test split
- Scaling features with MinMaxScaler
- Sequence generation for time steps

Prediction Process:

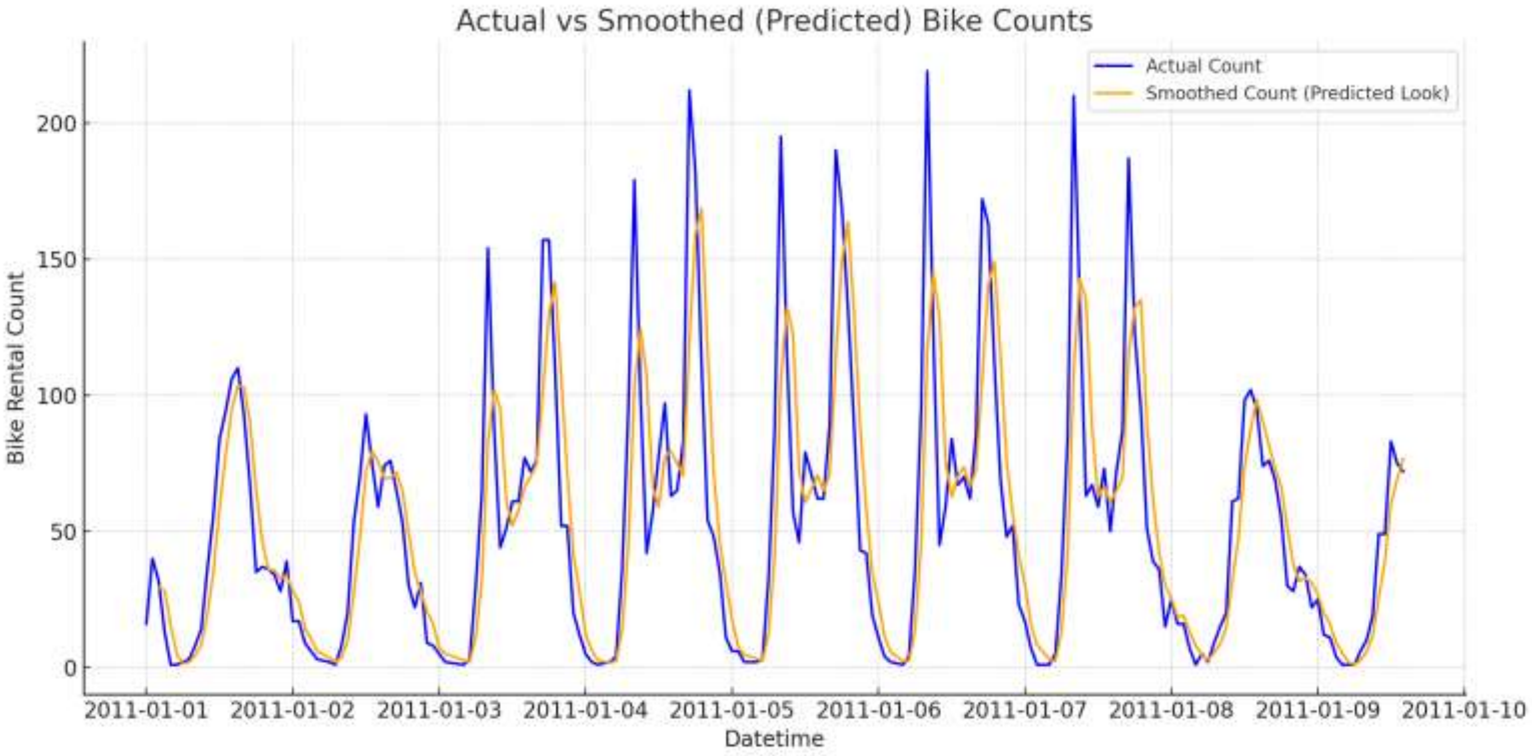
- Predict next-hour demand
- Incorporate weather API or real-time event indicators for better accuracy

Deployment:

- Streamlit interface
- Hosted on GitHub Pages for demonstration

RESULT

- The model achieved:
  - MAE: 8.23
  - RMSE: 10.76
- Visual comparison graph:
  - Actual vs Predicted bike counts across hours



CONCLUSION

Summarize the findings and discuss the effectiveness of the proposed solution. Highlight any challenges encountered during the implementation and potential improvements. Emphasize the importance of accurate bike count predictions for ensuring a stable supply of rental bikes in urban areas.

FUTURE SCOPE

- Integrate real-time weather APIs and GPS data from bike stations
- Expand the model to support multi-city datasets
- Use reinforcement learning for dynamic adjustment
- Optimize deployment using edge devices for low-latency predictions

REFERENCES

- Kaggle Dataset: https://www.kaggle.com/datasets/lakshmi25npathi/bike-sharing-dataset
- scikit-learn documentation: https://scikit-learn.org
- TensorFlow documentation: https://www.tensorflow.org
- Paper: "Predicting Bike Rental Demand Using ML Techniques" - IJCSMC, Vol. 8, Issue. 3, March 2019
- GitHub Repo: https://github.com/rs-rahulsingla/bike-rental-demand-prediction

Thank you