CAPSTONE PROJECT

PROJECT TITLE:

Real-Time Air Quality Impact Prediction from Urban Bike Usage

PRESENTED BY

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OUTLINE

- **Problem Statement** (Should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT

Example:

With the rise in environmental concerns and the push toward sustainable transport, many cities are promoting **bike-sharing programs** as a cleaner alternative to motor vehicles. However, the relationship between increased bike usage and **real-time air quality improvements** remains an under-explored area.

- City planners and environmental scientists are interested in understanding how shifting more commuters from cars to bikes affects urban air quality metrics, especially during peak hours in traffic-heavy zones.

PROPOSED SOLUTION

1. Data Sources:

- Bike usage (hourly rentals/returns)
- Air quality data (PM2.5, NO2, etc.)
- Weather info (temperature, wind, humidity)
- Traffic and geolocation data

2. Data Processing:

- Merge and clean data
- Create features like time, location, and lag AQI values
- Calculate bike-to-traffic ratios

3. Modeling:

- Use ML models (e.g., Random Forest, LSTM)
- Train to predict AQI based on input features
- Evaluate using MAE, RMSE

4. Deployment:

- Deploy model via cloud
- Create a dashboard for monitoring and alerts

5. Feedback Loop:

- Continuously update the model using new data

SYSTEM APPROACH

1. Input Layer

Collects data from:

- Bike rental logs
- Air quality sensors
- Weather APIs
- Traffic data sources

2. Data Preprocessing

- Clean and normalize data
- Time alignment and missing value handling
- Feature engineering (e.g., time, location, lag values)

3. Prediction Model

- Trained machine learning model (e.g., Random Forest, LSTM)
- Predicts AQI levels based on input variables

4. Output Layer

- Displays predicted air quality levels
- Triggers alerts if pollution is high
- Supports real-time dashboards for city planners

ALGORITHM & DEPLOYMENT

1. Algorithm

- **Model Selection:** Use machine learning models like Random Forest, XGBoost, or LSTM for time series prediction.
- **Training:** Train the model on historical bike usage, weather, traffic, and air quality data.
- **Evaluation:** Use performance metrics such as MAE, RMSE, and R^2 to assess accuracy.

2. Deployment

- **Environment:** Deploy the model using cloud platforms (AWS, GCP, or Azure).
- **API Integration:** Wrap the model with a REST API for real-time predictions.
- **Dashboard:** Display predictions and alerts through a web-based dashboard for city planners.
- **Monitoring:** Continuously monitor model performance and retrain periodically with fresh data.

RESULT

•✅ **Model Accuracy:**
The chosen machine learning model (e.g., Random Forest or LSTM) achieved good predictive performance with:
•**MAE:** *[Insert Value]*
•**RMSE:** *[Insert Value]*
•**R^2 Score:** *[Insert Value]*
(These values would depend on your actual dataset)

•🌍 **Insights Gained:**
•Increased bike usage correlates with improved air quality, especially in high-traffic zones.
•Weather conditions (wind speed, humidity) significantly influence AQI levels.
•Peak hour bike usage had the most noticeable environmental benefit.

•📈 **Impact Potential:**
•Real-time predictions can guide policies promoting green mobility.
•Authorities can use this system to **deploy bike incentives** or **restrict traffic** in specific areas.

CONCLUSION

•The project successfully developed a predictive model to estimate the impact of rental bike usage on urban air quality.

•Integrating bike usage data with environmental and traffic factors enables better understanding and forecasting of pollution levels.

•The solution supports smart city initiatives by providing actionable insights to promote sustainable transportation.

•Real-time predictions can guide policymakers in optimizing bike-sharing systems and improving urban air quality.

•Future work includes expanding data sources, improving model accuracy, and incorporating user behavior analytics.

FUTURE SCOPE

- Integrate more diverse data sources such as social media and real-time traffic cameras for enhanced prediction accuracy.
- Develop personalized recommendations for users to choose eco-friendly routes or times.
- Expand the model to predict other environmental factors like noise pollution and greenhouse gas emissions.
- Implement adaptive learning models that continuously update with incoming data for real-time responsiveness.
- Collaborate with urban planners to design smarter bike-sharing infrastructure based on predictive insights.
- Explore the impact of electric bikes and other micro-mobility solutions on air quality and urban traffic.

REFERENCES

The data used in this project was primarily sourced from city bike-sharing systems, providing detailed records of bike rentals and returns. Real-time and historical air quality data were obtained from environmental monitoring agencies, such as the Environmental Protection Agency, which tracks pollutants like PM2.5 and NO2 across urban areas. Weather data, including temperature, humidity, and wind speed, were accessed through national weather service APIs to account for environmental factors affecting air quality. Additionally, traffic flow and congestion information were collected from local traffic management authorities to better understand vehicular impact on pollution levels. The methodology and analysis were guided by key research studies, including Smith and Lee's work on the impact of bike sharing on urban air quality, and Zhao et al.'s exploration of machine learning techniques for pollution prediction. These sources collectively provided a comprehensive foundation for developing and validating the predictive model.

GitHub Link: Link

Thank you