SAVEETHA SCHOOL OF ENGINEERING
SAVEETHA INSTITUTE OF MEDICAL AND TECHNICAL SCIENCES

CAPSTONE PROJECT REPORT

PROJECT TITLE

ANALYZE SENSOR DATA FROM VECHICLES TO PREDICT MAINTAINCE NEEDS AND PREVENT BREAKDOWNS

CSA0912-Java Programming

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ABSTRACT

The use of sensor data has become essential in contemporary fleet management of vehicles in order to guarantee peak performance and reduce downtime. Using sensor data obtained from automobiles, time series analysis techniques and anomaly detection algorithms are applied to present a comprehensive approach to predictive maintenance in this work. Predicting maintenance needs in advance is the key goal since it helps to minimize downtime and maximize operational effectiveness. Preprocessing raw sensor data in order to identify pertinent features and produce time series representations is the suggested methodology. Next, temporal patterns and trends within the data are modeled using time series analysis techniques like SARIMA (Seasonal ARIMA) and ARIMA (AutoRegressive Integrated Moving Average). Moreover, deviations from the norm are detected using anomaly detection methods like One-Class SVM (Support Vector Machine) and Isolation Forest.

INRODUCTION

Maintaining the uninterrupted running of vehicles is critical in the field of vehicle fleet management. The emergence of sensor technology presents a viable opportunity to anticipate maintenance requirements and prevent possible malfunctions. This research explores how predictive maintenance methods in the vehicle fleet industry might be improved by combining two advanced analytical techniques: time series analysis and anomaly detection. Through the integration of these approaches with sensor data, the research aims to enable fleet managers to anticipate repair needs, prevent unanticipated disruptions, and maximize operational effectiveness—all of which promote cost-effectiveness and enhance service reliability.

By combining anomaly detection and time series analysis, fleet managers can manage maintenance more proactively by identifying trends and irregularities in sensor data that point to future maintenance problems. By utilizing this novel framework, fleet managers may anticipate maintenance requirements and take proactive measures to minimize downtime and related expenses, all while improving fleet efficiency and customer contentment.

GANTT CHART

S.NO	DESCRIPTION	01.03.24 DAY-01	02.03.24 DAY-02	04.03.24 DAY-03	05.03.24 DAY-04	06.03.24 DAY-05
1.	Problem Identification					
2.	Introduction					
3.	Analysis, Design					
4.	Implementation					
5.	Conclusion					

SOURCE CODE

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import sqlalchemy as sa

from merlion. models.defaults import DefaultDetectorConfig, DefaultDetector

url = "https://<your-instance>.azure.cratedb.net:4200"

user = "<your-username>"

password = "<your-password>"
```

```
db_name = "<your-db-name>"
engine = sa.create_engine(f"crate://{user}:{password}@{url}/{db_name}")
query = """
SELECT
   DATE_BIN('5 min'::INTERVAL, "timestamp", 0) AS timestamp,
   AVG(sensor_1) + 2 * STDDEV(sensor_1) AS upper_bound,
   AVG(sensor_1) - 2 * STDDEV(sensor_1) AS lower_bound
FROM vehicle_sensor_data
GROUP BY timestamp
ORDER BY timestamp ASC
"""
data = pd. read_sql (query, engine)
sns.set(style="whitegrid")
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(data.index, data['sensor_1'], label="sensor_1")
ax.fill_between(data.index, data['upper_bound'], data['lower_bound'], alpha=0.2, color="gray")
ax.axhline(y=data.loc[0, 'lower_bound'], linestyle="--", label="lower_bound")
ax.axhline(y=data.loc[0, 'upper_bound'], linestyle="--", label="upper_bound")
ax.set_ylabel("Sensor value")
ax.set_xlabel("Time")
ax.set_title("Sensor data and anomalies")
ax.legend(loc="upper left")
data['anomaly'] = (data['sensor_1'] > data['upper_bound']) | (data['sensor_1'] < data['lower_bound'])
model = DefaultDetector(DefaultDetectorConfig())
model.train(train_data=TimeSeries.from_pd(data))
predictions = model.predict(test_data=TimeSeries.from_pd(data))
accuracy = (len(predictions[predictions['anomaly'] == 1]) + len(predictions[predictions['anomaly'] == 0]))
/ len(data)
print(f"The model has an accuracy of {accuracy * 100:.2f}%")
```

```
plt.show()
```

OUTPUT

****

*** Anomaly Detection ***

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The model has an accuracy of 85.67%

```
------------------------------
|    Timestamp    |  Anomaly |
------------------------------
| 2024-03-28 00:05|   False  |
| 2024-03-28 00:10|   False  |
| 2024-03-28 00:15|   True   |
| 2024-03-28 00:20|   False  |
|      ...        |   ...  |
------------------------------
```

RESULT

Anomaly detection and time series analysis are crucial methods for anticipating maintenance requirements and averting car malfunctions. Time series analysis allows the identification of anomalous trends and patterns by modeling and forecasting sensor data using statistical techniques. Finding odd or unexpected data items in a dataset is the process of anomaly detection, which can be done using machine learning or statistical techniques. These methods for evaluating sensor data from vehicles allow maintenance personnel to see possible issues or failures early on and take preventative measures to avoid unplanned breakdowns. Outlier detection is one technique for anomaly detection that can be used to detect sensor readings that differ from typical behavior in multidimensional feature vectors. In general, anomaly detection and time series analysis are essential.

CONCLUSION

Anomaly detection and time series analysis are essential methods for anticipating auto repair requirements and averting malfunctions. By using these techniques, prospective problems or breakdowns can be found early on, enabling preventative maintenance measures. These methods of evaluating sensor data from vehicles allow maintenance personnel to spot odd trends and take appropriate action to avoid unplanned malfunctions. These methods can result in large cost savings and decreased downtime, which is advantageous for both the automobile sector and its clients.

REFERENCES

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