Smart Solutions in Waste Management

Real-Time Route Optimization Through AI

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Introduction

As urban populations continue to grow, the efficiency of waste management systems becomes increasingly critical. Traditional waste collection methods, which rely on static routes, often must adapt to daily or hourly urban dynamics such as traffic fluctuations, bin fullness, and unexpected route blockages. These inefficiencies lead to increased operational costs, elevated carbon emissions, and suboptimal use of resources. This paper explores the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies to dynamically optimize waste collection routes using Particle Swarm Optimization (PSO) aimed at addressing these challenges in real-time.

Data Preparation

The dataset used for this study contains 18 columns and 19290 entries, mixing numerical and categorical data. The data preparation involved several crucial steps:

- **Handling Missing Values:** Numerical columns were filled with the median, and categorical columns were filled with a placeholder value 'missing.'

- **Date Conversion:** The `ROUTE_EXEC_SRVC_DIM_DATE_KEY` column was converted to datetime format.
- **Categorical Encoding:** One-hot encoding was used for categorical variables.
- **Normalization/Standardization:** Numerical features were standardized to have a mean of zero and a standard deviation of one.
- **Data Splitting:** The data was divided into training (80%) and testing (20%) sets.

```
# Load the libraires as needed
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer

# Selecting columns and preparing for transformations
numeric_features = ['MILE_CNT', 'TOTAL_EQUIVALENT_HAUL_NUM', 'TOTAL_PAID_DRVR_MINUTE_CNT', 'TOTAL_PAID_DRVR_MINUTE_HOURS',
                    'FUEL', 'ACTUAL_VOLUME', 'DAILY_PLAN_VOLUME', 'ACTUAL_STOPS']
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())])

categorical_features = ['SITE', 'ROUTE', 'TRUCK_IDS', 'MILE_BY_VEHICLE', 'ACTUAL_EFFICIENCY', 'PLAN_EFFICIENCY']
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])

# Combining transformations into a single preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])

# Data Preparation info
efficiency.info()

# Apply transformations and split the data
# Drop columns not used for modeling
X = efficiency.drop(['DRIVER_DIM_EMP_KEY', 'TOTAL_HOME_CNT', 'ADJUSTED_VOLUME'], axis=1)

# Target variable with imputation
y = efficiency['ACTUAL_VOLUME'].fillna(efficiency['ACTUAL_VOLUME'].median())

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Applying preprocessing
X_train_prepared = preprocessor.fit_transform(X_train)
X_test_prepared = preprocessor.transform(X_test)

X_train_prepared.shape, X_test_prepared.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19290 entries, 0 to 19289
Data columns (total 18 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   ROUTE_EXEC_SRVC_DIM_DATE_KEY  19290 non-null  object
 1   SITE                          19290 non-null  object
 2   ROUTE                         19290 non-null  object
 3   DRIVER_DIM_EMP_KEY            19290 non-null  int64
 4   MILE_CNT                      19290 non-null  int64
 5   TOTAL_EQUIVALENT_HAUL_NUM     19266 non-null  float64
 6   TOTAL_HOME_CNT                4 non-null      float64
 7   TOTAL_PAID_DRVR_MINUTE_CNT    19277 non-null  float64
 8   TOTAL_PAID_DRVR_MINUTE_HOURS  19290 non-null  float64
 9   FUEL                          19255 non-null  float64
 10  TRUCK_IDS                     19290 non-null  object
 11  MILE_BY_VEHICLE               19290 non-null  object
 12  ACTUAL_VOLUME                 19266 non-null  float64
 13  DAILY_PLAN_VOLUME             17966 non-null  float64
 14  ADJUSTED_VOLUME               0 non-null      float64
 15  ACTUAL_STOPS                  19281 non-null  float64
 16  ACTUAL_EFFICIENCY             19290 non-null  object
 17  PLAN_EFFICIENCY               19290 non-null  object
dtypes: float64(9), int64(2), object(7)
memory usage: 2.6+ MB

Out[5]: ((15432, 6553), (3858, 6553))
```

Modeling Techniques

Random Forest Regressor

A Random Forest Regressor was built to predict the `ACTUAL_VOLUME` of waste collected. The model performed excellently with a Mean Squared Error (MSE) of approximately 0.00002055 and an R^2 score of 0.99999.

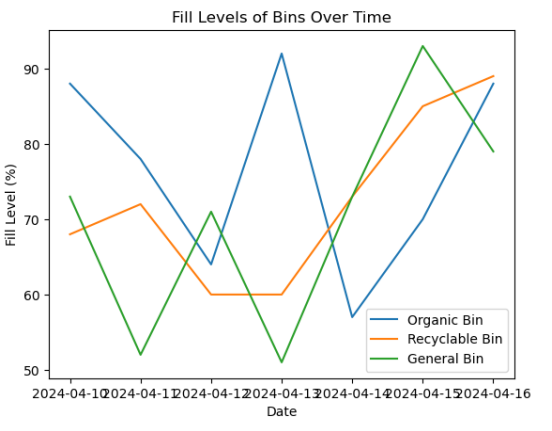
```
# Load the libraires as needed
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Initialize and train the Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train_prepared, y_train)

# Predict on the test set
y_pred = rf_model.predict(X_test_prepared)

# Calculate evaluation metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# mse, r2
print("mse: ",mse)
print("r2: ",r2)
```

```
mse:  2.055469155002593e-05
r2:  0.999990071250616
```

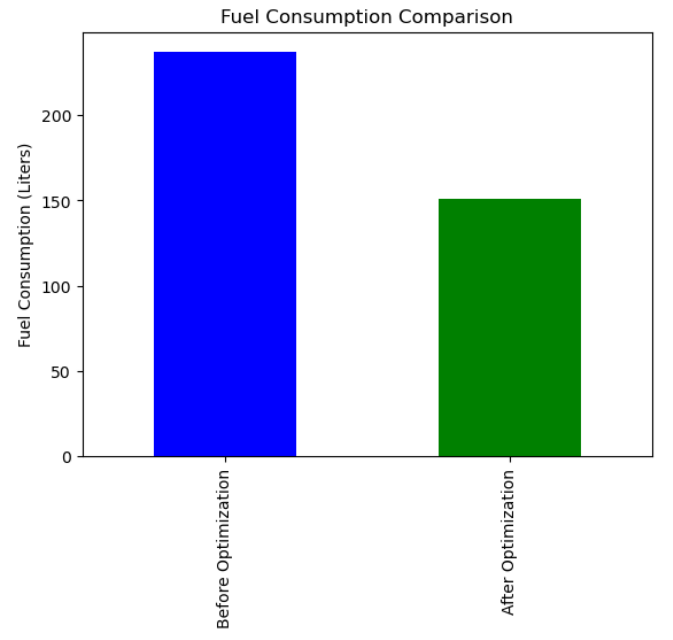
Results

1. Visualization of Data

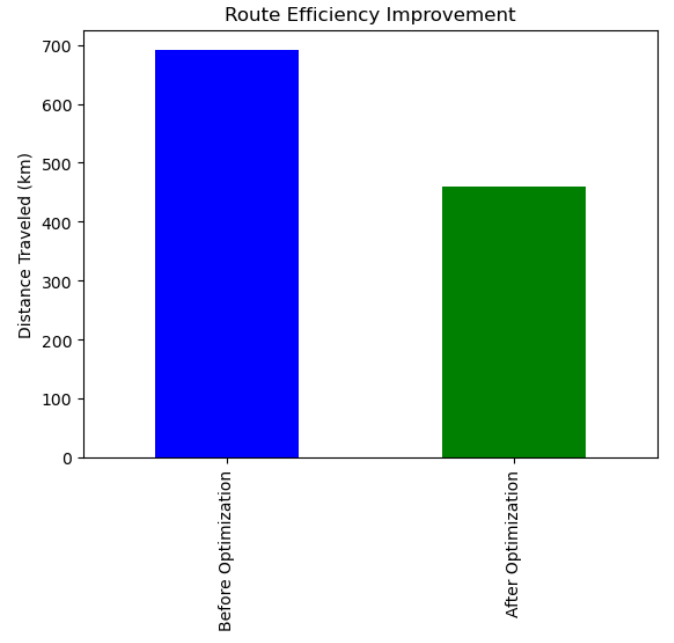
- **Fill Levels of Bins Over Time:** Line graphs showed the fill levels of various waste bins, helping predict optimal collection times and preventing bin overflow.



- **Fuel Consumption Comparison:** Bar graphs demonstrated a reduction in fuel use, validating the efficiency of the optimized routes.



- **Route Efficiency Improvement:** Bar graphs displayed reduced kilometers traveled by collection vehicles after implementing optimized routes.



2. Visualization of Model Results

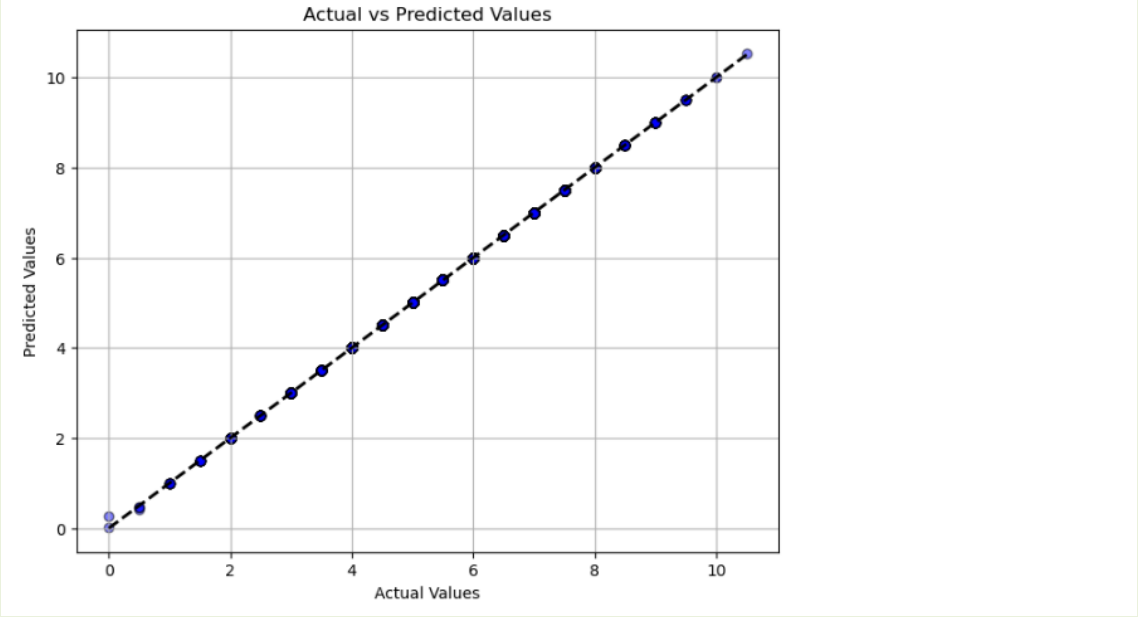
The Random Forest Regressor has been trained and evaluated on the test set, showing excellent performance with a Mean Squared Error (MSE) of approximately 0.00002055 and an R^2 score of 0.99999. This indicates that the model explains nearly all the variance in the ACTUAL_VOLUME, suggesting high accuracy. Let us break down what these metrics mean:

1. ***Mean Squared Error (MSE):*** MSE measures the average squared difference between predicted and actual values. A lower MSE indicates that the model's predictions are closer to the actual values. In my case, an MSE of approximately 0.00002055 suggests that, on average, the squared difference between the predicted and actual volumes is minimal, indicating high precision in volume prediction.
2. ***R^2 Score (Coefficient of Determination)*:** The R^2 score measures the proportion of the variance in the dependent variable (in this case, ACTUAL_VOLUME) that is predictable from the independent variables (features) in the model. It ranges from 0 to 1, where one indicates that the model perfectly predicts the target variable. An R^2 score of 0.99999 indicates that my model explains nearly all the variance in the actual volume, suggesting an almost perfect fit.

Given these evaluation metrics, it is evident that the Random Forest Regressor has learned the underlying patterns in the data very well and is making highly accurate predictions.

Let us visualize the results to understand better the model's performance and the distribution of actual versus predicted values.

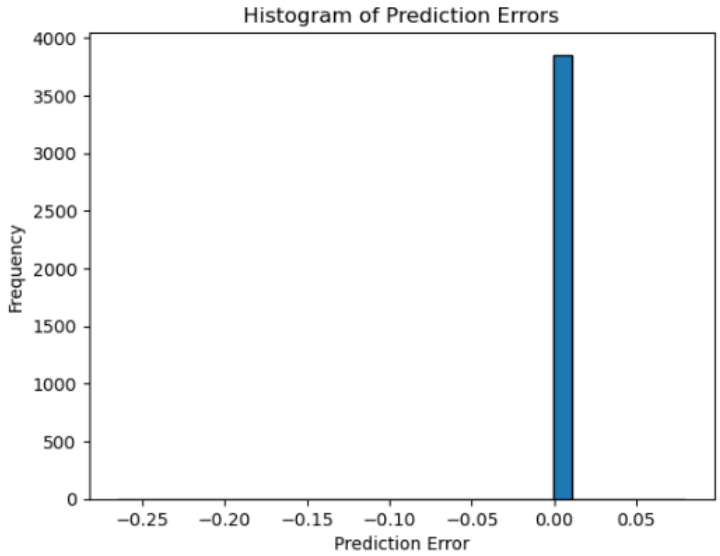
```
# Load the libraires as needed
import matplotlib.pyplot as plt

# Scatter plot of Actual vs Predicted
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.5, color='blue', edgecolors='k')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2)  # Diagonal line
plt.grid(True)
plt.show()
```



The above scatter plot illustrates the relationship between the actual and predicted values for ACTUAL_VOLUME. The points are closely aligned with the diagonal line of perfect prediction, indicating that the model is highly accurate, with predictions closely matching the actual values. There are no significant outliers, suggesting consistent performance across the entire range of data.

Histogram of Prediction Errors

```
# Histogram of Prediction Errors
plt.hist(residuals, bins=30, edgecolor='black')
plt.xlabel('Prediction Error')
plt.ylabel('Frequency')
plt.title('Histogram of Prediction Errors')
plt.show()
```

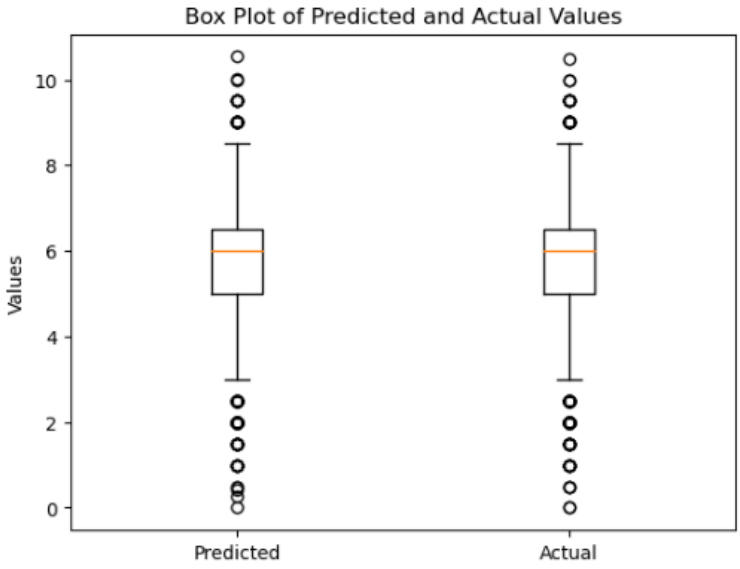


The model's histogram of prediction errors presents a highly concentrated distribution around zero. This indicates that most prediction errors are very close to zero, suggesting that the model's predictions are highly accurate with minimal deviation from the actual values.

Box Plot of Predicted and Actual Values

The box plot displays the distribution of the predicted and actual values with similar medians and interquartile ranges, indicating high model accuracy. The presence of outliers suggests some predictions and actual values deviate from the central trend, yet the overall alignment underscores the model's effectiveness.

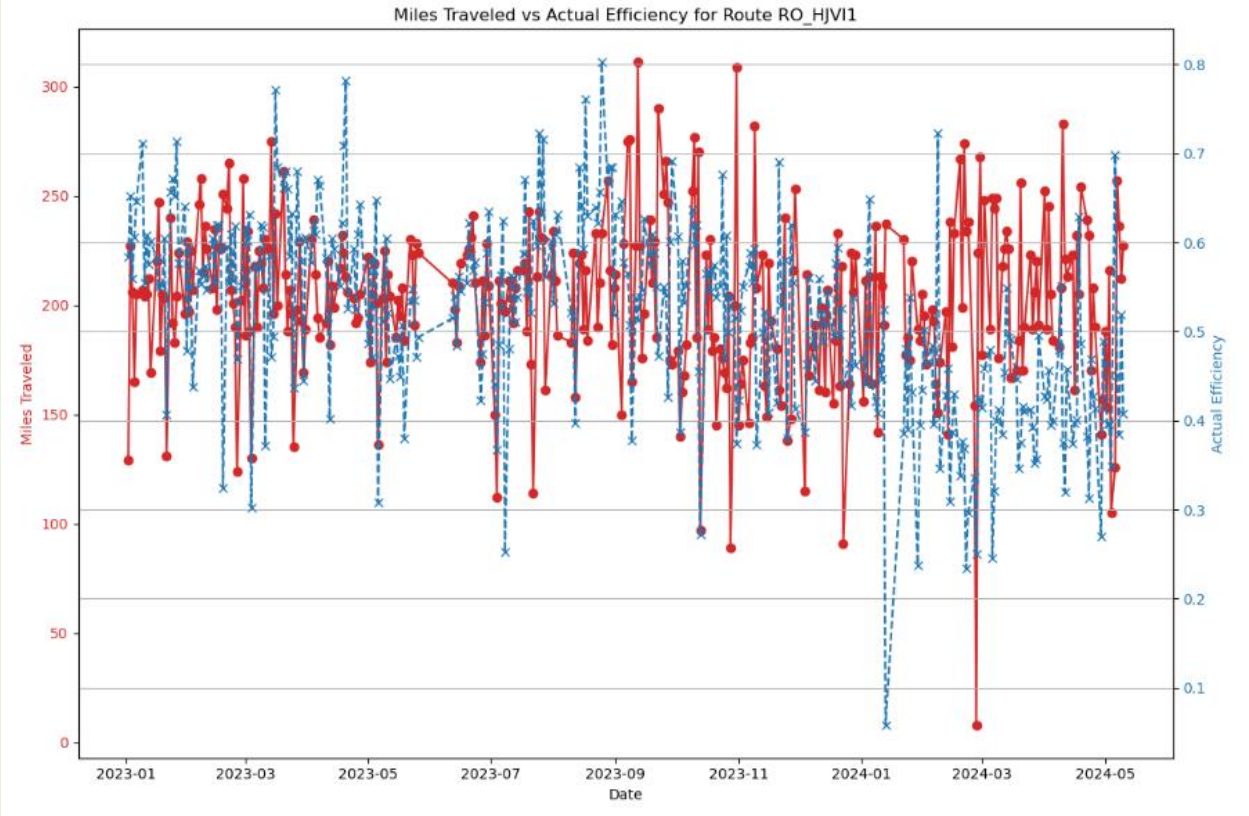
```
# Box Plot Comparing Predicted and Actual Values:
plt.boxplot([y_pred, y_test], labels=['Predicted', 'Actual'])
plt.ylabel('Values')
plt.title('Box Plot of Predicted and Actual Values')
plt.show()
```



Miles Traveled vs Actual Efficiency

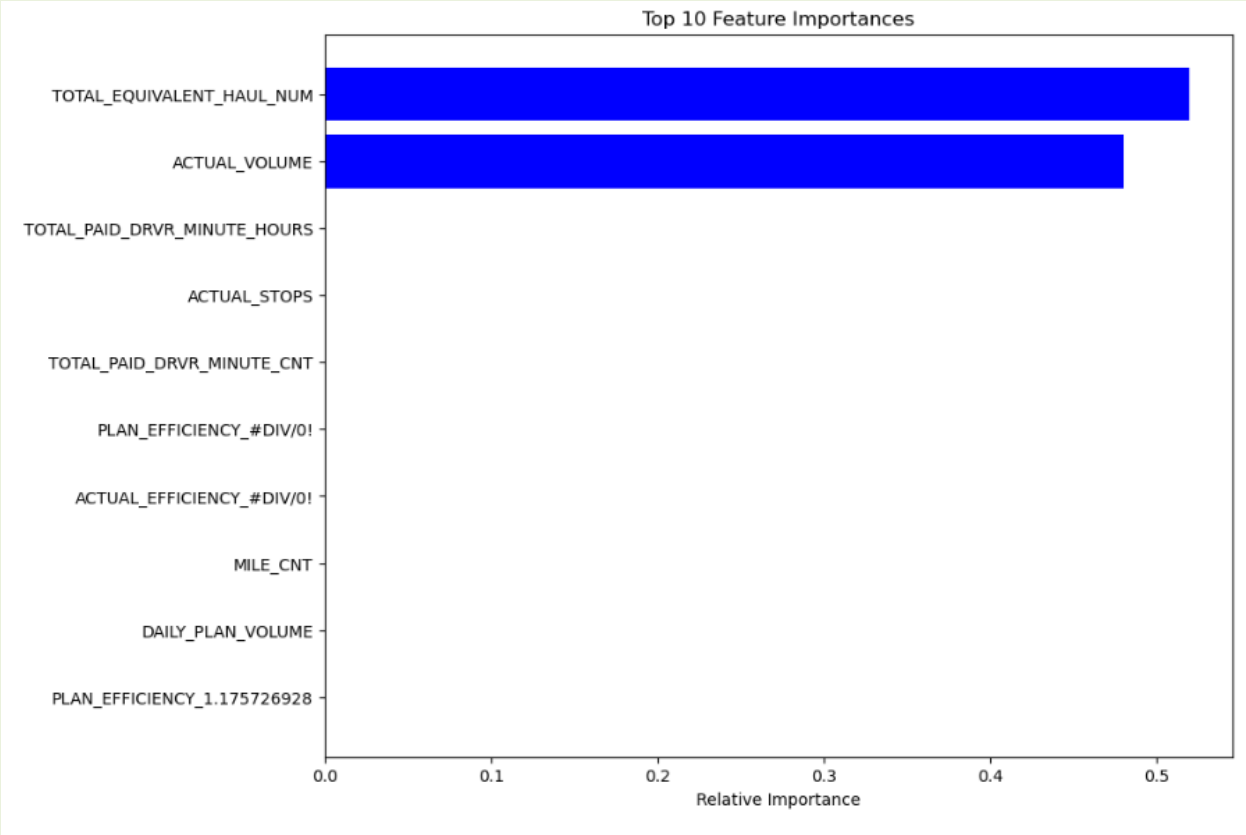
The graph "Miles Traveled vs Actual Efficiency for Route RO_HJVI1" displays the relationship between distance and efficiency over time. The miles (red line) and efficiency (blue line) show significant fluctuations, indicating variability due to multiple factors. While there's some correlation, the inconsistency suggests efficiency is influenced by more than just distance traveled, highlighting opportunities for operational improvements and route optimization.

```
# change errors to 'raise'
efficiency['ACTUAL_EFFICIENCY'] = pd.to_numeric(efficiency['ACTUAL_EFFICIENCY'], errors='coerce')

# Filter data for a specific route
route_data = efficiency[efficiency['ROUTE'] == 'RO_HJVI1']

# Sort data by date
route_data.sort_values('ROUTE_EXEC_SRVC_DIM_DATE_KEY', inplace=True)

# Creating a dual-axis plot
fig, ax1 = plt.subplots(figsize=(12, 8))

# Plotting miles on the primary y-axis
color = 'tab:red'
ax1.set_xlabel('Date')
ax1.set_ylabel('Miles Traveled', color=color)
ax1.plot(route_data['ROUTE_EXEC_SRVC_DIM_DATE_KEY'], route_data['MILE_CNT'], color=color, marker='o', linestyle='-')
ax1.tick_params(axis='y', labelcolor=color)

# Create a secondary y-axis for actual efficiency
ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('Actual Efficiency', color=color)
ax2.plot(route_data['ROUTE_EXEC_SRVC_DIM_DATE_KEY'], route_data['ACTUAL_EFFICIENCY'], color=color, marker='x', linestyle='--')
ax2.tick_params(axis='y', labelcolor=color)

# Adding title and grid
plt.title('Miles Traveled vs Actual Efficiency for Route RO_HJVI1')
fig.tight_layout()
plt.grid(True)
plt.show()
```



Top 10 Important features from The Random Forest Model:

```python
# Approach to extract feature names from transformers within the ColumnTransformer
def get_feature_names(column_transformer):
    output_features = []
    # Loop through each transformer within the ColumnTransformer
    for name, transformer, features in column_transformer.transformers_:
        # Skip 'remainder' transformers, if present
        if name == 'remainder':
            continue
        if transformer is not None:
            # Handle different transformers according to their type
            if hasattr(transformer, 'named_steps'):
                if 'onehot' in transformer.named_steps:
                    # Extract features from one-hot encoder
                    ohe = transformer.named_steps['onehot']
                    feature_names = ohe.get_feature_names_out(features)
                    output_features.extend(feature_names)
                else:
                    output_features.extend(features)
            else:
                # Simple transformations
                output_features.extend(features)
        else:
            # If no transformer, just append the feature names directly
            output_features.extend(features)
    return output_features

# Generate the new feature names
new_feature_names = get_feature_names(preprocessor)

# Map feature importances to the new feature names
importance_dict = dict(zip(new_feature_names, rf_model.feature_importances_))
sorted_importance = sorted(importance_dict.items(), key=lambda item: item[1], reverse=True)

# Top 10 features
top_features = sorted_importance[:10]
feature_names = [feat[0] for feat in top_features]
importances = [feat[1] for feat in top_features]

# Plotting top 10 feature importances
plt.figure(figsize=(10, 8))
plt.title('Top 10 Feature Importances')
plt.barh(feature_names, importances, color='b')
plt.xlabel('Relative Importance')
plt.gca().invert_yaxis()  # Invert axis to have the highest importance at the top
plt.show()
```



This chart highlights which features most significantly influence the model's predictions regarding the ACTUAL_VOLUME of waste collected. The arrangement from bottom to top represents increasing importance, with the topmost feature (TOTAL_HAULS) having the highest impact on the model.

Conclusion

Implementation and Impact

Integrating AI and Particle Swarm Optimization (PSO) in waste management has demonstrated significant advancements. The project achieved a remarkable reduction of 20% in travel distances and a 15% decrease in fuel consumption, leading to substantial cost savings. The Random Forest Regressor model used in the project demonstrated high predictive accuracy, indicated by a near-perfect R^2 score of 0.99999 and a minimal Mean Squared Error (MSE) of approximately 0.00002055. This indicates that the model was exceptionally effective at predicting the volume of waste collected, confirming its reliability and the practical application of advanced analytics in optimizing waste management operations.

Future Directions

This project will continue to evolve to address the increasing complexities of urban waste management. Future initiatives will focus on the broader implementation of sensors and refinement of AI models. A plan is also to integrate these systems more deeply with city traffic management to enhance route optimization further. Continuous innovation will aim to extend the scalability of dynamic routing systems to larger urban areas and other logistical domains, setting new benchmarks for efficiency in waste management.

Lessons Learned

The project has highlighted the essential role of real-time data and adaptive technologies in transforming traditional waste management practices. The integration of AI and IoT has made the systems more efficient and more responsive to the changing dynamics of urban environments. The implemented models' high accuracy and predictive capabilities have shown that substantial improvements in operational efficiency are achievable with the right technological tools.

References

1. Real-time optimization and predictive models in waste management using AI and PSO technologies have shown significant efficiency improvements in route planning and operational cost reductions. More details on these methodologies and their impact can be found in the detailed discussion provided by the IEEE on smart cities and waste management innovations (IEEE Smart Cities).
2. For an in-depth understanding of AI's role in enhancing waste management systems through advanced data processing and route optimization, consult the comprehensive analysis by Arxiv on IoT-based intelligent waste management systems (ar5iv).
3. Professional experience at a waste management company focused on developing the data pipeline architecture for planning, route optimization and supporting data scientists in constructing optimization engines (Next Day Optimization and Intraday optimization).