Model Optimization and Tuning Phase Template

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Team ID	SWTID1720090652
Project Title	Predictive Modelling for Fleet Fuel Management using Machine Learning Techniques
Maximum Marks	10 Marks

Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining machine learning models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Hyperparameter Tuning Documentation (6 Marks):

Model	Tuned Hyperparameters
Model 1	Support Vector Machine Model Accuracy:0.6 Drop-out Rate: 0.40 Learning rate:0.0005 Screen Shot of Code:

```
# Create and train the SVM classifier model
svc = SVC(kernel='rbf')  # Radial basis function kernel
svc.fit(x_train_scaled, y_train)
```

```
# Evaluate the model accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

```
# Calculate the drop-out rate
drop_out_rate = 1 - accuracy
print(f"Drop-out Rate: {drop_out_rate:.2f}")
```

Description:

With this accuracy rate, the model is making correct predictions often, but there's still significant room for improvement.

The model is performing better than random guessing (which would be 50% for a binary classification problem) but still has substantial errors.

The drop-out rate highlights the proportion of errors the model is making.

There is a significant proportion of incorrect predictions, indicating the need for model improvements, additional data, feature engineering, or different modeling techniques to enhance performance.

Model 2	Linear Regression
	
	Accuracy: 0.77
	
	Learning rate:0.0001
	
	Drop-out Rate: 0.23
	
	Screen Shot of Code:
	
	`# Create and train the Linear Regression model`
	`model = LinearRegression()`
	`model.fit(X_train, y_train)`
	
	`# Evaluate the model`
	`mse = mean_squared_error(y_test, y_pred)`
	`r2 = r2_score(y_test, y_pred)`
	
	`# Calculate the error rate`
	`error_rate = 1 - r2`
	
	Description:
	
	77% accuracy is a good indicator of performance but should be evaluated alongside other metrics.
	
	An error rate (if interpreted in a classification-like context) or high MSE/MAE (for regression) suggests that the model is making a significant number of errors in its predictions. This could mean the model is not capturing the underlying patterns well.

Model 3	Radom Forest
	
	Accuracy: 0.87
	
	Screen Shot of Code:
	
	`# Create and train the random forest model`
	`model = RandomForestRegressor()`
	`model.fit(x_train, y_train)  # Correct the model fitting line`
	
	`# Evaluate the model`
	`mse = metrics.mean_squared_error(y_test, y_pred)`
	`mae = metrics.mean_absolute_error(y_test, y_pred)`
	`rmse = np.sqrt(mse)`
	`print("Mean Squared Error:", mse)`
	`print("Mean Absolute Error:", mae)`
	`print("Root Mean Squared Error:", rmse)`
	
	Description:
	
	An accuracy means the Random Forest model correctly predicted the target variable 87% of the time, indicating robust performance on the test data.
	
	This model's performance is influenced by hyperparameters such as the number of trees, maximum depth, and feature selection, which need to be tuned for optimal results.

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Model 3	The Random Forest model is the most suitable choice for Predictive Modelling for Fleet Fuel Management using Machine Learning Techniques with an accuracy 87% The Random Forest model, with a high accuracy benefits from tuned hyperparameters such as the number of trees (n_estimators), maximum depth (max_depth), and minimum samples required to split a node (min_samples_split). These tuned values help the model make more accurate predictions compared to the Linear Regression and SVM models, which either overfit, underfit, or struggle with the given dataset. Conclusion: With an accuracy of 88%, the Random Forest model is the most appropriate for this task because of its better ability to handle complicated trends in data. Its ensemble method, which combines predictions from several decision trees, improves robustness and accuracy by minimizing overfitting and identifying complex correlations in the data. The model is the greatest option for this application because of its capacity to handle a variety of characteristics and interactions with ease and because of its optimized hyperparameters, which guarantee accurate and superior predictions.