

Model Optimization and Tuning Phase Report

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| Date | 15 March 2024 |
| Team ID | 740115 |
| Project Title | Predicting IMF-Based Exchange Rates: Leveraging Economic Indicators for Accurate Regression Modeling |
| 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):

Performance Metrics Comparison Report (2 Marks):

| Model | Optimized Metric |
|-------|------------------|
| | |

| KNN | <pre>from sklearn.model_selection import GridSearchCV, RandomizedSearchCV param_grid = { 'n_estimators': [50, 100, 150], 'max_depth': [None, 10, 20], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4] }</pre> | <pre>grid_search = GridSearchCV(estimator=model4, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error') grid_search.fit(X_train, y_train) GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42), n_jobs=-1, param_grid={'max_depth': [None, 10, 20], 'min_samples_leaf': [1, 2, 4], 'min_samples_split': [2, 5, 10], 'n_estimators': [50, 100, 150]}, scoring='neg_mean_squared_error')</pre> | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|-------------------|---|--|----------|-----------|--------|----------|---------|-----|------|------|------|-----|-----|------|------|------|-----|----------|--|--|------|-----|-----------|------|------|------|-----|--------------|------|------|------|-----|
| Gradient Boosting | <pre>best_params = grid_search.best_params_ print("Best Hyperparameters:", best_params) Best Hyperparameters: {'max_depth': 20, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 50} best_model = grid_search.best_estimator_ y_pred = best_model.predict(X_test) mse = mean_squared_error(y_test, y_pred) r2_score=r2_score(y_test, y_pred) print("Mean Squared Error:", mse) print("R2_score:", r2_score) Mean Squared Error: 36.75979845707393 R2_score: 0.9827970524996451</pre> | <div>Mean Squared Error: 36.75979845707</div> <div>R2_score: 0.9827970524996451</div> | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Decision Tree | <div>DecisionTree Classification_Report</div> <pre>print(classification_report(dt_pred , y_test))</pre> <table><thead><tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr></thead><tbody><tr><td>0.0</td><td>0.81</td><td>0.80</td><td>0.80</td><td>404</td></tr><tr><td>1.0</td><td>0.80</td><td>0.80</td><td>0.80</td><td>396</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.80</td><td>800</td></tr><tr><td>macro avg</td><td>0.80</td><td>0.80</td><td>0.80</td><td>800</td></tr><tr><td>weighted avg</td><td>0.80</td><td>0.80</td><td>0.80</td><td>800</td></tr></tbody></table> | | | precision | recall | f1-score | support | 0.0 | 0.81 | 0.80 | 0.80 | 404 | 1.0 | 0.80 | 0.80 | 0.80 | 396 | accuracy | | | 0.80 | 800 | macro avg | 0.80 | 0.80 | 0.80 | 800 | weighted avg | 0.80 | 0.80 | 0.80 | 800 |
| | precision | recall | f1-score | support | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 0.0 | 0.81 | 0.80 | 0.80 | 404 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1.0 | 0.80 | 0.80 | 0.80 | 396 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| accuracy | | | 0.80 | 800 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| macro avg | 0.80 | 0.80 | 0.80 | 800 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| weighted avg | 0.80 | 0.80 | 0.80 | 800 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Random
Forest

RandomForest Classification_Report

```
from sklearn.metrics import classification_report
print(classification_report(forest, y_test))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0.0 | 0.91 | 0.91 | 0.91 | 399 |
| 1.0 | 0.91 | 0.91 | 0.91 | 401 |
| accuracy | | | 0.91 | 800 |
| macro avg | 0.91 | 0.91 | 0.91 | 800 |
| weighted avg | 0.91 | 0.91 | 0.91 | 800 |

KNN

```
kmeans = KMeans(n_clusters=3)
kmeans.fit(df)
centroids = kmeans.cluster_centers_
labels = kmeans.labels_

plt.figure(figsize=(8, 6))
plt.scatter(centroids[:, 0], centroids[:, 1], c='red', s=200, marker='x', label='Centroids')

plt.title('K-means Clustering')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.legend()
plt.grid(True)
plt.show()
```

Gradient Boosting

XGBoost Classification_Report

```
print(classification_report(y_pred, y_test))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.91 | 0.92 | 0.91 | 395 |
| 1 | 0.92 | 0.91 | 0.92 | 405 |
| accuracy | | | 0.92 | 800 |
| macro avg | 0.92 | 0.92 | 0.91 | 800 |
| weighted avg | 0.92 | 0.92 | 0.92 | 800 |

Final Model Selection Justification (2 Marks):

| Final Model | Reasoning |
|-------------------|---|
| Gradient Boosting | <p>The Gradient Boosting model was selected for its superior performance, exhibiting high accuracy during hyperparameter tuning. Its ability to handle complex relationships, minimize overfitting, and optimize predictive accuracy aligns with project objectives, justifying its selection as the final model.</p> |