Model Optimization and Tuning Phase Template

Date	July 2024
Team ID	739859
Project Title	Auto insurance fraud detection using michine learning
Maximum Marks	10 Marks

Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network 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 (8 Marks):

Model	Tuned Hyperparameters

<table>
<tr>
<td>

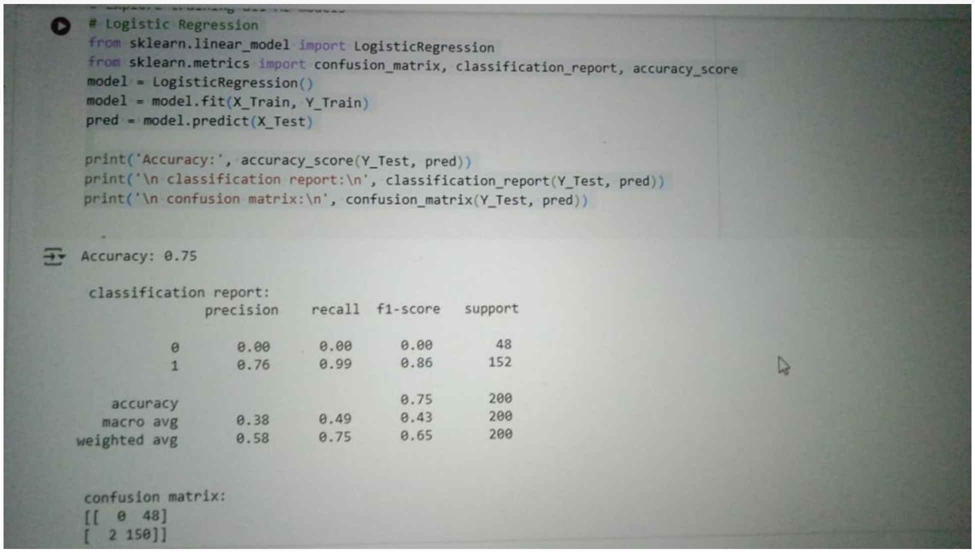
Logistic

Regression

</td>
<td>

```
#importing the library for grid search
from sklearn.model_selection import GridSearchCV
```

The ‘lr_param_grid’ specifies different values for regularization strength (C), solvers (solver), and penalty types (penalty). GridSearchCV (lr_cv) is employed with 5-fold cross-validation (cv=5), evaluating model performance based on accuracy (scoring="accuracy"). The process uses all available CPU cores (n_jobs=-1) for parallel processing and provides verbose output (verbose=True) to track progress.



```
# Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
model = LogisticRegression()
model = model.fit(X_Train, Y_Train)
pred = model.predict(X_Test)

print('Accuracy:', accuracy_score(Y_Test, pred))
print('\n classification report:\n', classification_report(Y_Test, pred))
print('\n confusion matrix:\n', confusion_matrix(Y_Test, pred))
```

```
Accuracy: 0.75

 classification report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        48
           1       0.76      0.99      0.86       152

    accuracy                           0.75       200
   macro avg       0.38      0.49      0.43       200
weighted avg       0.58      0.75      0.65       200


 confusion matrix:
 [[  0  48]
 [  2 150]]
```

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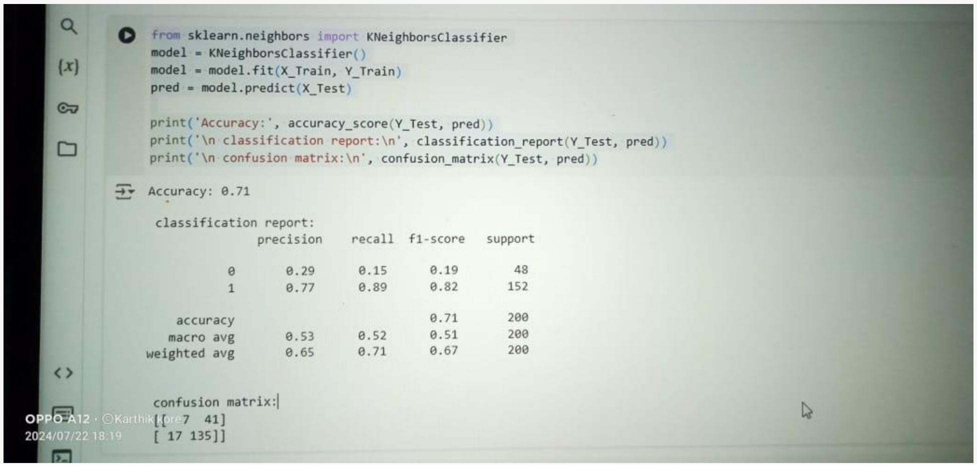
<table>
<tr>
<td>Random Forest</td>
<td>
The parameter grid (rfc_param_grid) for hyperparameter tuning. It specifies different values for the number of trees (n_estimators), splitting criterion (criterion), maximum depth of trees (max_depth), and maximum number of features considered for splitting (max_features). GridSearchCV (rfc_cv) is employed with 3-fold cross-validation (cv=3), evaluating model performance based on accuracy (scoring="accuracy").



```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
model = model.fit(X_Train, Y_Train)
pred = model.predict(X_Test)

print('Accuracy:', accuracy_score(Y_Test, pred))
print('\n classification report:\n', classification_report(Y_Test, pred))
print('\n confusion matrix:\n', confusion_matrix(Y_Test, pred))
```

```
Accuracy: 0.71

 classification report:
               precision    recall  f1-score   support

           0       0.29      0.15      0.19        48
           1       0.77      0.89      0.82       152

    accuracy                           0.71       200
   macro avg       0.53      0.52      0.51       200
weighted avg       0.65      0.71      0.67       200


 confusion matrix:
 [[  7  41]
 [ 17 135]]
```

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</td>
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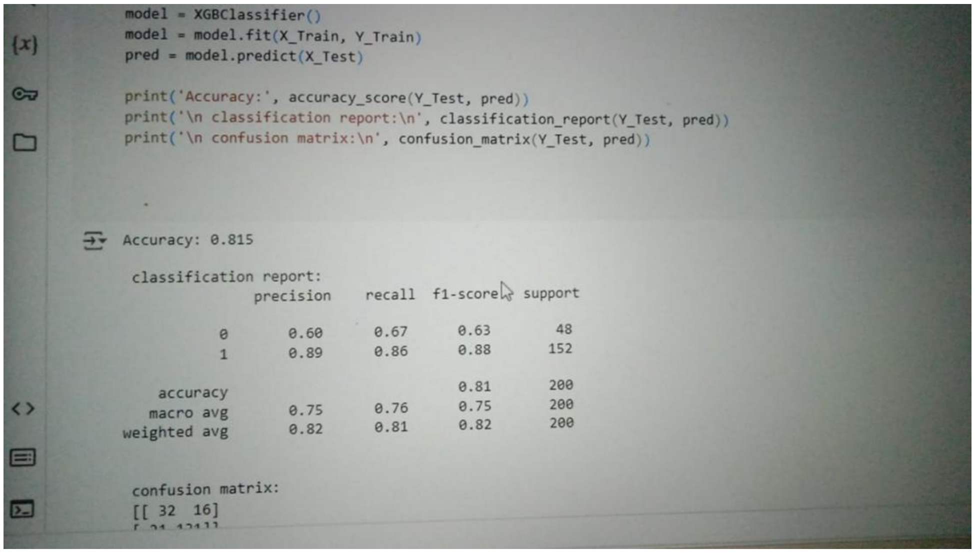
<tr>
<td>XGBoost</td>
<td>
The (params) define a grid for hyperparameter tuning of the XGBoost Classifier (XGBClassifier), including min_child_weight, gamma, colsample_bytree, and max_depth. The XGBClassifier is configured with a learning rate of 0.5, 100 estimators, using a binary logistic regression objective, and utilizing 3 threads for processing. GridSearchCV (xg_cv) is used with 5-fold cross-validation (cv=5), refitting the best model (refit=True), evaluating based on accuracy (scoring="accuracy")

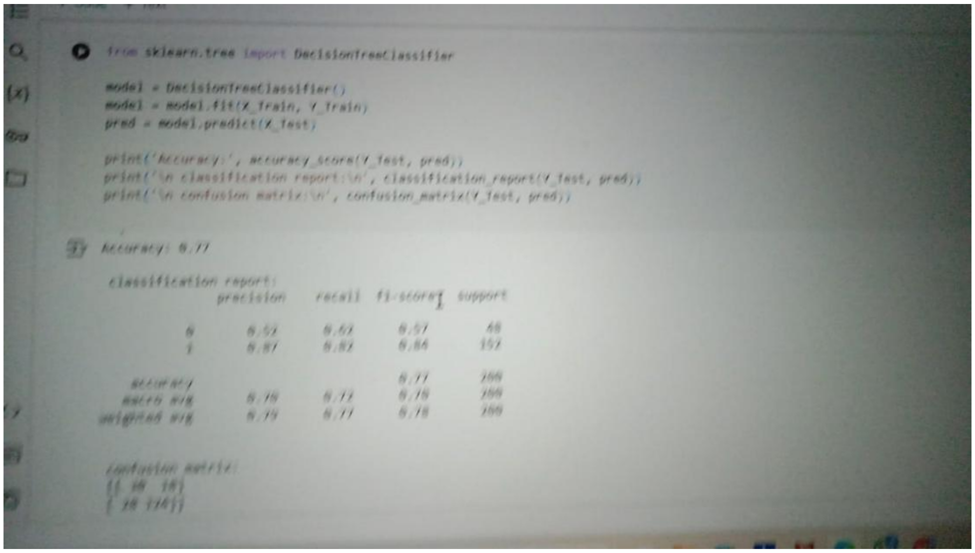


```
model = XGBClassifier()
model = model.fit(X_Train, Y_Train)
pred = model.predict(X_Test)

print('Accuracy:', accuracy_score(Y_Test, pred))
print('\n classification report:\n', classification_report(Y_Test, pred))
print('\n confusion matrix:\n', confusion_matrix(Y_Test, pred))
```

```
Accuracy: 0.815

 classification report:
               precision    recall  f1-score   support

           0       0.60      0.67      0.63        48
           1       0.89      0.86      0.88       152

    accuracy                           0.81       200
   macro avg       0.75      0.76      0.75       200
weighted avg       0.82      0.81      0.82       200


 confusion matrix:
 [[ 32  16]
```
</td>
</tr>
</table>

<table>
<tr>
<td>Decision Tree</td>
<td>

The parameters (params) define a grid for hyperparameter tuning of the Decision Tree Classifier (DecisionTreeClassifier), including max_depth, min_samples_leaf, and criterion ('gini' or 'entropy'). GridSearchCV (dec_cv) is used with 5-fold cross-validation (cv=5), evaluating model performance based on accuracy (scoring="accuracy")



```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier()
model = model.fit(X_train, Y_train)
pred = model.predict(X_test)

print('Accuracy:', accuracy_score(Y_test, pred))
print('\n classification report:\n', classification_report(Y_test, pred))
print('\n confusion matrix:\n', confusion_matrix(Y_test, pred))
```

```
Accuracy: 0.77

classification report:
               precision    recall  f1-score   support

           0       0.52      0.62      0.57        48
           1       0.87      0.82      0.84       152

    accuracy                           0.77       200
   macro avg       0.70      0.72      0.70       200
weighted avg       0.79      0.77      0.78       200


confusion matrix:
[[ 30  18]
 [ 28 124]]
```

</td>
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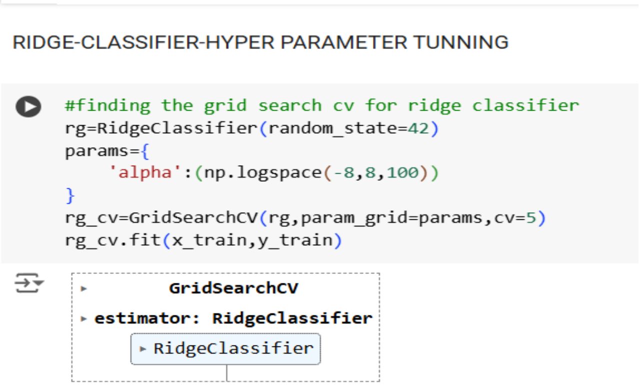
<tr>
<td>Ridge Classifier</td>
<td>

The parameters (params) define a grid for hyperparameter tuning of the Decision Tree Classifier (DecisionTreeClassifier), including max_depth, min_samples_leaf, and criterion ('gini' or 'entropy'). GridSearchCV (dec_cv) is used with 5-fold cross-validation (cv=5), evaluating model performance based on accuracy (scoring="accuracy")



RIDGE-CLASSIFIER-HYPER PARAMETER TUNNING

```
#finding the grid search cv for ridge classifier
rg=RidgeClassifier(random_state=42)
params={
    'alpha':(np.logspace(-8,8,100))
}
rg_cv=GridSearchCV(rg,param_grid=params,cv=5)
rg_cv.fit(x_train,y_train)
```

```
 ▸        GridSearchCV
 ▸ estimator: RidgeClassifier
      ▸ RidgeClassifier
```

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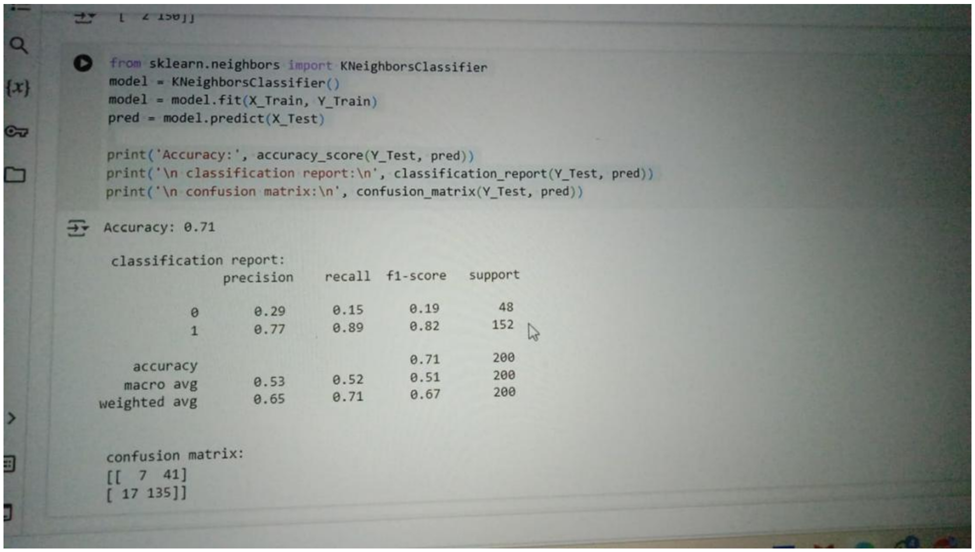
</table>

<table>
<tr>
<td>K- Nearest
Neighbors</td>
<td>

The parameters (params) define a grid for hyperparameter tuning of the K-Nearest Neighbors Classifier (KNeighborsClassifier), including n_neighbors, weights ('uniform' or 'distance'), and metric ('minkowski', 'euclidean', or 'manhattan'). GridSearchCV (knn_cv) is used with 5-fold cross-validation (cv=5), evaluating model performance based on accuracy (scoring="accuracy")



```
[  2 150]]
```

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
model = model.fit(X_Train, Y_Train)
pred = model.predict(X_Test)

print('Accuracy:', accuracy_score(Y_Test, pred))
print('\n classification report:\n', classification_report(Y_Test, pred))
print('\n confusion matrix:\n', confusion_matrix(Y_Test, pred))
```

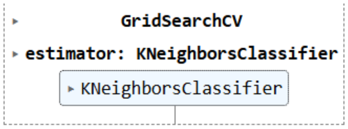
```
Accuracy: 0.71

 classification report:
               precision    recall  f1-score   support

           0       0.29      0.15      0.19        48
           1       0.77      0.89      0.82       152

    accuracy                           0.71       200
   macro avg       0.53      0.52      0.51       200
weighted avg       0.65      0.71      0.67       200


 confusion matrix:
 [[  7  41]
 [ 17 135]]
```



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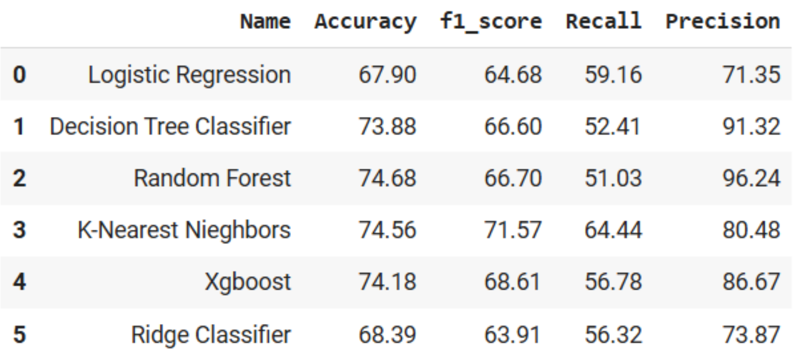
</table>

Final Model Selection Justification (2 Marks):

<table>
<tr><th>Final Model</th><th>Reasoning</th></tr>
<tr><td><b>Random Forest</b></td><td>
Random Forest model is chosen for its robustness in handling complex datasets and its ability to mitigate overfitting while providing high predictive accuracy.



<table>
<tr><th></th><th>Name</th><th>Accuracy</th><th>f1_score</th><th>Recall</th><th>Precision</th></tr>
<tr><td>0</td><td>Logistic Regression</td><td>67.90</td><td>64.68</td><td>59.16</td><td>71.35</td></tr>
<tr><td>1</td><td>Decision Tree Classifier</td><td>73.88</td><td>66.60</td><td>52.41</td><td>91.32</td></tr>
<tr><td>2</td><td>Random Forest</td><td>74.68</td><td>66.70</td><td>51.03</td><td>96.24</td></tr>
<tr><td>3</td><td>K-Nearest Nieghbors</td><td>74.56</td><td>71.57</td><td>64.44</td><td>80.48</td></tr>
<tr><td>4</td><td>Xgboost</td><td>74.18</td><td>68.61</td><td>56.78</td><td>86.67</td></tr>
<tr><td>5</td><td>Ridge Classifier</td><td>68.39</td><td>63.91</td><td>56.32</td><td>73.87</td></tr>
</table>

Above all the models Random Forest model have the highest accuracy among all the models.
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</table>