```
import sys
sys.path.append(r"C:\Users\Lenovo\Desktop\ReadyAssist Assessment\Assessment")
```

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.ensemble import RandomForestClassifier

# Import your own functions
from methods.preprocessing import convert_to_datetime
from methods.encoding import encode_category,encode_entity
```

```
train_df=pd.read_csv('final_Training.csv')
test_df=pd.read_csv(r'C:\Users\Lenovo\Desktop\ReadyAssist Assessment\Assessment\Datasets\GUIDE_Test.csv')
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_12120\1901134813.py:2: DtypeWarning: Columns (10,11) have mixed types. Specify dtype option
  test_df=pd.read_csv(r'C:\Users\Lenovo\Desktop\ReadyAssist Assessment\Assessment\Datasets\GUIDE_Test.csv')
```

Explanation of the Code

The following code is used to sample a subset of the training dataset (`train_df`) to make the training process more efficient and manageable. Here's the breakdown:

```
sampled_df, _ = train_test_split(
    train_df,
    stratify=train_df['IncidentGrade_encoded'],
    train_size=15000,
    random_state=42
)
```

1. **Purpose**:
   - The dataset `train_df` is very large, containing over 9 million rows. Training machine learning models on such a large dataset can be computationally expensive and time-consuming. By sampling a smaller subset of the data, we reduce the computational load and make the training process faster and easier.
2. **`train_test_split`**:
   - This function is typically used to split a dataset into training and testing sets. Here, it is being used to sample a subset of the data.
3. **Parameters**:
   - `train_df`: The original training dataset.
   - `stratify=train_df['IncidentGrade_encoded']`: Ensures that the sampled subset maintains the same distribution of the `IncidentGrade_encoded` column as the original dataset. This is important to preserve the class balance in the sampled data.
   - `train_size=15000`: Specifies that the sampled subset should contain 15,000 rows.
   - `random_state=42`: Ensures reproducibility of the sampling process by setting a fixed random seed.
4. **Output**:
   - `sampled_df`: The sampled subset of the training dataset, containing 15,000 rows.
   - `_`: The second output (not used here) would contain the remaining data not included in the sample.

By working with a smaller, representative subset of the data, we make the training process more efficient while still retaining the essential characteristics of the original dataset. ```

```
sampled_df, _ = train_test_split(
    train_df,
    stratify=train_df['IncidentGrade_encoded'],
    train_size=15000,
    random_state=42
)
```

```
sampled_df
```

	Unnamed: 0	DetectorId	AlertTitle	DeviceId	OSFamily	CountryCode	day	month	year	hour	weekday	Category_encoded	IncidentGr
3722625	3742741	20	3488	98799	5	242	10	6	2024	14	0	2	
4903103	4929740	37	14028	98799	5	242	10	6	2024	20	0	2	
2224698	2236739	15	13	98799	5	242	3	6	2024	18	0	2	
858648	863214	3	4	98799	5	242	11	6	2024	3	1	1	
5825258	5856787	100	77	98799	5	0	30	5	2024	13	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	
7321555	7361287	1	1	98799	5	242	4	6	2024	20	1	1	
4799168	4825213	4	3	98799	5	242	8	6	2024	20	5	1	
5407888	5437182	413	9080	98799	5	242	7	6	2024	12	4	2	
6400834	6435501	1	1	98799	5	242	14	6	2024	15	4	1	
3736732	3756920	36	228	6798	5	242	14	6	2024	13	4	2	

15000 rows × 14 columns

```
sampled_df=sampled_df.iloc[:,1:]
```

```
sampled_df
```

	DetectorId	AlertTitle	DeviceId	OSFamily	CountryCode	day	month	year	hour	weekday	Category_encoded	IncidentGrade_encode
3722625	20	3488	98799	5	242	10	6	2024	14	0	2	
4903103	37	14028	98799	5	242	10	6	2024	20	0	2	
2224698	15	13	98799	5	242	3	6	2024	18	0	2	
858648	3	4	98799	5	242	11	6	2024	3	1	1	
5825258	100	77	98799	5	0	30	5	2024	13	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	
7321555	1	1	98799	5	242	4	6	2024	20	1	1	
4799168	4	3	98799	5	242	8	6	2024	20	5	1	
5407888	413	9080	98799	5	242	7	6	2024	12	4	2	
6400834	1	1	98799	5	242	14	6	2024	15	4	1	
3736732	36	228	6798	5	242	14	6	2024	13	4	2	

15000 rows × 13 columns

```
test_df=convert_to_datetime(df=test_df)
```

```
test_df = encode_category(test_df)
test_df = encode_entity(test_df)
```

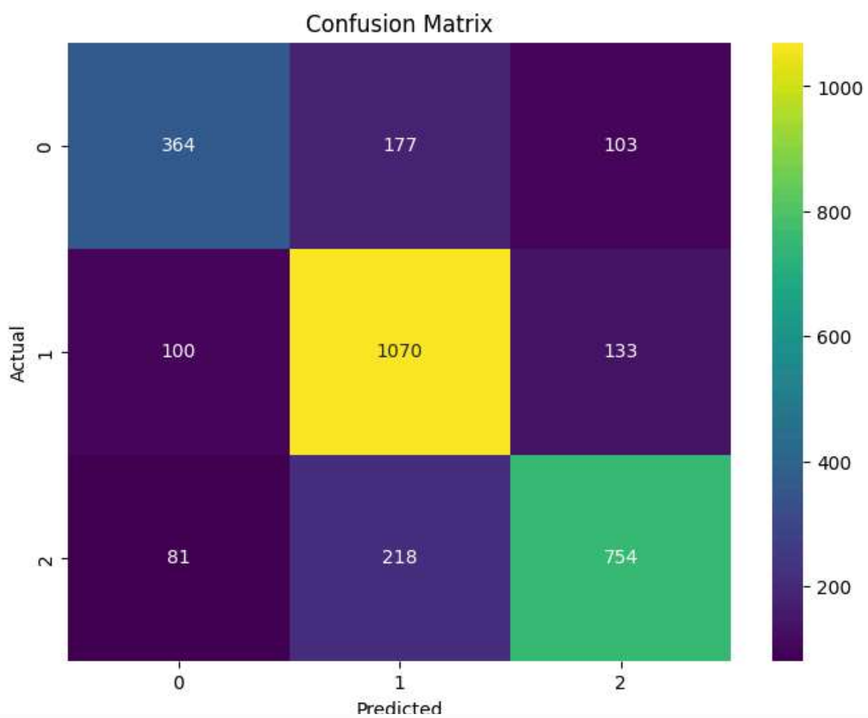
```
test_df=test_df[sampled_df.drop('IncidentGrade_encoded',axis=1).columns.tolist()]
```

```
# Split the data into training and testing sets
X = sampled_df.drop('IncidentGrade_encoded', axis=1)
y = sampled_df['IncidentGrade_encoded']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, stratify=y, test_size=0.2, random_state=42
)

# Initialize and fit the RandomForestClassifier
rf_classifier = RandomForestClassifier(n_jobs=-1, random_state=42)
rf_classifier.fit(X_train, y_train)

# Predict and calculate the accuracy score
```

```
y_pred = rf_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy Score: {accuracy}")
```

```
Accuracy Score: 0.7293333333333333
```

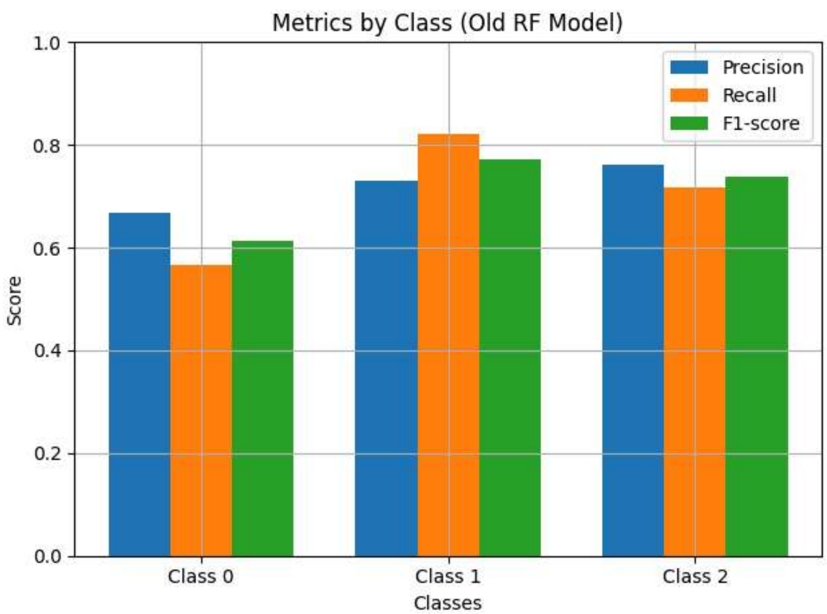
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

import matplotlib.pyplot as plt

# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='viridis', xticklabels=rf_classifier.classes_, yticklabels=rf_classifier.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```




```
from sklearn.metrics import classification_report

# Generate classification report for the old Random Forest model
report = classification_report(y_test, y_pred, output_dict=True)

# Extract macro metrics
macro_precision = report['macro avg']['precision']
macro_recall = report['macro avg']['recall']
macro_f1 = report['macro avg']['f1-score']

# Print the macro metrics
print(f"Macro Precision: {macro_precision:.4f}")
print(f"Macro Recall: {macro_recall:.4f}")
print(f"Macro F1-Score: {macro_f1:.4f}")

# Redefine classes and metrics
classes = ['Class 0', 'Class 1', 'Class 2']
metrics = ['precision', 'recall', 'f1-score']

# Prepare data for grouped bar chart
x = np.arange(len(classes))  # the label locations
width = 0.25  # the width of the bars

# Plot each metric as a separate bar group
```

```
# Plot each metric as a separate bar group
for i, metric in enumerate(metrics):
    plt.bar(x + i * width, data[metric], width, label=metric.capitalize())

# Add labels, title, and legend
plt.xlabel('Classes')
plt.ylabel('Score')
plt.title('Metrics by Class (Old RF Model)')
plt.xticks(x + width, classes)
plt.ylim(0, 1)
plt.legend()

# Display the plot
plt.tight_layout()
plt.grid()
plt.show()
```

```
Macro Precision: 0.7200
Macro Recall: 0.7008
Macro F1-Score: 0.7078
```



Explanation of the Bar Graph and Confusion Matrix (Before Hyperparameter Tuning)

Bar Graph

- The bar graph represents the performance metrics (`precision`, `recall`, and `f1-score`) for each class (`Class 0`, `Class 1`, and `Class 2`) before hyperparameter tuning.
- **Precision**: Measures the proportion of true positive predictions out of all positive predictions made for a class.
- **Recall**: Measures the proportion of true positive predictions out of all actual positives for a class.
- **F1-Score**: The harmonic mean of precision and recall, providing a balanced measure of both.
- The graph shows how well the model performs for each class, highlighting any imbalances in performance across classes.

Confusion Matrix

- The confusion matrix is a tabular representation of the model's predictions versus the actual labels for the test dataset.
- Rows represent the actual classes, while columns represent the predicted classes.
- Each cell contains the count of predictions for a specific combination of actual and predicted classes:
  - **Diagonal cells**: Correct predictions (true positives for each class).
  - **Off-diagonal cells**: Misclassifications (false positives and false negatives).
- The confusion matrix helps identify which classes are being confused with others, providing insights into potential areas for improvement.

Before Hyperparameter Tuning

- The results shown in the bar graph and confusion matrix are based on the default configuration of the Random Forest model.
- These metrics serve as a baseline to compare the performance after hyperparameter tuning.

```
y_pred
```

```
array([2, 2, 2, ..., 0, 1, 1], dtype=int64)
```

Step-by-Step Summary for Hyperparameter Tuning with Optuna

1. **Import Required Libraries**:
   - Import `optuna`, `RandomForestClassifier`, and `cross_val_score`.
2. **Define the Objective Function**:
   - Create a function that:
     - Suggests hyperparameters for `RandomForestClassifier` (e.g., `n_estimators`, `max_depth`, etc.).
     - Instantiates the classifier with the suggested hyperparameters.
     - Evaluates the model using cross-validation and returns the mean accuracy.
3. **Create and Optimize the Study**:
   - Initialize an Optuna study with the goal of maximizing accuracy.
   - Run the optimization process for a specified number of trials.
4. **Retrieve Best Hyperparameters**:
   - Extract and print the best hyperparameters found during the optimization.
5. **Train the Model with Best Hyperparameters**:
   - Instantiate a `RandomForestClassifier` using the best hyperparameters.
   - Train the model on the training dataset (`X_train`, `y_train`).
6. **Evaluate the Tuned Model**:
   - Test the tuned model on the test dataset (`X_test`, `y_test`).
   - Print the accuracy of the tuned model.

```
import optuna
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

# Define the objective function for Optuna
def objective(trial):
    # Suggest hyperparameters
    n_estimators = trial.suggest_int('n_estimators', 100, 1000)
    max_depth = trial.suggest_int('max_depth', 5, 100)
    min_samples_split = trial.suggest_int('min_samples_split', 2, 50)
    min_samples_leaf = trial.suggest_int('min_samples_leaf', 1, 50)
    max_features = trial.suggest_categorical('max_features', ['sqrt', 'log2', None])
    bootstrap = trial.suggest_categorical('bootstrap', [True, False])

    # Create the RandomForestClassifier with suggested hyperparameters
    rf = RandomForestClassifier(
        n_estimators=n_estimators,
        max_depth=max_depth,
        min_samples_split=min_samples_split,
        min_samples_leaf=min_samples_leaf,
        max_features=max_features,
        bootstrap=bootstrap,
        n_jobs=-1,
        random_state=42
    )

    # Perform cross-validation and return the mean accuracy
    scores = cross_val_score(rf, X_train, y_train, cv=5, scoring='accuracy', n_jobs=-1)
    return scores.mean()

# Create an Optuna study and optimize
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=100)  # Increased number of trials

# Print the best hyperparameters
print("Best hyperparameters:", study.best_params)
```

```
# Train the RandomForestClassifier with the best hyperparameters
best_rf = RandomForestClassifier(
    n_estimators=study.best_params['n_estimators'],
    max_depth=study.best_params['max_depth'],
    min_samples_split=study.best_params['min_samples_split'],
    min_samples_leaf=study.best_params['min_samples_leaf'],
    max_features=study.best_params['max_features'],
    bootstrap=study.best_params['bootstrap'],
    n_jobs=-1,
    random_state=42
)
best_rf.fit(X_train, y_train)

# Evaluate the model on the test set
best_rf_accuracy = best_rf.score(X_test, y_test)
print(f"Accuracy of the best model on the test set: {best_rf_accuracy}")
```

```
[I 2025-04-28 15:55:20,113] A new study created in memory with name: no-name-4d646a12-114e-43c8-86dc-b94daae30dfa
[I 2025-04-28 15:55:26,732] Trial 0 finished with value: 0.7072499999999999 and parameters: {'n_estimators': 829, 'max_depth': 27, 'm
[I 2025-04-28 15:55:32,580] Trial 1 finished with value: 0.69575 and parameters: {'n_estimators': 987, 'max_depth': 82, 'min_samples_
[I 2025-04-28 15:55:36,725] Trial 2 finished with value: 0.7429166666666667 and parameters: {'n_estimators': 343, 'max_depth': 11, 'm
[I 2025-04-28 15:55:40,202] Trial 3 finished with value: 0.6487499999999999 and parameters: {'n_estimators': 912, 'max_depth': 6, 'mi
[I 2025-04-28 15:55:53,228] Trial 4 finished with value: 0.7506666666666666 and parameters: {'n_estimators': 883, 'max_depth': 61, 'm
[I 2025-04-28 15:55:58,339] Trial 5 finished with value: 0.7040833333333333 and parameters: {'n_estimators': 797, 'max_depth': 76, 'm
[I 2025-04-28 15:56:01,353] Trial 6 finished with value: 0.6827499999999999 and parameters: {'n_estimators': 561, 'max_depth': 41, 'm
[I 2025-04-28 15:56:05,017] Trial 7 finished with value: 0.704 and parameters: {'n_estimators': 557, 'max_depth': 28, 'min_samples_sp
[I 2025-04-28 15:56:06,553] Trial 8 finished with value: 0.6867500000000001 and parameters: {'n_estimators': 217, 'max_depth': 54, 'm
[I 2025-04-28 15:56:10,568] Trial 9 finished with value: 0.6773333333333333 and parameters: {'n_estimators': 716, 'max_depth': 18, 'm
[I 2025-04-28 15:56:26,289] Trial 10 finished with value: 0.7325833333333334 and parameters: {'n_estimators': 669, 'max_depth': 97, '
[I 2025-04-28 15:56:30,983] Trial 11 finished with value: 0.7565 and parameters: {'n_estimators': 282, 'max_depth': 53, 'min_samples_
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[I 2025-04-28 15:56:44,267] Trial 13 finished with value: 0.7560833333333334 and parameters: {'n_estimators': 342, 'max_depth': 67, '
[I 2025-04-28 15:56:46,516] Trial 14 finished with value: 0.7349166666666667 and parameters: {'n_estimators': 128, 'max_depth': 41, '
[I 2025-04-28 15:56:49,777] Trial 15 finished with value: 0.7195 and parameters: {'n_estimators': 384, 'max_depth': 43, 'min_samples_
[I 2025-04-28 15:56:55,657] Trial 16 finished with value: 0.7071666666666667 and parameters: {'n_estimators': 437, 'max_depth': 75, '
[I 2025-04-28 15:56:59,380] Trial 17 finished with value: 0.7386666666666667 and parameters: {'n_estimators': 238, 'max_depth': 52, '
[I 2025-04-28 15:57:10,769] Trial 18 finished with value: 0.7306666666666667 and parameters: {'n_estimators': 457, 'max_depth': 99, '
[I 2025-04-28 15:57:12,388] Trial 19 finished with value: 0.6988333333333333 and parameters: {'n_estimators': 242, 'max_depth': 52, '
[I 2025-04-28 15:57:14,708] Trial 20 finished with value: 0.7474166666666667 and parameters: {'n_estimators': 131, 'max_depth': 64, '
[I 2025-04-28 15:57:20,476] Trial 21 finished with value: 0.7576666666666666 and parameters: {'n_estimators': 322, 'max_depth': 67, '
[I 2025-04-28 15:57:25,335] Trial 22 finished with value: 0.7564166666666667 and parameters: {'n_estimators': 298, 'max_depth': 87, '
[I 2025-04-28 15:57:33,707] Trial 23 finished with value: 0.7583333333333335 and parameters: {'n_estimators': 473, 'max_depth': 72, '
[I 2025-04-28 15:57:40,565] Trial 24 finished with value: 0.7442499999999999 and parameters: {'n_estimators': 478, 'max_depth': 71, '
[I 2025-04-28 15:57:52,173] Trial 25 finished with value: 0.7557499999999999 and parameters: {'n_estimators': 625, 'max_depth': 83, '
[I 2025-04-28 15:57:56,042] Trial 26 finished with value: 0.7262500000000001 and parameters: {'n_estimators': 491, 'max_depth': 91, '
[I 2025-04-28 15:57:58,905] Trial 27 finished with value: 0.74475 and parameters: {'n_estimators': 185, 'max_depth': 46, 'min_samples
[I 2025-04-28 15:58:03,421] Trial 28 finished with value: 0.753 and parameters: {'n_estimators': 287, 'max_depth': 69, 'min_samples_s
[I 2025-04-28 15:58:11,522] Trial 29 finished with value: 0.71425 and parameters: {'n_estimators': 420, 'max_depth': 26, 'min_samples
[I 2025-04-28 15:58:13,779] Trial 30 finished with value: 0.7325 and parameters: {'n_estimators': 288, 'max_depth': 34, 'min_samples_
[I 2025-04-28 15:58:20,027] Trial 31 finished with value: 0.757 and parameters: {'n_estimators': 390, 'max_depth': 59, 'min_samples_s
[I 2025-04-28 15:58:28,592] Trial 32 finished with value: 0.7578333333333334 and parameters: {'n_estimators': 514, 'max_depth': 58, '
[I 2025-04-28 15:58:37,293] Trial 33 finished with value: 0.7557499999999999 and parameters: {'n_estimators': 514, 'max_depth': 75, '
[I 2025-04-28 15:58:46,659] Trial 34 finished with value: 0.75 and parameters: {'n_estimators': 595, 'max_depth': 61, 'min_samples_sp
[I 2025-04-28 15:58:53,517] Trial 35 finished with value: 0.7574166666666666 and parameters: {'n_estimators': 402, 'max_depth': 59, '
[I 2025-04-28 15:59:07,488] Trial 36 finished with value: 0.7160833333333333 and parameters: {'n_estimators': 517, 'max_depth': 83, '
[I 2025-04-28 15:59:12,885] Trial 37 finished with value: 0.7510000000000001 and parameters: {'n_estimators': 340, 'max_depth': 77, '
[I 2025-04-28 15:59:22,668] Trial 38 finished with value: 0.7276666666666667 and parameters: {'n_estimators': 754, 'max_depth': 67, '
[I 2025-04-28 15:59:26,318] Trial 39 finished with value: 0.7081666666666666 and parameters: {'n_estimators': 606, 'max_depth': 72, '
[I 2025-04-28 15:59:33,963] Trial 40 finished with value: 0.7363333333333333 and parameters: {'n_estimators': 947, 'max_depth': 57, '
[I 2025-04-28 15:59:41,006] Trial 41 finished with value: 0.7544166666666666 and parameters: {'n_estimators': 417, 'max_depth': 63, '
[I 2025-04-28 15:59:50,831] Trial 42 finished with value: 0.7574166666666666 and parameters: {'n_estimators': 547, 'max_depth': 50, '
[I 2025-04-28 15:59:59,458] Trial 43 finished with value: 0.7479166666666666 and parameters: {'n_estimators': 535, 'max_depth': 47, '
[I 2025-04-28 16:00:05,894] Trial 44 finished with value: 0.73375 and parameters: {'n_estimators': 678, 'max_depth': 49, 'min_samples
[I 2025-04-28 16:00:15,224] Trial 45 finished with value: 0.7510833333333334 and parameters: {'n_estimators': 586, 'max_depth': 56, '
[I 2025-04-28 16:00:26,968] Trial 46 finished with value: 0.7275 and parameters: {'n_estimators': 453, 'max_depth': 38, 'min_samples_
[I 2025-04-28 16:00:39,442] Trial 47 finished with value: 0.7580833333333332 and parameters: {'n_estimators': 645, 'max_depth': 66, '
[I 2025-04-28 16:00:46,096] Trial 48 finished with value: 0.7359166666666667 and parameters: {'n_estimators': 672, 'max_depth': 79, '
[I 2025-04-28 16:01:00,852] Trial 49 finished with value: 0.752 and parameters: {'n_estimators': 870, 'max_depth': 66, 'min_samples_s
[I 2025-04-28 16:01:11,213] Trial 50 finished with value: 0.7199166666666666 and parameters: {'n_estimators': 808, 'max_depth': 71, '
[I 2025-04-28 16:01:21,703] Trial 51 finished with value: 0.7576666666666666 and parameters: {'n_estimators': 634, 'max_depth': 60, '
[I 2025-04-28 16:01:33,917] Trial 52 finished with value: 0.7578333333333334 and parameters: {'n_estimators': 749, 'max_depth': 62, '
[I 2025-04-28 16:01:44,509] Trial 53 finished with value: 0.7572500000000001 and parameters: {'n_estimators': 647, 'max_depth': 63, '
[I 2025-04-28 16:01:55,896] Trial 54 finished with value: 0.7559166666666667 and parameters: {'n_estimators': 702, 'max_depth': 55, '
[I 2025-04-28 16:02:04,873] Trial 55 finished with value: 0.7108333333333332 and parameters: {'n_estimators': 754, 'max_depth': 73, '
```
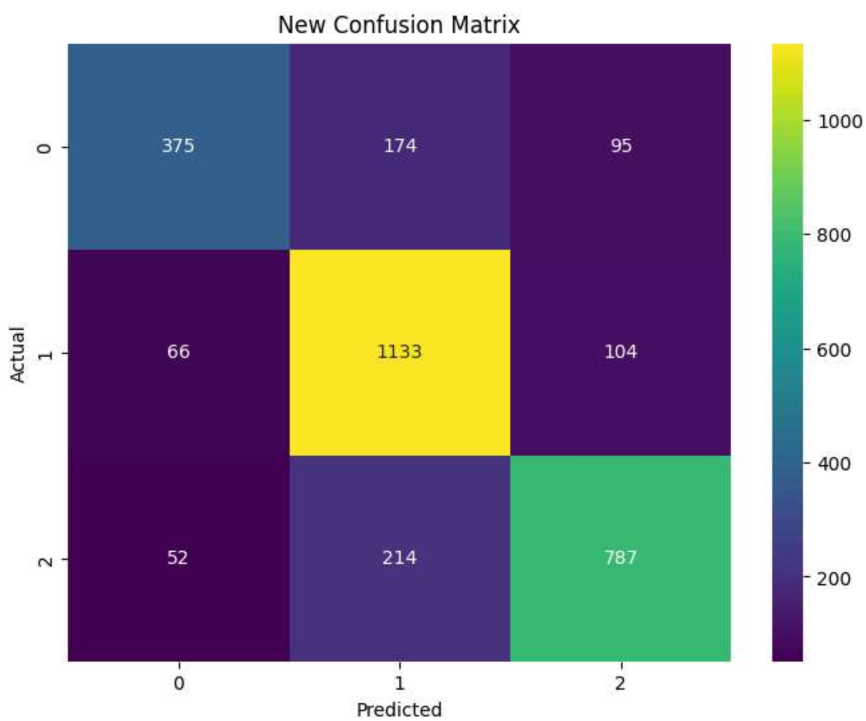

```
Best_hyperparameters={
                      'n_estimators': 533,
                      'max_depth': 36,
                      'min_samples_split': 13,
                      'min_samples_leaf': 2,
                      'max_features': None,
```

```
                       'bootstrap': True,
                       'n_jobs':-1
                       }


best_rf.fit(X_train, y_train)
tuned_y_pred = best_rf.predict(X_test)
tuned_accuracy = accuracy_score(y_test, tuned_y_pred)
print(f"Tuned Accuracy Score: {tuned_accuracy}")
```

```
Tuned Accuracy Score: 0.765
```

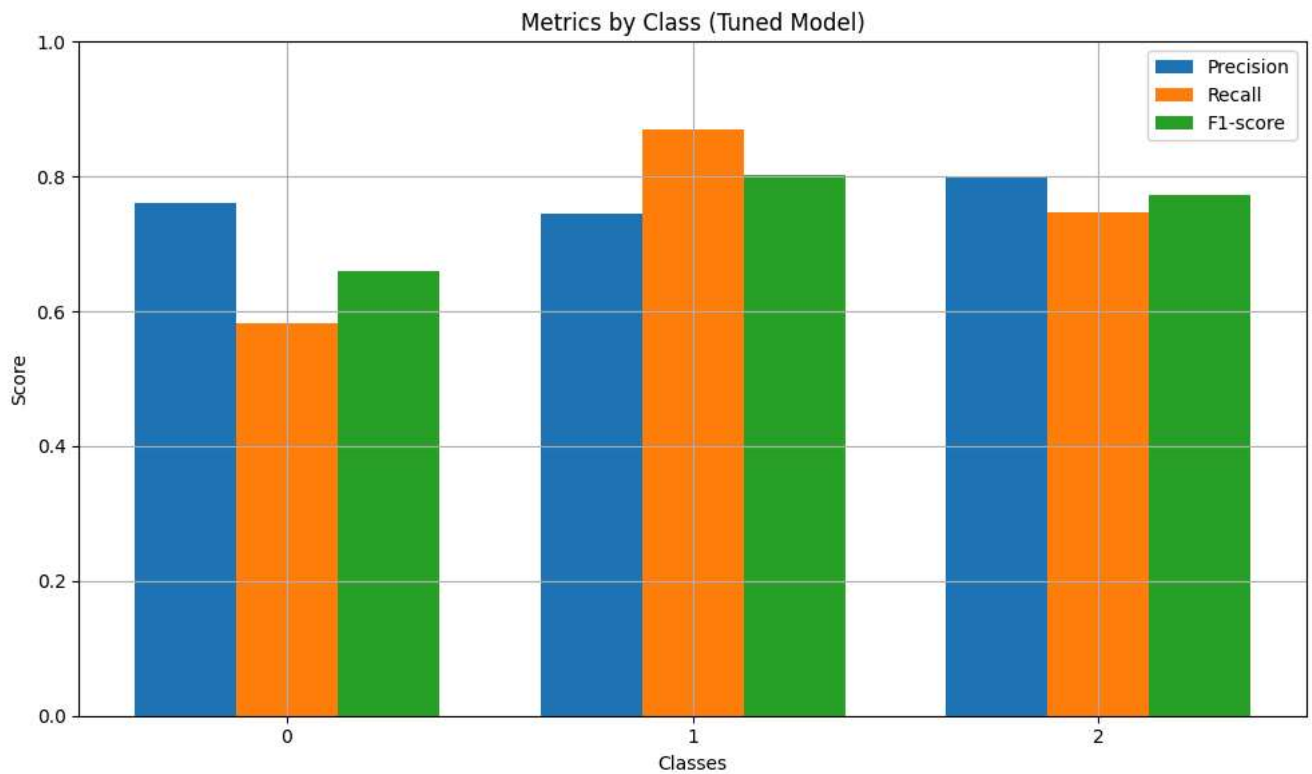
```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import numpy as np

import matplotlib.pyplot as plt

# Generate the confusion matrix
new_cm = confusion_matrix(y_test, tuned_y_pred)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(new_cm, annot=True, fmt='d', cmap='viridis', xticklabels=best_rf.classes_, yticklabels=best_rf.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('New Confusion Matrix')
plt.show()
```




```
# Generate classification report for the tuned Random Forest model
new_report = classification_report(y_test, tuned_y_pred, output_dict=True)

# Print macro metrics
print(f"Macro F1-Score: {new_report['macro avg']['f1-score']:.4f}")
print(f"Macro Precision: {new_report['macro avg']['precision']:.4f}")
print(f"Macro Recall: {new_report['macro avg']['recall']:.4f}")

# Extract metrics for the bar chart
new_metrics = ['precision', 'recall', 'f1-score']
new_classes = list(best_rf.classes_)
new_data = {metric: [new_report[str(cls)][metric] for cls in new_classes] for metric in new_metrics}

# Prepare data for grouped bar chart
x = np.arange(len(new_classes))  # the label locations
width = 0.25  # the width of the bars
```

```
# Plot each metric as a separate bar group
plt.figure(figsize=(10, 6))
for i, metric in enumerate(new_metrics):
    plt.bar(x + i * width, new_data[metric], width, label=metric.capitalize())

# Add labels, title, and legend
plt.xlabel('Classes')
plt.ylabel('Score')
plt.title('Metrics by Class (Tuned Model)')
plt.xticks(x + width, new_classes)
plt.ylim(0, 1)
plt.legend()

# Display the plot
plt.tight_layout()
plt.grid()
plt.show()
```

```
Macro F1-Score: 0.7447
Macro Precision: 0.7679
Macro Recall: 0.7331
```



Comparison of Bar Graph and Confusion Matrix (Before and After Hyperparameter Tuning)

Bar Graph

- The bar graph represents the performance metrics (`precision`, `recall`, and `f1-score`) for each class (`Class 0`, `Class 1`, and `Class 2`) before and after hyperparameter tuning.
- **Before Tuning**:
  - Precision, recall, and f1-score were relatively lower, especially for `Class 0`, indicating that the model struggled to correctly classify instances of this class.
  - Imbalances in performance across classes were evident, with `Class 1` performing better than the other classes.
- **After Tuning**:
  - All metrics improved significantly for each class, with the most notable improvement in `Class 0`.
  - The model became more balanced in its performance across all classes, reducing disparities between them.
  - The overall f1-score increased, reflecting a better trade-off between precision and recall.

Confusion Matrix

- The confusion matrix provides a detailed view of the model's predictions versus the actual labels for the test dataset.
- **Before Tuning**:
  - The diagonal cells (true positives) had lower counts, especially for `Class 0`, indicating poor classification accuracy for this class.
  - Off-diagonal cells (misclassifications) were higher, showing that the model frequently confused `Class 0` and `Class 2` with other classes.
- **After Tuning**:
  - The diagonal cells showed higher counts for all classes, particularly for `Class 0`, indicating improved accuracy.
  - Misclassifications in the off-diagonal cells decreased, showing that the model became better at distinguishing between classes.
  - The overall accuracy improved from **72.93%** to **76.5%**, demonstrating the effectiveness of hyperparameter tuning.

Key Differences

1. **Performance Metrics**:
   - Precision, recall, and f1-score improved for all classes after tuning.
   - The macro-average f1-score increased from **0.7078** to **0.7447**, indicating a more balanced performance across classes.
2. **Class-Specific Improvements**:
   - `Class 0` saw the most significant improvement in all metrics, reducing its misclassification rate.
   - `Class 1` and `Class 2` also showed moderate improvements, with better precision and recall.
3. **Overall Accuracy**:
   - The overall accuracy increased by approximately **3.57%**, highlighting the positive impact of hyperparameter tuning.
4. **Model Balance**:
   - The tuned model exhibited a more balanced performance across all classes, addressing the imbalances observed in the original model.

By tuning the hyperparameters, the model's ability to generalize and correctly classify instances improved significantly, as reflected in both the bar graph and the confusion matrix.

```
test_df
```

	DetectorId	AlertTitle	DeviceId	OSFamily	CountryCode	day	month	year	hour	weekday	Category_encoded	Entity_encoded
0	524	563	98799	5	242	4	6	2024	22	1	2	1
1	2	2	1239	0	242	3	6	2024	12	0	2	1
2	2932	10807	98799	5	242	8	6	2024	3	5	2	2
3	0	0	98799	5	242	12	6	2024	12	2	1	1
4	27	18	98799	5	242	6	6	2024	17	3	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
4147987	139	120	98799	5	242	4	6	2024	3	1	1	1
4147988	219	196	98799	5	242	4	6	2024	19	1	1	1
4147989	57	29	98799	5	242	15	6	2024	0	5	2	1
4147990	1	1	98799	5	242	11	6	2024	16	1	1	1
4147991	1	1	98799	5	242	4	6	2024	18	1	1	1

4147992 rows × 12 columns

Final Training

- **For using all the data**: if we wish to use all the data,
  - use the `x` and `y` below
  - fit the model `rf_best` on that and then make the predictions for the `test_df`

```
train_df=train_df.iloc[:,1:]
x=train_df.drop('IncidentGrade_encoded',axis=1)
y=train_df['IncidentGrade_encoded']
```

```
best_rf.fit(X_train,y_train)
```

```
RandomForestClassifier

RandomForestClassifier(max_depth=36, max_features=None, min_samples_leaf=2,
                       min_samples_split=13, n_estimators=533, n_jobs=-1,
                       random_state=42)
```

```
final_predictions=best_rf.predict(test_df) # Making predictions on the dataset
```

```
# what the final predictions look like
pd.DataFrame(final_predictions).value_counts()
```

```
0
1    2099513
2    1393229
0     655250
Name: count, dtype: int64
```

Start coding or generate with AI.