TITLE OF PROJECT REPORT

Customer Support Case Type Classification

(Classify support cases into billing, technical, or general queries)

A PROJECT REPORT

SUBMITTED BY

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Introduction:

Customer Support Case Type Classification is a machine learning approach aimed at categorizing support queries into predefined classes such as billing, technical, or general. This classification enables businesses to streamline their customer service processes by automatically routing cases to the appropriate departments, reducing response time, and improving efficiency. By leveraging features like message length and response time, predictive models can be trained to accurately classify new cases. This report explores the use of supervised learning for classification, evaluates model performance using metrics such as accuracy, precision, and recall, and visualizes results through confusion matrix heatmaps for better interpretability.

Methodology:

The classification of customer support cases into billing, technical, or general categories was achieved using a supervised machine learning approach. The process followed these key steps:

1. **Data Collection and Preprocessing:**
   The dataset consisted of structured features such as message_length, response_time, and a target label case_type. Missing values were handled, and categorical labels were encoded using label encoding.
2. **Feature Selection:**
   The features message_length and response_time were selected based on their relevance to the nature of the query.
3. **Model Development:**
   The data was split into training and testing sets (typically 70:30 ratio). A Random Forest Classifier was employed due to its robustness and ability to handle non-linear relationships.
4. **Model Training and Prediction:**
   The model was trained on the training set and then used to predict the case types in the test set.
5. **Evaluation:**
   Model performance was evaluated using accuracy, precision,

and recall. A confusion matrix heatmap was generated for visual analysis of classification performance.

6. **Exploratory Clustering (Optional):**
   For unsupervised insight, K-Means clustering was applied to identify natural groupings in the data, supporting segmentation when labels are unavailable.

CODE TYPED:

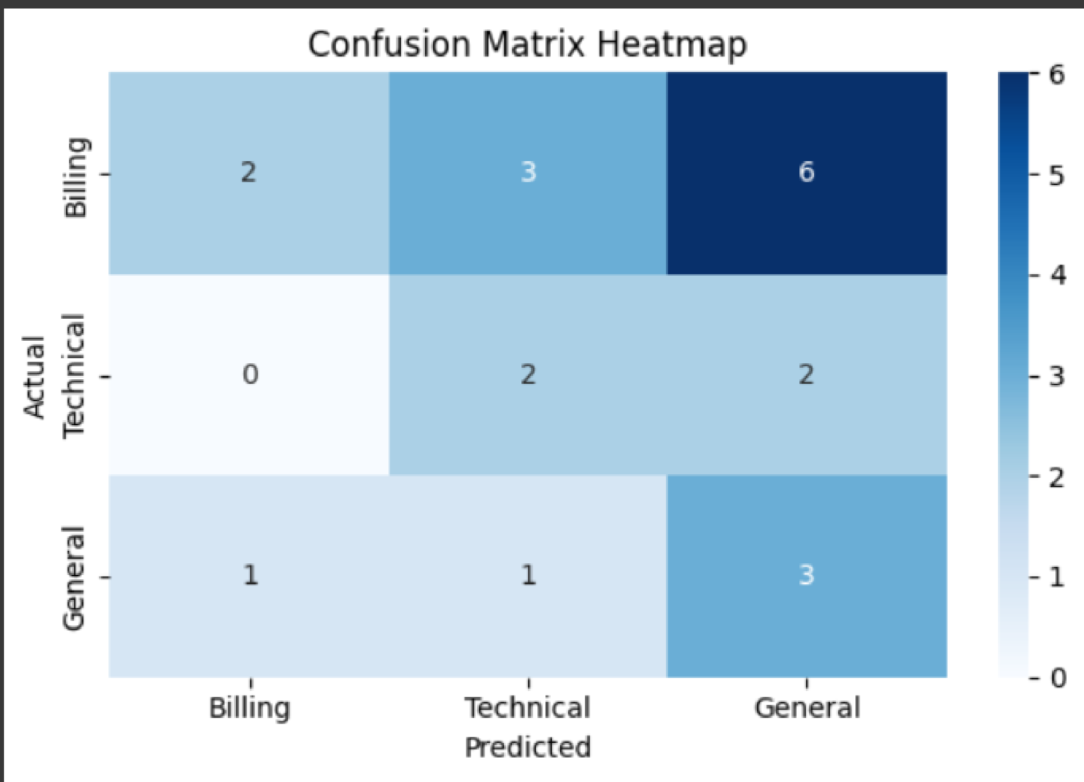
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    confusion_matrix, classification_report
)
from sklearn.preprocessing import LabelEncoder

# Step 1: Load data
data = pd.read_csv("/content/support_cases.csv")

# Step 2: Check for missing values
print("Missing values:\n", data.isnull().sum())

# Step 3: Drop missing values
```

```
data.dropna(inplace=True)

# Step 4: Encode case_type labels into numeric format
label_mapping = {'billing': 0, 'technical': 1, 'general': 2}
data = data[data['case_type'].isin(label_mapping)]  # Only valid labels
data['label_encoded'] = data['case_type'].map(label_mapping)

# Step 5: Define features and target
X = data[['message_length', 'response_time']]
y = data['label_encoded']

# Step 6: Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)

# Step 7: Train Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Step 8: Make predictions
y_pred = model.predict(X_test)

# Step 9: Evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted',
zero_division=0)
recall = recall_score(y_test, y_pred, average='weighted', zero_division=0)
```

```
print("Evaluation Metrics:")
print(f"Accuracy : {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall   : {recall:.4f}")

# Step 10: Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
labels = ['Billing', 'Technical', 'General']

plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=labels, yticklabels=labels)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix Heatmap")
plt.tight_layout()
plt.show()

# Step 11: Classification Report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=labels))
```

SCREENSHOTS OF OUTPUT:

```
Missing values:
 message_length    0
response_time     0
case_type         0
dtype: int64
Evaluation Metrics:
Accuracy : 0.3500
Precision: 0.5015
Recall   : 0.3500
```



```
Classification Report:
              precision    recall  f1-score   support

     Billing       0.67      0.18      0.29        11
   Technical       0.33      0.50      0.40         4
     General       0.27      0.60      0.38         5

    accuracy                           0.35        20
   macro avg       0.42      0.43      0.35        20
weighted avg       0.50      0.35      0.33        20
```

REFERENCES:

https://www.kaggle.com/datasets/suraj520/customer-support-ticket-dataset