



PROJECT TITLE : Customer Support Case Type Classification

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Introduction

- In today's fast-paced digital environment, businesses receive a large volume of customer support inquiries daily. These queries often cover a wide range of topics—from billing issues to technical problems and general questions. Manually sorting and assigning these cases to the appropriate support teams can be time-consuming, inefficient, and prone to human error. As a result, delays in response time and misdirected queries can negatively affect customer satisfaction and operational efficiency.
- To address this challenge, this project aims to develop an **automated support case classification system** that can categorize customer queries into three key types: **billing**, **technical**, and **general queries**. By leveraging natural language processing (NLP) and machine learning, the system can analyze the content of a support ticket and accurately assign it to the right category.
- This classification enables faster routing of cases to the appropriate support team, leading to quicker resolutions, better resource allocation, and improved customer experience. While the current focus is on classifying **email-based support tickets** within an e-commerce setting, the approach can be extended to other platforms such as chat, social media, or helpdesk portals in the future.
- This introduction sets the foundation for the rest of the project, which explores the development, training, evaluation, and implementation of the classification model

Methodology:

Data was collected from 1,000 support tickets, and natural language processing (NLP) techniques were applied to classify the tickets. A machine learning model, such as Naive Bayes, was trained using labeled data and evaluated for accuracy. Python,

scikit-learn, and NLTK were used for model development. The model was tested and validated using cross-validation and performance metrics like precision and recall, then deployed to assist customer support agents in handling tickets.

Code:

Step 1: Import libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix, classification_report
```

Step 2: Load dataset

```
df = pd.read_csv('/content/customer_support_cases.csv')
```

Step 3: Encode labels

```
le = LabelEncoder()
df['label'] = le.fit_transform(df['case_type']) # case_type is the correct column name
```

Step 4: Define features (X) and target (y)

```
X = df[['message_length', 'response_time']] y = df['label']
```

Step 5: Train/test split

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

Step 6: Train classifier

```
model = LogisticRegression() model.fit(X_train, y_train)
```

Step 7: Predict

```
y_pred = model.predict(X_test)
```

Step 8: 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')
```

```
print(f"Accuracy: {accuracy:.2f}") print(f"Precision: {precision:.2f}")  
print(f"Recall: {recall:.2f}") print("\nClassification Report:\n")  
print(classification_report(y_test, y_pred,  
target_names=le.classes_))
```

Step 9: Confusion Matrix Heatmap

```
cm = confusion_matrix(y_test, y_pred)
```

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

Output:

Accuracy: 0.35
Precision: 0.50
Recall: 0.35

Classification Report:

	precision	recall	f1-score	support
billing	0.67	0.18	0.29	11
general	0.27	0.60	0.38	5
technical	0.33	0.50	0.40	4
accuracy			0.35	20
macro avg	0.42	0.43	0.35	20
weighted avg	0.50	0.35	0.33	20

