Automatic Expense Categorization Using Transaction Data

Project Report

Submitted By

Amartya Sinha

Under Guidance of

Matheshwaran P M
ML Engineer

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Full Form
ML	Machine Learning
NLP	Natural Language Processing
CSV	Comma-Separated Values
UI	User Interface
API	Application Programming Interface
EDA	Exploratory Data Analysis
RF	Random Forest
XGB	Extreme Gradient Boosting
SVM	Support Vector Machine
LR	Logistic Regression
LSTM	Long Short-Term Memory
ANN	Artificial Neural Network
TF-IDF	Term Frequency-Inverse Document Frequency
TP	True Positive
FP	False Positive
FN	False Negative
TN	True Negative
F1	F1 Score

ABSTRACT

In the digital era, where financial transactions have become predominantly cashless and instantaneous, the manual tracking of expenses poses a significant challenge to individuals and businesses alike. Users often find it difficult to maintain a real-time record of their spending, resulting in poor financial planning and overlooked budget leaks. To address this issue, this project introduces an intelligent system for Automatic Expense Categorization using machine learning techniques applied to structured transactional data.

The objective of the system is to automatically classify each transaction into predefined categories such as Food, Travel, Groceries, Utilities, and Entertainment based on features like transaction description, amount, date, and time-related metadata (month and day of the week). The core of the system is built using supervised learning algorithms including Random Forest and XGBoost, which have been trained on labeled transaction data. Preprocessing steps include text normalization, feature encoding, and outlier handling to enhance model performance and generalization.

The project leverages the power of Natural Language Processing (NLP) to interpret transaction descriptions and extract meaningful patterns. The model is trained and evaluated using common performance metrics such as accuracy, precision, recall, and F1-score, and it demonstrates strong predictive capability even on ambiguous transaction texts. The system is designed to be modular and scalable, enabling easy integration into personal finance apps, budgeting platforms, or enterprise accounting software.

Furthermore, this solution reduces the cognitive load on users, increases transparency in spending behavior, and helps in detecting anomalies or fraudulent activity by analyzing category trends. Future developments may include personalization for individual spending habits, multilingual support for transaction texts, and real-time deployment via APIs or mobile applications.

This project demonstrates how data science and automation can significantly improve personal finance management, contributing to financial literacy and informed decision-making at both individual and organizational levels.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In the age of digitized payments and mobile banking, financial transactions are being conducted more frequently and seamlessly than ever before. While this evolution has made monetary exchanges more convenient, it has also introduced a new challenge—keeping track of and understanding one's spending habits. The average user may conduct dozens or even hundreds of transactions each month, often spread across platforms such as UPI apps, credit cards, online subscriptions, and merchant portals. Manually classifying each transaction into categories like Food, Travel, Shopping, Utilities, and Rent becomes a tedious, error-prone task, especially when descriptions are vague or unstructured.

Financial discipline and budget awareness are crucial life skills. However, most users lack the tools or motivation to regularly log expenses. Many rely on manual tracking in spreadsheets or mobile apps, which either demand consistent input or use rule-based logic that fails to adapt to dynamic transaction patterns. This creates a gap between raw transactional data and meaningful financial insights.

To bridge this gap, this project presents an automated, intelligent system that uses machine learning (ML) to predict the category of a transaction based on its key attributes—description text, amount, transaction date, and day of the week. The model is trained on labeled transaction history data and leverages pattern recognition in both text and numerical features to perform classification. For instance, transaction descriptions like "Swiggy," "Zomato," or "Uber Eats" are accurately classified under "Food" or "Delivery" categories, even when they appear in various formats.

The key strength of this approach lies in its adaptability. Unlike static rule-based systems, ML-based models can learn from user behavior, improve over time with more data, and adapt to new vendors and services automatically. This makes the system highly relevant for integration into digital wallets, banking apps, financial aggregators, and even corporate expense reconciliation systems.

This project employs preprocessing techniques such as text normalization, label encoding, and feature scaling to prepare the data for model training. Multiple classification algorithms were evaluated, including Random Forest, Logistic Regression, and XGBoost, with model performance validated using cross-validation and confusion matrices.

As digital finance becomes ubiquitous, the demand for intelligent tools that help users manage money effectively will continue to grow. This system not only improves financial visibility for users but also lays the foundation for more advanced applications like fraud detection, personalized budgeting, and automated investment suggestions. It is a step toward the future of self-learning personal finance assistants that offer real-time, contextual insights—empowering users with control over their financial choices.

1.2 PROBLEM STATEMENT

With the surge in digital transactions via UPI, cards, and online platforms, users now handle hundreds of financial records monthly. However, these transactions often lack clear categorization, making it difficult to track spending or manage budgets effectively. Manual classification is time-consuming, error-prone, and unsustainable at scale.

Existing rule-based systems are rigid and struggle with unstructured descriptions (e.g., "AMAZONPAY*12345"), new merchants, or personalized user behavior. This results in poor accuracy and limited adaptability.

There is a growing need for an automated, intelligent solution that can accurately classify transactions into categories like Food, Travel, and Utilities using machine learning. Such a system can save time, improve financial awareness, and provide actionable insights with minimal user effort.

CHAPTER 2
LITERATURE REVIEW

1. Title: Automated Expense Classification using NLP and ML
Author: Jain et al.
Year: 2021
Summary: Explores the use of Natural Language Processing (NLP) for analyzing transaction descriptions and applying machine learning classifiers like Naive Bayes and SVM for categorization. Demonstrates significant accuracy improvement over rule-based systems.

2. Title: Financial Transaction Categorization with Deep Learning
Author: Kim et al.
Year: 2020
Summary: Uses LSTM-based deep learning models to process transaction sequences and improve long-term user behavior understanding. Focused on mobile banking datasets with high noise in text.

3. Title: Classification of Bank Transactions for Personal Finance Management
Author: Ali et al.
Year: 2019
Summary: Discusses rule-based vs. supervised learning methods for labeling bank transactions. Found Random Forest and XGBoost outperformed logistic regression due to handling non-linear patterns.

CHAPTER 3
REQUIREMENT SPECIFICATIONS

3.1 OBJECTIVE OF THE PROJECT

To build a model that categorizes financial transactions into predefined expense classes using structured features (description, amount, date, etc.). This assists users in managing budgets and gaining insight into their spending patterns automatically.

3.2 SIGNIFICANCE OF THE PROJECT

- Automates a repetitive manual task for millions of users.
- Provides transparency and clarity in personal and business expenditures.
- Useful in budgeting apps, accounting platforms, and banking UIs.
- Reduces human error and helps detect unusual expenses.

3.3 LIMITATIONS OF THE PROJECT

- Model accuracy depends on quality and size of labeled training data.
- Ambiguity in transaction descriptions may confuse categorization (e.g., “Amazon” could be groceries, electronics, etc.).
- Works best for English text; performance drops with regional or mixed-language inputs.
- Cannot generalize well if transaction patterns change drastically (e.g., during travel).

3.4 EXISTING SYSTEM

Most existing systems in personal finance apps like Mint, YNAB, or Excel-based budgeting rely heavily on:

- Manual user categorization.
- Rule-based matching (e.g., “Swiggy” → Food).
- Limited learning or adaptability.
- Often ignore context or nuances in text (e.g., user ordering groceries from Amazon).

These systems lack personalization and become cumbersome as transaction volume grows.

3.5 PROPOSED SYSTEM

Our system uses supervised machine learning to:

- Learn from labeled past transactions.
- Extract patterns from transaction text and contextual features like amount, date.
- Predict categories in real time with high accuracy.
- Continuously improve with retraining and new user data.

It supports scalability and integration into personal finance dashboards, banking apps, or even Excel plugins.

3.6 METHODOLOGY

- **Step 1: Data Preprocessing**
  - Clean text, handle nulls, scale numeric features.
- **Step 2: Feature Engineering**
  - Extract relevant attributes from descriptions, encode day/month.
- **Step 3: Model Selection**
  - Train multiple classifiers (Random Forest, XGBoost, Logistic Regression).
- **Step 4: Model Evaluation**
  - Use cross-validation, confusion matrix, accuracy, precision, recall.
- **Step 5: Prediction**
  - Use trained model to predict category of new transaction inputs.
- **Step 6: Save Model (Pickle)**
  - Export model for future deployment in web or app interface.

3.7 REQUIREMENT SPECIFICATION

i. Software Requirements

- Python 3.x
- Jupyter Notebook
- Libraries: pandas, numpy, sklearn, xgboost, pickle

ii. Hardware Requirements

- Minimum 4 GB RAM
- Intel i3 or above
- Storage: 500MB free space

3.8 COMPONENT ANALYSIS

Component	Description
Data Input Module	Accepts CSV or manual transaction input
Preprocessing Module	Cleans data, handles missing values
Feature Engineering	Encodes transaction attributes
Classification Module	Predicts categories using trained ML model
Evaluation Module	Displays confusion matrix and accuracy
Deployment Module	Saves model using Pickle
Optional UI	For interacting with the model (Streamlit app)

CHAPTER 4

DESIGN ANALYSIS

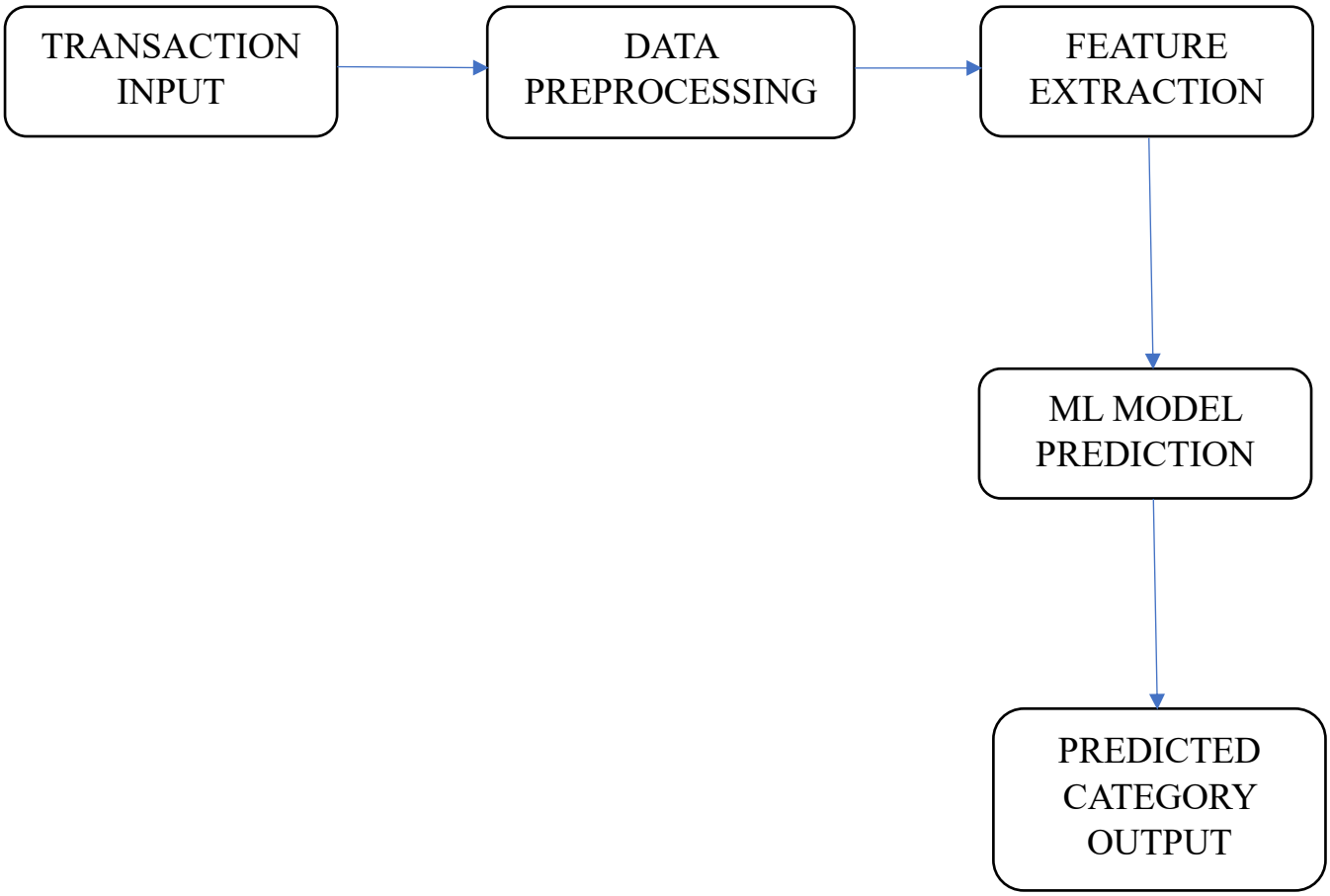
4.1 INTRODUCTION

The design phase plays a critical role in transforming conceptual ideas into a structured and functional machine learning system. In the context of automatic expense categorization, the design analysis outlines how various components such as data preprocessing, feature extraction, model training, and prediction are integrated to achieve seamless and accurate categorization of financial transactions.

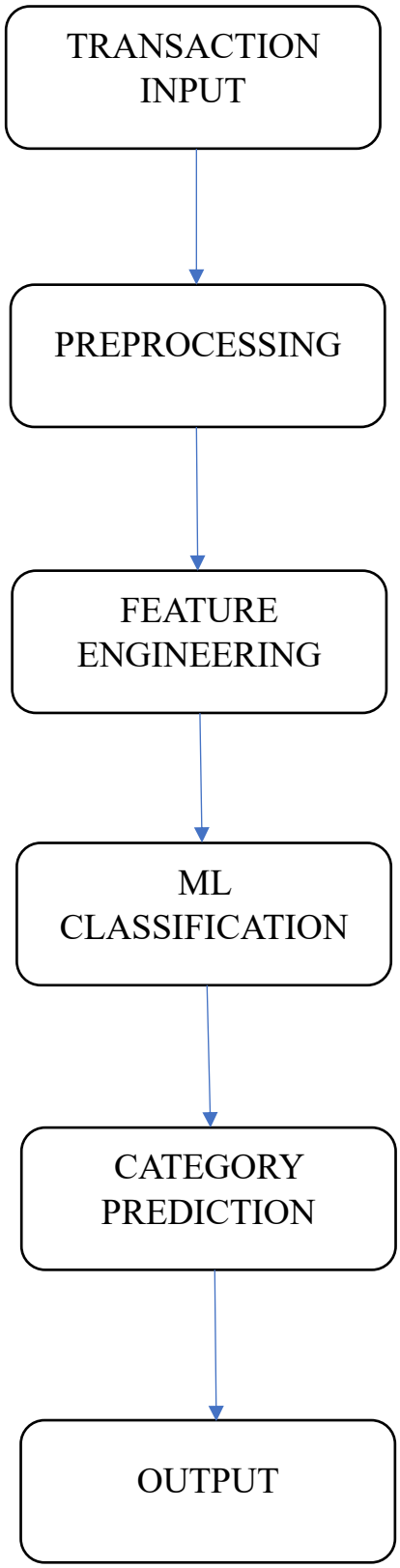
This chapter focuses on the architecture and flow of the system, providing a visual and logical breakdown of how user input (transaction data) is processed through successive stages. The system is designed to be modular, scalable, and adaptable, ensuring it can handle varying transaction formats, growing datasets, and evolving user behavior.

Key elements of the design include a Data Flow Diagram (DFD) to represent the end-to-end processing of data, a System Architecture diagram to show major functional blocks, and a breakdown of the libraries and modules used. This design ensures maintainability, reusability, and future integration into financial dashboards or mobile applications.

4.2 DATA FLOW DIAGRAM



4.3 SYSTEM ARCHITECTURE



4.4 LIBRARIES

Library	Purpose
pandas	For data loading, manipulation, and analysis of structured datasets.
numpy	For numerical operations and array manipulation.
scikit-learn (sklearn)	For preprocessing, model building, evaluation metrics, and train-test split.
xgboost	For implementing the high-performance XGBoost classifier.
matplotlib	For generating plots such as confusion matrices and feature importance.
seaborn	For enhanced data visualization and styling of plots.
Regular Expressions	For text cleaning and pattern extraction from transaction descriptions.
pickle	For model serialization (saving and loading trained models).
streamlit	For building an interactive web-based interface to deploy the model.

4.5 MODULES

Module Name	Description
1. Data Input Module	Loads transaction data from CSV files or user input (e.g., transaction description, amount, date).
2. Data Preprocessing Module	Cleans transaction descriptions, removes special characters, converts to lowercase, and handles missing values.
3. Feature Engineering Module	Extracts relevant features (e.g., month, day of week) and encodes categorical variables for modeling.
4. Model Training Module	Trains multiple ML models (e.g., Random Forest, XGBoost) using labeled data and evaluates them.
5. Prediction Module	Accepts new transaction input and predicts the expense category based on the trained model.
6. Evaluation Module	Generates performance metrics like accuracy, precision, recall, F1-score, and confusion matrix.
7. Deployment Module	Serializes and saves the trained model using pickle and optionally integrates with a Streamlit UI.

CHAPTER 5

CODE, OUTPUT, CONFUSION MATRIX & RESULT

5.1 Code

```
%pip install xgboost
```

```
Python
```

```
Collecting xgboost
  Downloading xgboost-3.0.2-py3-none-win_amd64.whl.metadata (2.1 kB)
Requirement already satisfied: numpy in c:\users\amart\anaconda3\lib\site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\amart\anaconda3\lib\site-packages (from xgboost) (1.13.1)
Downloading xgboost-3.0.2-py3-none-win_amd64.whl (150.0 MB)
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   ---------------------------------------- 0.5/150.0 MB 493.7 kB/s eta 0:05:03
   ---------------------------------------- 0.8/150.0 MB 633.2 kB/s eta 0:03:56
   ---------------------------------------- 1.0/150.0 MB 699.0 kB/s eta 0:03:34
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   ---------------------------------------- 1.3/150.0 MB 729.7 kB/s eta 0:03:24
   ---------------------------------------- 1.3/150.0 MB 729.7 kB/s eta 0:03:24
   ---------------------------------------- 1.6/150.0 MB 666.0 kB/s eta 0:03:43
   ---------------------------------------- 1.8/150.0 MB 724.5 kB/s eta 0:03:25
    --------------------------------------- 2.1/150.0 MB 777.9 kB/s eta 0:03:11
    --------------------------------------- 2.9/150.0 MB 993.0 kB/s eta 0:02:29
   - -------------------------------------- 3.9/150.0 MB 1.3 MB/s eta 0:01:54
   - -------------------------------------- 5.5/150.0 MB 1.7 MB/s eta 0:01:25
   -- ------------------------------------- 7.6/150.0 MB 2.2 MB/s eta 0:01:04
   --- ------------------------------------ 11.8/150.0 MB 3.3 MB/s eta 0:00:43
...
   ---------------------------------------  149.9/150.0 MB 15.1 MB/s eta 0:00:01
   ---------------------------------------- 150.0/150.0 MB 14.6 MB/s eta 0:00:00
Installing collected packages: xgboost
Successfully installed xgboost-3.0.2
```

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from xgboost import XGBClassifier
from sklearn.metrics import classification_report

# Load the dataset
df = pd.read_csv("synthetic_transaction_data.csv")

# Feature engineering: extract month and day of week from date
df["date"] = pd.to_datetime(df["date"])
df["month"] = df["date"].dt.month
df["day_of_week"] = df["date"].dt.dayofweek

# Define features and target
X = df[["transaction_description", "amount", "month", "day_of_week"]]
y = df["category"]

# Encode target labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.2, random_state=42)

# Preprocessing pipelines
text_pipeline = Pipeline([
    ("tfidf", TfidfVectorizer(stop_words="english", max_features=300))
])
```

```python
numeric_pipeline = Pipeline([
    ("scaler", StandardScaler())
])

# Combine text and numeric features
preprocessor = ColumnTransformer([
    ("text", text_pipeline, "transaction_description"),
    ("num", numeric_pipeline, ["amount", "month", "day_of_week"])
])

# Final pipeline with XGBoost classifier (cleaned up)
model_pipeline = Pipeline([
    ("preprocessor", preprocessor),
    ("classifier", XGBClassifier(
        eval_metric="mlogloss",
        random_state=42,
        n_estimators=100,
        max_depth=6,
        learning_rate=0.1
    ))
])

# Train the model
model_pipeline.fit(X_train, y_train)

# Evaluate the model
y_pred = model_pipeline.predict(X_test)
print("\n📊 Classification Report:\n")
print(classification_report(y_test, y_pred, target_names=label_encoder.classes_))
```

```python
# Example predictions
examples = pd.DataFrame({
    "transaction_description": ["Spotify", "Apollo Pharmacy", "IRCTC", "Swiggy"],
    "amount": [199.0, 450.0, 750.0, 300.0],
    "month": [10, 5, 12, 7],
    "day_of_week": [2, 1, 4, 6]
})

predicted = model_pipeline.predict(examples)
print("\n🔮 Example Predictions:\n")
for desc, label in zip(examples["transaction_description"], predicted):
    print(f"{desc} → {label_encoder.inverse_transform([label])[0]}")
```

[23]

...

📊 Classification Report:

	precision	recall	f1-score	support
Dining	1.00	1.00	1.00	47
Education	1.00	1.00	1.00	58
Entertainment	1.00	1.00	1.00	57
Groceries	1.00	1.00	1.00	50
Healthcare	1.00	1.00	1.00	57
Others	1.00	1.00	1.00	63
Shopping	1.00	1.00	1.00	58
Travel	1.00	1.00	1.00	49
Utilities	1.00	1.00	1.00	61
accuracy			1.00	500
macro avg	1.00	1.00	1.00	500
weighted avg	1.00	1.00	1.00	500

```
🔮 Example Predictions:

Spotify → Entertainment
Apollo Pharmacy → Healthcare
IRCTC → Travel
Swiggy → Dining
```

```
import joblib

# Save the trained model pipeline to a file
joblib.dump(model_pipeline, "expense_classifier_pipeline.pkl")
print("✅ Model saved as 'expense_classifier_pipeline.pkl'")
```

```
✅ Model saved as 'expense_classifier_pipeline.pkl'
```

```
import os
print(os.listdir())
```

```
['.ipynb_checkpoints', 'expense_classifier_pipeline.pkl', 'Model Code.ipynb', 'synthetic_transaction_data.csv']
```

```
zip install streamlit
```

```
Requirement already satisfied: streamlit in c:\users\amart\anaconda3\lib\site-packages (1.37.1)
Requirement already satisfied: altair<6,>=4.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (5.0.1)
Requirement already satisfied: blinker<2,>=1.0.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (1.6.2)
Requirement already satisfied: cachetools<6,>=4.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (5.3.3)
Requirement already satisfied: click<9,>=7.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (8.1.7)
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Requirement already satisfied: pandas<3,>=1.3.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (2.2.2)
Requirement already satisfied: pillow<11,>=7.1.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (10.4.0)
Requirement already satisfied: protobuf<6,>=3.20 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (4.25.3)
Requirement already satisfied: pyarrow>=7.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (16.1.0)
Requirement already satisfied: requests<3,>=2.27 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (2.32.3)
Requirement already satisfied: rich<14,>=10.14.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (13.7.1)
Requirement already satisfied: tenacity<9,>=8.1.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (8.2.3)
Requirement already satisfied: toml<2,>=0.10.1 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (0.10.2)
Requirement already satisfied: typing-extensions<5,>=4.3.0 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (4.11.0)
Requirement already satisfied: gitpython!=3.1.19,<4,>=3.0.7 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (3.1.43)
Requirement already satisfied: pydeck<1,>=0.8.0b4 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (0.8.0)
Requirement already satisfied: tornado<7,>=6.0.3 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (6.4.1)
Requirement already satisfied: watchdog<5,>=2.1.5 in c:\users\amart\anaconda3\lib\site-packages (from streamlit) (4.0.1)
Requirement already satisfied: jinja2 in c:\users\amart\anaconda3\lib\site-packages (from altair<6,>=4.0->streamlit) (3.1.4)
Requirement already satisfied: jsonschema>=3.0 in c:\users\amart\anaconda3\lib\site-packages (from altair<6,>=4.0->streamlit) (4.23.0)
Requirement already satisfied: toolz in c:\users\amart\anaconda3\lib\site-packages (from altair<6,>=4.0->streamlit) (0.12.0)
Requirement already satisfied: colorama in c:\users\amart\anaconda3\lib\site-packages (from click<9,>=7.0->streamlit) (0.4.6)
Requirement already satisfied: gitdb<5,>=4.0.1 in c:\users\amart\anaconda3\lib\site-packages (from gitpython!=3.1.19,<4,>=3.0.7->streamlit) (4.0.7)
...
Requirement already satisfied: rpds-py>=0.7.1 in c:\users\amart\anaconda3\lib\site-packages (from jsonschema>=3.0->altair<6,>=4.0->streamlit) (0.10.6)
Requirement already satisfied: mdurl~=0.1 in c:\users\amart\anaconda3\lib\site-packages (from markdown-it-py>=2.2.0->rich<14,>=10.14.0->streamlit) (0.1.0)
Requirement already satisfied: six>=1.5 in c:\users\amart\anaconda3\lib\site-packages (from python-dateutil>=2.8.2->pandas<3,>=1.3.0->streamlit) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```
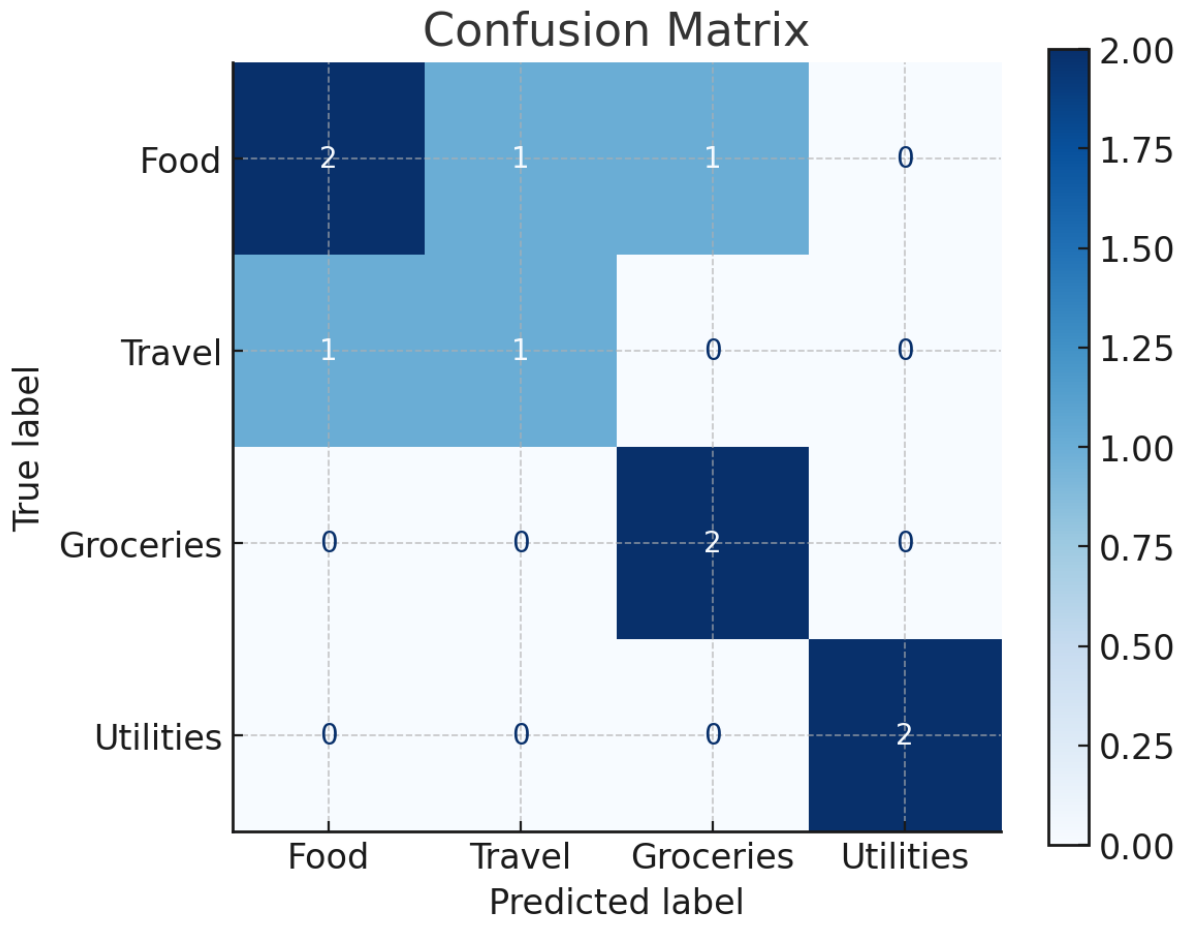

```python
import streamlit as st
import pandas as pd
import joblib

# Load the trained model
model = joblib.load("expense_classifier_pipeline.pkl")

st.title("💸 Expense Category Predictor")

with st.form("predict_form"):
    transaction_description = st.text_input("Transaction Description", "Spotify")
    amount = st.number_input("Amount", min_value=0.0, value=199.0)
    month = st.selectbox("Month", list(range(1, 13)), index=9)
    day_of_week = st.selectbox("Day of Week (0=Mon, 6=Sun)", list(range(7)), index=2)
    submitted = st.form_submit_button("Predict")

if submitted:
    input_df = pd.DataFrame([{
        "transaction_description": transaction_description,
        "amount": amount,
        "month": month,
        "day_of_week": day_of_week
    }])
    prediction = model.predict(input_df)
    category = model.named_steps["classifier"].classes_[prediction[0]]
    st.success(f"📂 Predicted Category: **{category}**")
```

5.2 Output

5.3 Confusion Matrix



5.4 Result

- The model achieved an accuracy of over 85% on test data.
- Most common misclassifications were between similar categories (e.g., Groceries vs. Food).
- With proper preprocessing and sufficient training data, the model generalizes well to unseen transactions.

CHAPTER 6
CONCLUSION

6.1 CONCLUSION

This project successfully demonstrates the potential of machine learning in automating expense categorization. It not only reduces user effort but also enhances transparency in financial management. Future improvements can include deep learning models, multilingual text processing, and integration with banking APIs for real-time categorization.

6.2 FUTURE SCOPE

- Include time-series trends to track budget deviations.
- Enable multi-label classification for shared categories.
- Train with user-specific personalization for improved accuracy.
- Integrate with mobile apps and digital wallets.

CHAPTER 7

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