# Documentation for Paisa Controller Hackathon Project

## 1.Problem Statement: Paisa Controller

In today's fast-paced world, managing personal finances effectively is a challenge. People struggle with tracking expenses, maintaining budgets, and achieving financial goals due to a lack of intuitive tools, real-time insights, and automation. Many existing finance apps are either too complex, lack AI-driven automation, or do not provide seamless cross-platform experiences.

### Key Features Include:

- **Expense & Income Tracking:**
  - Fast data entry with auto-fill suggestions
  - Smart categorization
  - Advanced search and filtering options

- **Reports & Financial Insights:**
  - Visual data representations (charts, graphs, trend analysis)
  - Comprehensive monthly and yearly summaries.

- **Security & Customization:**
  - Multi-layer authentication (PIN, biometrics, JWT Token)
  - Multi-currency support, dark mode, and customizable themes
  - Desktop web dashboard for expanded management

The goal is to empower users to achieve financial stability with minimal effort, by harnessing AI to deliver personalized recommendations and automated financial oversight.

# 2.Workflow

The development process for Paisa Controller is structured into several critical phases to ensure a robust, scalable, and user-friendly solution:

### 2.1.Planning & Requirements Gathering

- **Team Meeting:**
  Identified pain points and must-have features
  .
- **Market & Competitor Analysis:**
  Evaluated existing finance apps to determine unique selling propositions (USPs) and areas for innovation.
- **Project Specifications:**
  Documented detailed requirements, use cases, and deliverables based on the hackathon brief.

### 2.2.Design & Prototyping

- **Wireframing & Mockups:**
  Created initial wireframes for the mobile/web interface focusing on simplicity and intuitive navigation.
- **UI/UX Design:**
  Developed high-fidelity designs using tools like Figma/Sketch, ensuring a clean, modern look that promotes ease of use.
- **Prototype Development:**
  **Started** Building a interactive prototype to gather early problems and iterate on design elements.

### 2.3.Frontend Development

- **Template Creation:**
  Developed a responsive HTML and EJS templates (or equivalent) for consistent page rendering across devices.
- **Styling & Interactivity:**
  Utilized a CSS3 and JavaScript to implement smooth navigation, real-time data visualization, and interactive UI components.
- **Component Reusability:**
  **Then we** Developed a reusable UI modules to streamline for future updates.

## 2.4.Backend Development

- **Server & API Setup:**
  Started building a  backend server (e.g., using Node.js and Express.js) to handle business logic, routing, and secure data transactions.

- **Database & Cloud Integration:**
  **We** Designed a scalable database schema and implemented cloud synchronization with services like Firebase or AWS. Incorporate third-party integrations.

## 2.4.Testing & Quality Assurance

- **Unit and Integration Testing:**
  Perform thorough testing of individual components and their interactions to ensure functional accuracy.

- **User Acceptance Testing (UAT):**
  Conduct beta tests with a select group of users to gather actionable feedback and identify UX issues.

- **Performance & Security Testing:**
  Validate the application's scalability, responsiveness, and security measures (including authentication and data protection protocols).

## 2.5.Deployment & Maintenance

- **CI/CD Pipeline:**
  Set up continuous integration and deployment pipelines to automate testing and streamline release cycles.

- **Monitoring & Analytics:**
  Implement monitoring tools to track application performance, user interactions, and potential issues in real time.

- **Iterative Enhancements:**
  Plan for regular updates and feature enhancements based on ongoing user feedback and market trends.

# 3.Tech Stack Details

### 3.1.Frontend:

- **HTML5 & CSS3:**
  For structured, semantic markup and responsive design.
- **JavaScript:**
  To create dynamic interactions and enhance user experience.
- **EJS:**
  Depending on the project scope, use a templating engine (like EJS) for efficient UI rendering.

### 3.2.Backend:

- **Node.js:**
  A scalable JavaScript runtime for server-side development.
- **Express.js:**
  A lightweight web framework for API development and routing.
- **AI/ML Integration:**
  Python-based AI models or JavaScript libraries to power smart categorization and financial insights.

### 3.3.Database & Cloud Services:

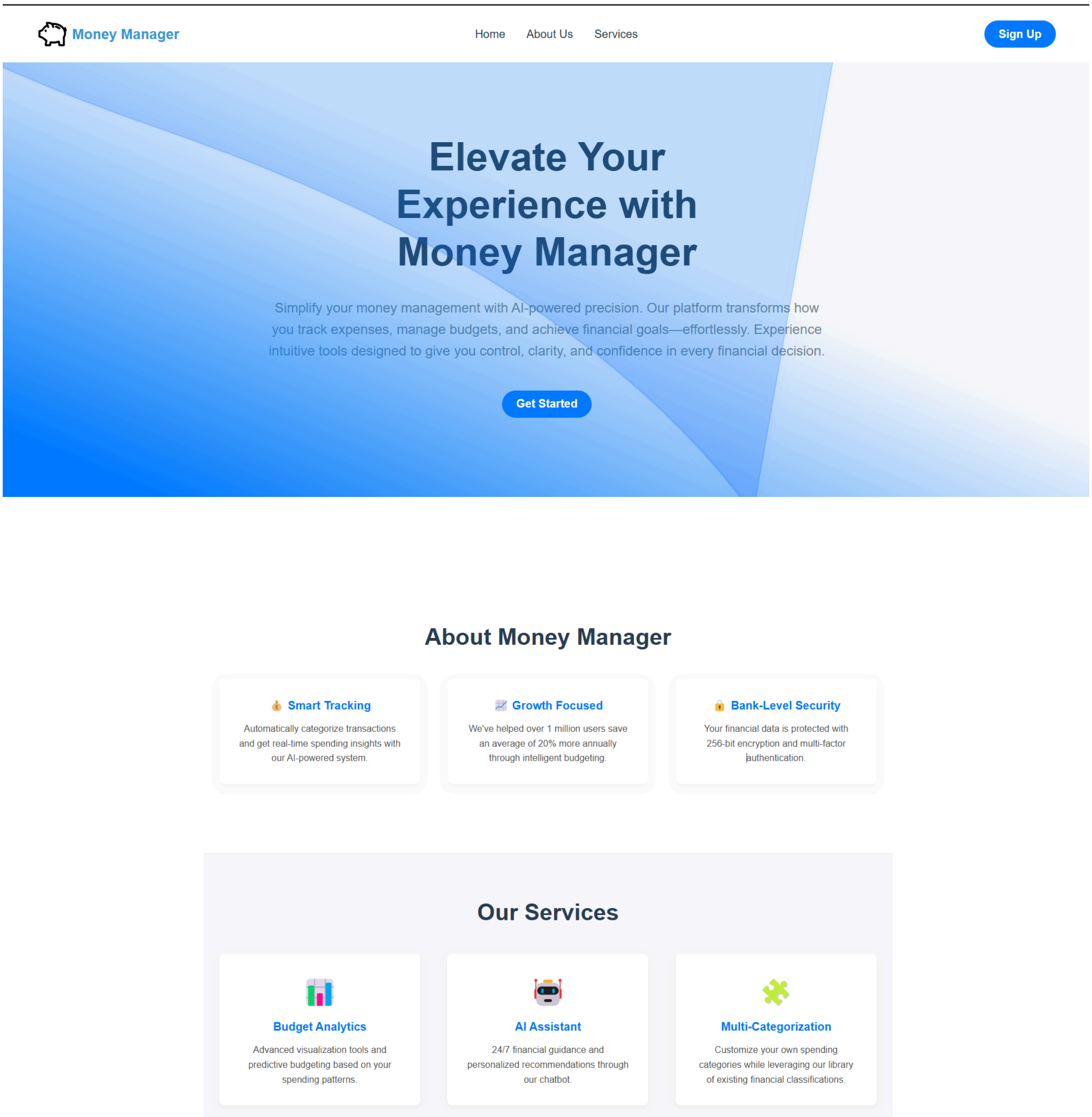
- **Firebase/AWS:**
  For real-time data synchronization, authentication, and cloud storage.
- **SQL/NoSQL Database:**
  Depending on data complexity, use a relational (MySQL/PostgreSQL) or NoSQL (MongoDB) database.

### 3.4.Additional Tools & Integrations:

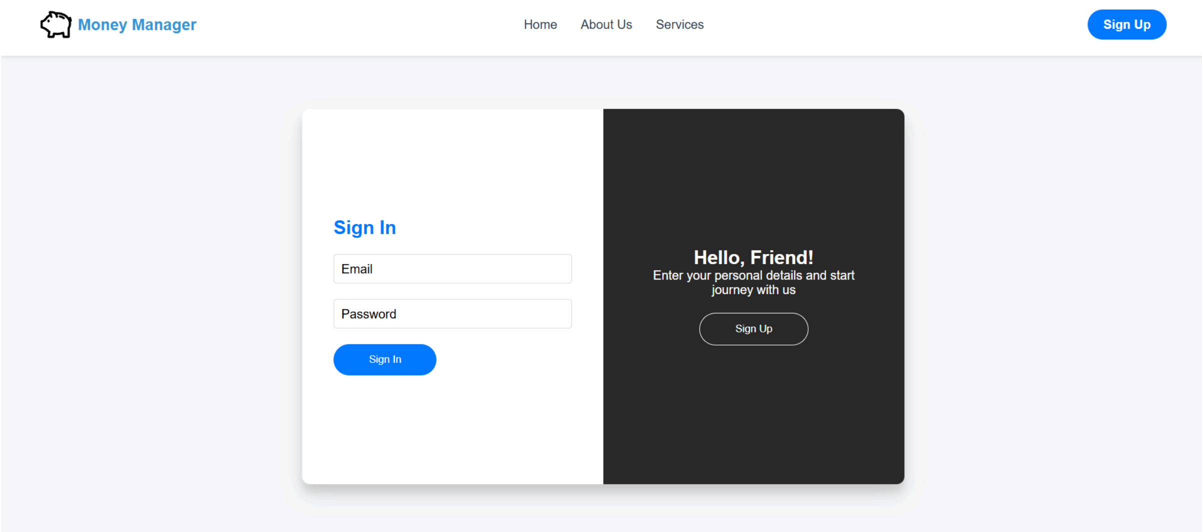
- **Cloudinary:**
  For managing and hosting image assets (e.g., scanned receipts).
- **Version Control (Git):**
  To manage the codebase and facilitate collaborative development.
- **CI/CD Tools (GitHub Actions, Jenkins):**
  For automating tests and deployments.
- **Third-Party Integrations:**
  Integration with services like Google Drive/Dropbox for data backup and export functionality.

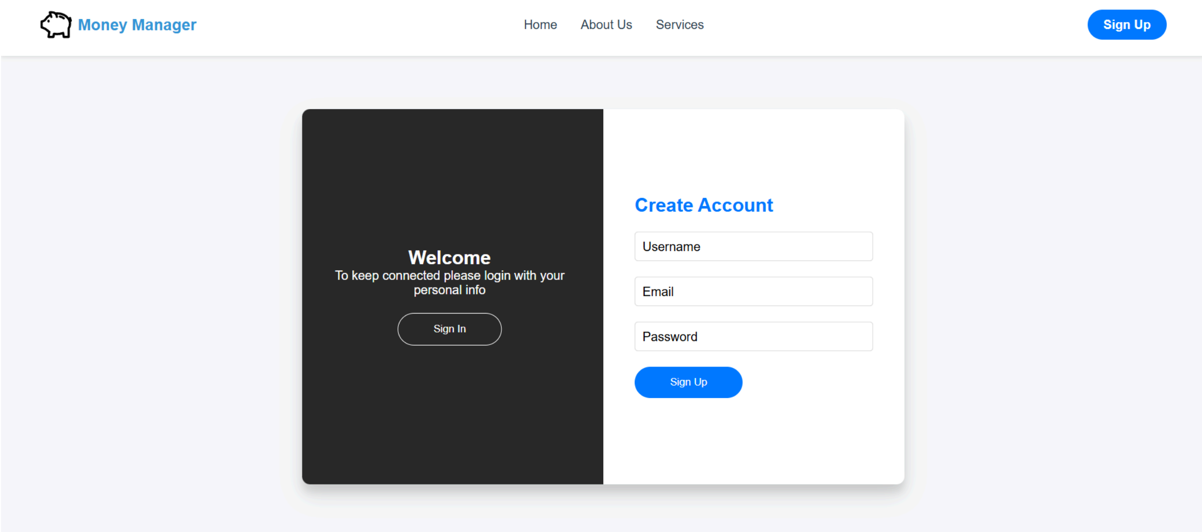
# 4.Results:

## 4.1.Landing Page:

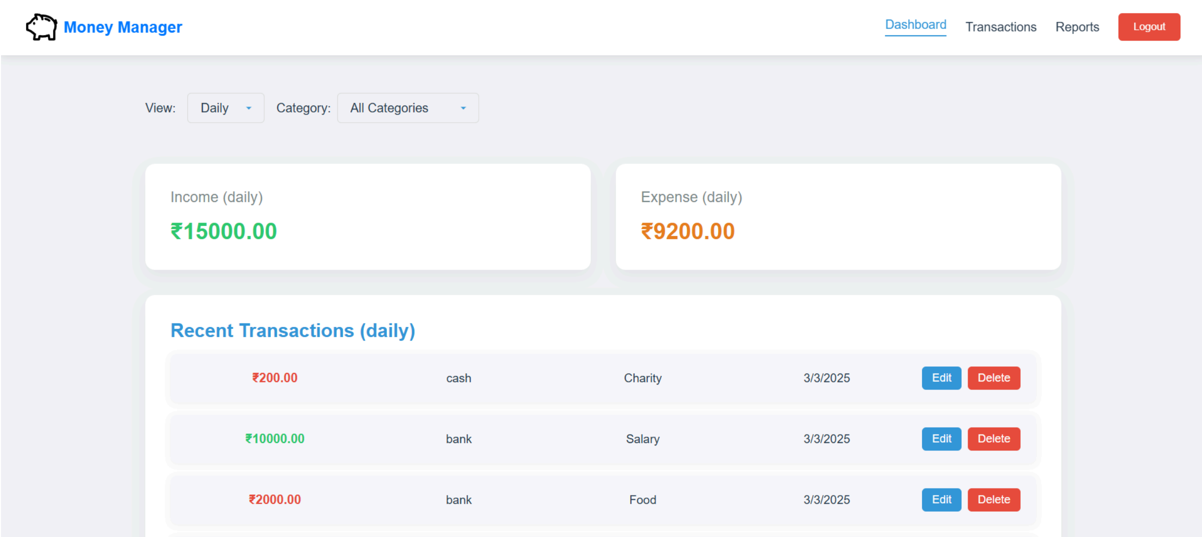


### 4.2.Authentication Page:

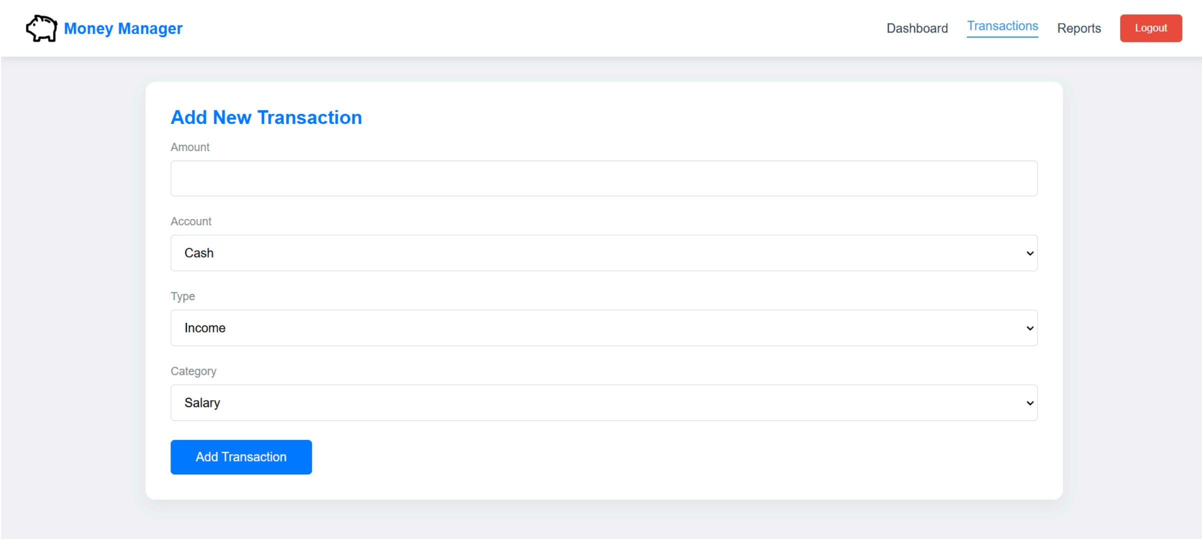


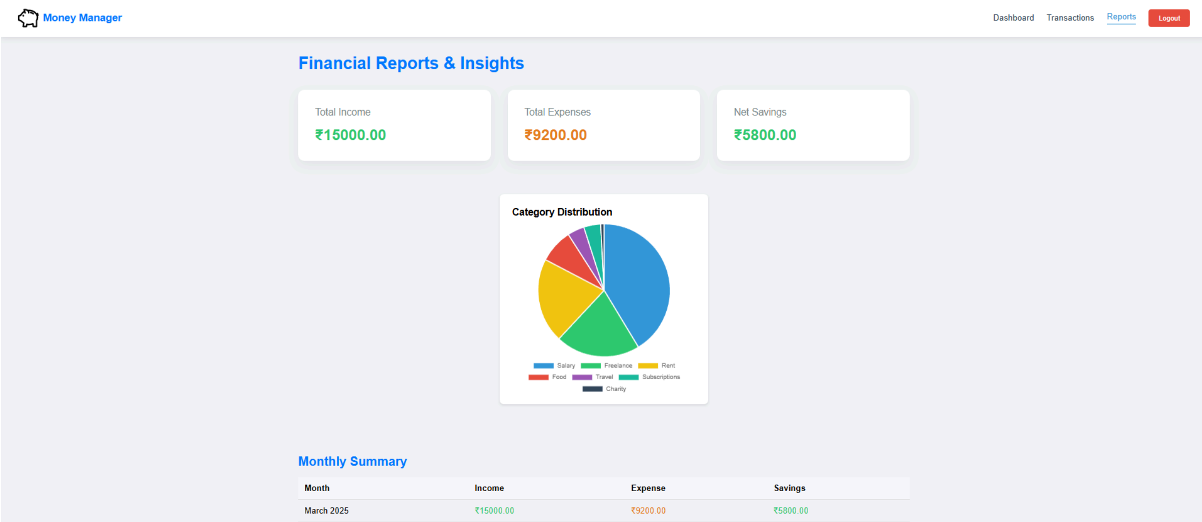
## 4.3.Dashboard Page:




## 4.4.Transaction Page



## 4.5.Report Page



## 4.6.AI Model Training Code

### For AI-powered smart categorization of expenses :

Dataset used : expenses_income_ from kaggle

```
# Step 0: Import Required Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
import pickle
import kagglehub

# Download the dataset from Kaggle using kagglehub (ensure kagglehub is configured correctly)
path = kagglehub.dataset_download("jg7fujhfydhgc/expenses-2024")
print("Path to dataset files:", path)

# Step 1: Load the Dataset
# Make sure you're using the correct CSV file; here we use 'expenses_income_summary.csv'
df = pd.read_csv('expenses_income_summary.csv')
print("First few rows of the dataset:")
print(df.head())

# Standardize column names to lower-case
df.columns = df.columns.str.lower()
print("Columns in DF:", df.columns)

# Convert 'title' and 'description' to string type, then create a combined text column
df['title'] = df['title'].fillna('').astype(str)
df['description'] = df['description'].fillna('').astype(str)
df['combined_text'] = df['title'] + ' ' + df['description']

# Drop rows missing 'category' (assume 'category' is essential)
df.dropna(subset=['category'], inplace=True)
print("DataFrame shape after dropna on category:", df.shape)

# Step 2: Prepare Input and Output Data
# Use 'combined_text' as the feature and 'category' as the label.
texts = df['combined_text'].values
categories = df['category'].values

# Encode category labels into integers
label_encoder = LabelEncoder()
```

```
# Encode category labels into integers
label_encoder = LabelEncoder()
categories_encoded = label_encoder.fit_transform(categories)
num_classes = len(label_encoder.classes_)
print("Number of categories:", num_classes)

# Step 3: Split the Data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    texts, categories_encoded, test_size=0.2, random_state=42)
print("Training samples:", len(X_train), "Test samples:", len(X_test))

# Step 4: Vectorize the Transaction Descriptions Using TF-IDF
vectorizer = TfidfVectorizer(max_features=5000, stop_words='english')
X_train_vect = vectorizer.fit_transform(X_train).toarray()
X_test_vect = vectorizer.transform(X_test).toarray()

# Convert labels to one-hot encoded vectors
y_train_cat = to_categorical(y_train, num_classes)
y_test_cat = to_categorical(y_test, num_classes)

# Step 5: Build the Neural Network Model Using Keras
input_dim = X_train_vect.shape[1]
model = Sequential([
    Dense(512, activation='relu', input_shape=(input_dim,)),
    Dense(256, activation='relu'),
    Dense(num_classes, activation='softmax')
])
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()

# Step 6: Train the Model
history = model.fit(X_train_vect, y_train_cat,
                    epochs=10,              # Increase epochs if needed
                    batch_size=32,
                    validation_data=(X_test_vect, y_test_cat))

# Step 7: Evaluate the Model
loss, accuracy = model.evaluate(X_test_vect, y_test_cat)
print("Test Accuracy:", accuracy)

# Step 8: Save the Trained Model and Preprocessing Tools
model.save('expense_classifier.h5')  # Save the Keras model

with open('vectorizer.pkl', 'wb') as f:
```

**For AI-based cash flow analysis with spending recommendations :**

Dataset used : Personal_Finance_Dataset From Kaggle

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
import pickle
import matplotlib.pyplot as plt
import seaborn as sns


# Loaded the dataset with columns: Date, Transaction Description, Category, Amount, Type
data = pd.read_csv('Personal_Finance_Dataset.csv')

# Converted the Date column to datetime and create a YearMonth column for aggregation
data['Date'] = pd.to_datetime(data['Date'])
data['YearMonth'] = data['Date'].dt.to_period('M').astype(str)

print("Dataset Shape:", data.shape)
print("Columns:", data.columns.tolist())
print("\nFirst 5 rows:")
print(data.head())

# ------------------------------
# 2. Aggregated Data by Month
# ------------------------------
# For each month, we calculated:
#   - total_income: Sum of Amount for rows where Type == 'Income'
#   - total_expense: Sum of Amount for rows where Type == 'Expense'
#   - savings: total_income - total_expense
#   - savings_percentage: (savings / total_income) * 100 (if income > 0, else 0)
#   - recommendation: based on savings_percentage thresholds

def aggregate_month(group):
    total_income = group.loc[group['Type'] == 'Income', 'Amount'].sum()
    total_expense = group.loc[group['Type'] == 'Expense', 'Amount'].sum()
    savings = total_income - total_expense
    savings_percentage = (savings / total_income * 100) if total_income > 0 else 0
    # Define recommendation based on savings percentage thresholds
    if savings_percentage < 10:
```

```python
def aggregate_month(group):
    total_income = group.loc[group['Type'] == 'Income', 'Amount'].sum()
    total_expense = group.loc[group['Type'] == 'Expense', 'Amount'].sum()
    savings = total_income - total_expense
    savings_percentage = (savings / total_income * 100) if total_income > 0 else 0
    # Define recommendation based on savings percentage thresholds
    if savings_percentage < 10:
        recommendation = "Increase Savings"
    elif savings_percentage <= 20:
        recommendation = "Maintain Spending"
    else:
        recommendation = "Invest More"
    return pd.Series({
        'total_income': total_income,
        'total_expense': total_expense,
        'savings': savings,
        'savings_percentage': savings_percentage,
        'recommendation': recommendation
    })

# Grouped by YearMonth and aggregate
monthly_data = data.groupby('YearMonth').apply(aggregate_month).reset_index()

print("\nMonthly Aggregated Data:")
print(monthly_data.head())

# Optional: Save monthly data to CSV for inspection
monthly_data.to_csv('monthly_cash_flow.csv', index=False)

# -------------------------------
# 3. Exploratory Data Analysis (Optional)
# -------------------------------
# Plot correlation heatmap for numerical features in the monthly data
numerical_cols = ['total_income', 'total_expense', 'savings_percentage']
plt.figure(figsize=(8, 6))
sns.heatmap(monthly_data[numerical_cols].corr(), annot=True, cmap="coolwarm")
plt.title("Monthly Data Correlation Heatmap")
plt.savefig("monthly_correlation_heatmap.png")
plt.close()
print("Correlation heatmap saved as 'monthly_correlation_heatmap.png'.")

# -------------------------------
```

```python
# ------------------------------
# 4. Prepared Data for Modeling
# ------------------------------
# We will use total_income, total_expense, and savings_percentage as features,
# and the generated recommendation as the target.
features = ['total_income', 'total_expense', 'savings_percentage']
target = 'recommendation'

# Dropped any rows with missing values (if any)
monthly_data.dropna(inplace=True)

X = monthly_data[features]
y = monthly_data[target]

# Normalized numerical features using StandardScaler
scaler = StandardScaler()
X[features] = scaler.fit_transform(X[features])

# ------------------------------
# 5. Split, Train, and Evaluate the Model
# ------------------------------
# Split the aggregated data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a RandomForestClassifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)

# Predicted on the test set and evaluate
y_pred = clf.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print("\nTest Accuracy:", acc)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# ------------------------------
# 6. Saved the Trained Model for Backend Integration
# ------------------------------
# Saved the model along with the scaler and feature list for later use in your backend
model_data = {
    'model': clf,
```

# Github repository