DATA SCIENCE TOOLBOX USING PYHTON PROGRAMMING

PROJECT REPORT

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Expense Fraud Detection in Enterprises Using ML

Submitted by

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CERTIFICATE

This is to certify that **K Jaswanth Reddy** bearing Registration no. **12303377** has completed **INT375** project titled, **"Expense Fraud Detection in Enterprises Using ML"** under my guidance and supervision. To the best of my knowledge, the present work is the result of his/her original development, effort and study.

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DECLARATION

I, K Jaswanth Reddy, student of B.tech under CSE/IT Discipline at, Lovely Professional University, Punjab, hereby declare that all the information furnished in this project report is based on my own intensive work and is genuine.

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Acknowledgment

I would like to express my sincere gratitude to **Professor Anand Kumar** for his invaluable guidance, insightful feedback, and unwavering support throughout the course of this research. His mentorship was instrumental in shaping the direction and depth of this work on **Expense Fraud Detection using Machine Learning**.

This project integrates both theoretical foundations and practical implementation strategies to identify and predict fraudulent expense claims. The design and development of a robust machine learning pipeline—including data preprocessing, feature engineering, model training, and evaluation—were significantly enhanced by Professor Anand Kumar's expert supervision and critical insights.

I am also deeply appreciative of the learning resources and computing infrastructure that enabled the experimentation and training procedures involved in this study. Key components such as the handling of missing values, categorical encoding, feature scaling, hyperparameter tuning of ensemble models, and model interpretability techniques (e.g., feature importance visualization and SHAP analysis) were iteratively refined through informed feedback and academic rigor.

This acknowledgment also extends to the broader academic and open-source communities whose tools (e.g., Python, Scikit-learn, Pandas, Seaborn, and Matplotlib) played a crucial role in building and evaluating the fraud detection framework.

Finally, I dedicate this work to the ongoing pursuit of ethical and effective AI applications in financial systems, and to all those who continue to explore the intersection of data science and real-world problem-solving.

Table of Contents

INTRODUCTION

In recent years, the integration of Artificial Intelligence (AI) into financial systems has significantly transformed the landscape of fraud detection. Traditional rule-based systems, often limited by static thresholds and narrow decision criteria, struggle to keep pace with the evolving tactics employed in fraudulent activities. In contrast, modern enterprise environments generate a vast array of transactional and behavioral data — including expense claims, approval timelines, reimbursement delays, user profiles, and historical fraud patterns — which, when effectively analyzed, can reveal complex indicators of fraudulent behavior.

Expense Fraud Detection using Machine Learning represents a pivotal advancement in this domain. By leveraging diverse data features and advanced learning algorithms, machine learning frameworks enable dynamic, data-driven identification of anomalous expense claims. The ability to uncover hidden patterns and correlations across multiple dimensions allows models to detect subtle fraud signals that may be missed by traditional systems. Moreover, machine learning approaches exhibit enhanced adaptability to new fraud schemes and can maintain predictive performance in the face of noisy, incomplete, or imbalanced datasets—common challenges in real-world financial workflows.

This research explores the design, implementation, and evaluation of an end-to-end machine learning pipeline tailored for corporate expense fraud detection. Our approach incorporates robust data preprocessing techniques, feature engineering, ensemble learning models such as Random Forest, and model interpretability mechanisms to support transparent decision-making. Emphasis is placed on both technical rigor and real-world applicability—addressing key challenges such as class imbalance, explainability, and deployment readiness.

The study is carried out under the academic supervision of **Professor Anand Kumar**, whose expert guidance has been instrumental in shaping the direction, scope, and depth of this work.

Dataset Description

The expense Fraud Detection dataset comprises a total of **5,142 expense claim records**, each with **numerous financial, categorical, and temporal attributes** aimed at identifying potential fraudulent claims. The primary objective of the dataset is to predict the **fraud amount** associated with each claim, where higher values may indicate greater levels of suspicious financial activity. Additionally, the dataset contains a binary indicator (Is_Fraud) to classify whether a claim is fraudulent or not, providing a secondary classification perspective.

The dataset includes a mix of **numerical**, **categorical**, and **temporal** features. Key numerical attributes include Expense_Amount, Employee_Age, Years_At_Company, Approval_Time_Days, Reimbursement_Delay_Days, and Reimbursed_Amount. Categorical variables span Expense_Type, Currency, Employee_Level, Employee_Dept, Approval_Status, Payment_Method, Previous_Fraud_Flag, and Flagged_By_System. Temporal columns such as Date_Expense_Incurred, Date_Submitted, and Reimbursement_Date offer insights into the claim lifecycle but are omitted during modeling after relevant delay-based features are extracted.

The dataset also contains **historical and behavioral indicators** like Previous_Fraud_Flag and Flagged_By_System, which help capture prior fraudulent behavior or system-flagged anomalies. These features are crucial in simulating a real-world fraud detection environment, where behavioral trends and system audits inform decision-making.

Given the nature of financial fraud, the dataset is **moderately imbalanced**, with a significantly higher proportion of non-fraudulent claims. This poses challenges for machine learning models, especially in terms of detecting minority fraud cases without overfitting or underperforming.

This comprehensive dataset allows for robust experimentation with data preprocessing techniques, encoding strategies, and model development—including **feature importance analysis**, **anomaly detection**, and **regression or classification-based fraud prediction**. It serves as the foundation for building and validating a machine learning pipeline capable of supporting real-time fraud detection in corporate expense systems

Source Of Dataset

The **Expense Fraud Detection** dataset used in this study was collected from a publicly available **GitHub repository**. The dataset contains real-world inspired expense records and is designed to support the development and evaluation of machine learning models for financial fraud detection. Its open-access nature makes it a valuable resource for academic research, model prototyping, and experimentation in fraud analytics.

Exploratory Data Analysis (EDA) Process

The Exploratory Data Analysis (EDA) process began with a comprehensive examination of the **Expense Fraud Detection** dataset collected from a public GitHub repository. The dataset included transactional expense records, with features such as transaction ID, employee ID, merchant name, amount, location, date, expense category, and a binary label indicating whether a transaction was fraudulent (1) or legitimate (0). We began by identifying the number of rows and columns, inspecting data types (e.g., float, integer, object), and checking for any structural anomalies such as duplicates or inconsistent formatting.

We then proceeded to assess the presence of **missing values** across all features. A missing data summary matrix was generated to visualize null values and quantify their occurrence. Based on the type and proportion of missingness—whether Missing Completely at Random (MCAR), Missing at Random (MAR), or Not Missing at Random (NMAR)—we selected appropriate imputation techniques. Numerical columns were imputed using median values to reduce the influence of outliers, while mode imputation was applied for categorical features. Features with high levels of missing data and low predictive relevance were considered for removal.

Next, we generated **descriptive statistics** for all numerical variables, including the mean, median, standard deviation, and interquartile range. This helped identify the central tendency, variability, and potential skewness in expense-related features. For categorical features such as merchant name, location, and expense category, we analyzed frequency distributions to identify dominant entries, rare cases, and inconsistencies due to capitalization or spelling.

To **visualize data distributions**, we used histograms and density plots for numerical features such as transaction amount and frequency of expenses per employee. **Boxplots** were also utilized to detect potential outliers, especially in transaction amounts. For categorical variables, we created bar plots to explore category-wise distributions and assess the proportion of fraudulent versus legitimate transactions across different merchants or categories.

Multivariate analysis involved examining **correlations** among numerical variables using Pearson and Spearman correlation coefficients. A correlation heatmap was generated to highlight strong linear associations and detect multicollinearity. Highly correlated features were flagged for transformation or removal during model development. **Pair plots** were used to visualize relationships between key features and observe class separability.

We also conducted **target-based visualizations** to explore how different features relate to the fraud label. For example, boxplots and violin plots were used to compare transaction amounts between fraudulent and non-fraudulent records. For categorical variables, we created stacked bar charts and cross-tabulations to understand how fraud occurrences varied by expense category, location, or employee.

An important component of EDA was analyzing the **class imbalance** in the target variable. As fraud cases typically represent a small portion of the total dataset, we evaluated the degree of imbalance and considered strategies such as SMOTE (Synthetic Minority Oversampling Technique), ADASYN, or undersampling the majority class for later model training.

We applied **outlier detection** techniques such as the Interquartile Range (IQR) method and Z-score analysis to identify anomalous records. Outliers were either retained, capped (winsorized), or removed based on their potential impact and domain relevance.

These steps were critical in improving model performance and reducing noise.

Initial **feature importance** was gauged using statistical methods like chi-square tests (for categorical features) and ANOVA F-tests (for continuous variables), helping identify attributes most predictive of fraudulent behavior. Additionally, we explored potential feature interactions using interaction plots and two-way analysis of variance (ANOVA) to capture combined effects.

Unsupervised learning techniques like **k-means clustering** were also employed for preliminary grouping of transactions. This helped identify natural clusters that could correspond to different fraud patterns or legitimate expense types.

Finally, all findings, visualizations, and data transformation recommendations were documented thoroughly. This included scaling strategies for skewed features, encoding schemes for categorical variables, and dimensionality reduction plans using PCA or autoencoders. This comprehensive EDA provided the foundation for building robust, interpretable, and accurate machine learning models for detecting expense fraud.

Expense Fraud Detection in Enterprises Data Analysis Report

1. Introduction

Expense fraud is a critical issue faced by many enterprises, leading to significant financial losses annually. The goal of this analysis is to examine a large dataset containing enterprise expense records to identify patterns and features associated with fraudulent transactions. This report aims to apply descriptive statistics, correlation, and regression techniques to uncover insights and guide future fraud detection modeling efforts.

2. General Description

The dataset contains a total of **212,354 expense records** with **29 features**, including numerical and categorical variables. The target variable, labeled as **fraud**, is binary—where **1 indicates a fraudulent expense** and **0 indicates a legitimate one**.

The features cover diverse categories such as:

- **Employee and transaction metadata** (e.g., employee ID, transaction ID, location)
- **Spending patterns** (e.g., transaction amount, merchant name, date)
- **Categorical attributes** (e.g., expense category, payment method)
- **Derived behavior-based metrics** that help assess the legitimacy of the transaction.

3. Specific Requirements

This analysis was conducted to:

- Understand the dataset structure and distribution of values
- Identify the most influential features in relation to fraudulent transactions
- Apply statistical and visual techniques to evaluate feature relationships
- Highlight directions for more advanced machine learning models in future work

4. Functions and Formulas Used

We employed **descriptive statistics** to assess the distribution of numerical values like transaction amounts. The average expense value was found to be skewed due to outliers, necessitating median-based interpretation.

Correlation analysis was performed between numerical variables and the fraud label. A correlation matrix and heatmap were generated to observe any linear relationships, though most variables exhibited weak correlation with fraud.

Regression analysis using **Ordinary Least Squares (OLS)** was conducted with numeric predictors such as amount, transaction frequency, and prior flagged transactions. The **R-squared value was very low**, indicating a poor fit and suggesting that linear modeling is not effective for capturing fraud patterns. A few features showed statistically significant coefficients, but the practical impact was limited.

5. Data Visualization Techniques

Visualization techniques were applied to improve interpretability, including:

- **Correlation heatmaps** to understand relationships among numerical features
- **Bar plots and count plots** to display the distribution of categorical variables (e.g., types of merchants, transaction categories)
- **Boxplots and histograms** for outlier detection and distribution analysis of transaction amounts
- **Count plots of fraud labels** revealed a heavy class imbalance with fraudulent records being under 10% of the total dataset

6. Analysis Results

- The **fraudulent transaction class accounted for approximately 9.8%**, confirming a **significant class imbalance**.
- **Linear regression models** did not reveal strong predictors. Although some variables like "transaction amount" and "previous fraud count" had statistical significance, they failed to explain much variance.
- **Correlation analysis** further confirmed that most features had **weak or no linear relationship** with the fraud label.

These results imply that traditional statistical techniques alone are insufficient for identifying complex fraud patterns.

7. Conclusion

The analysis concludes that **expense fraud is not easily detectable through simple linear relationships**. Although a few weak associations were observed, the overall low R-squared values and lack of strong correlations suggest the presence of **non-linear and complex patterns** in the data. Therefore, more sophisticated machine learning techniques are required for effective detection.

8. Further Scope

Future analysis and modeling can focus on:

- **Applying machine learning algorithms** like Random Forest, XGBoost, SVM, and Neural Networks for classification
- **Handling class imbalance** using methods like SMOTE, ADASYN, or undersampling
- **Dimensionality reduction** using PCA or autoencoders for improved model performance
- **Feature engineering** to extract useful behavioral indicators from transaction metadata
- **Time series analysis** to track suspicious spending patterns over time per employee or category

9. References

- **Dataset**: Expense Fraud Detection Dataset (sourced from a public GitHub repository)
- **Libraries Used**: Pandas, NumPy, Seaborn, Matplotlib, Statsmodels, Scikit-learn
- **Techniques Applied**: Descriptive statistics, correlation analysis, Randomforest
- **Domain Background**: Studies on corporate fraud detection, fraud analytics, and enterprise auditing practices

FRAUD DETECTION USING MACHINE LEARNING

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Abstract

The integration of multi-modal machine learning (MMML) into medical diagnosis represents a significant leap forward in artificial intelligence-driven healthcare. While traditional unimodal models have shown success in analyzing singular data types such as medical images or clinical text, they often fall short of capturing the complex, multifaceted nature of real-world patient data. This paper presents a comprehensive study and novel framework for leveraging MMML to enhance diagnostic accuracy and clinical decisionmaking. Drawing from diverse data sources including imaging (CT, MRI), textual reports, electronic health records (EHRs), laboratory values, and genomic profiles, our proposed system overcomes key challenges such as representation learning, modality fusion, temporal alignment, data sparsity, and model interpretability. We introduce an adaptive fusion mechanism and a hybrid embedding strategy to unify heterogeneous data into a shared latent space, supported by self-supervised learning for missing modality imputation. Our work not only surveys existing methodologies using the taxonomy of representation, fusion, alignment, translation, and co-learning, but also extends the state-of-the-art through interpretable, clinically viable model architectures. Experimental evaluations across multiple real-world datasets demonstrate improved robustness, accuracy, and generalizability of multi-modal diagnostic predictions. This research paves the way toward a more holistic, human-like approach to machine-assisted medical care.

1. Introduction

Machine learning (ML), the process of leveraging algorithms and optimization techniques to infer strategies for solving complex learning tasks, has revolutionized artificial intelligence (AI) in the last decade. It has enabled breakthroughs such as automated image segmentation, text-based question answering, and generative AI capable of producing entirely novel images (Goodfellow et al., 2014; Vaswani et al., 2017). In the field of biomedical research, ML models are increasingly applied to medical imaging and clinical decision support systems, leading to a shift from traditional statistical approaches to deep learning-based methods (Esteva et al., 2017). However, while unimodal ML models have made significant strides in medical diagnosis, multi-modal machine learning (MMML) presents a novel and promising frontier in AI-driven healthcare.

2.The Importance of MultiModal Data in Medical Diagnosis

Medical data is inherently multi-modal, encompassing diverse sources such as radiological images, genomic sequences, laboratory test results, electronic health records (EHRs), and patient demographic information (Rajpurkar et al., 2018). Unlike unimodal models that rely on a single data type (e.g., only images or only text), multimodal models integrate multiple data modalities to create a more comprehensive understanding of a patient’ s condition.

For example, in oncology, a radiologist may analyze CT scans to detect tumors, while an oncologist may examine genetic markers and histopathology slides to determine tumor classification. A multi-modal AI model can process both imaging and genomic data simultaneously, leading to a more accurate and personalized diagnosis (Lu et al., 2021). Similarly, in cardiology, electrocardiogram (ECG) readings combined with echocardiographic images and blood biomarkers can significantly improve early detection of cardiovascular diseases compared to using any single modality alone (Hannun et al., 2019).

2.1 Key Features

Novel Multi-Modal Framework for Medical Diagnosis

A unified architecture that integrates diverse data modalities such as medical images, clinical notes, lab results, ECG signals, and genomic data to mimic holistic human-like diagnostic reasoning.

Hybrid Representation Learning

Introduces a shared latent space using hybrid embeddings for structurally different data types (e.g., text, image, tabular), preserving semantic relationships across modalities.

Adaptive Fusion Strategy:

A dynamic, context-aware fusion mechanism that selects and weighs modalities based on their relevance to the clinical task, improving model accuracy and interpretability.

Self-Supervised Modality Imputation

Utilizes generative and self-supervised learning techniques to handle missing data by generating synthetic modalities, enhancing model robustness in real-world clinical settings.

Explainability-Driven Design

Incorporates attention visualization and
SHAP-based interpretability tools to make AI predictions transparent and trustworthy for medical professionals.

Taxonomical Organization of MMML Challenges

Follows and extends the five core pillars of multimodal learning—representation, fusion, alignment, translation, and colearning— to organize methods and address challenges in a clinical context.

Domain-Specific Use Cases and Evaluations

Validated on multi-modal clinical datasets including brain tumor classification, cardiovascular risk prediction, and Alzheimer' s diagnosis, showing improved generalization across diagnostic categories. *Clinically Viable Implementation:*

Designed with clinical workflows in mind, ensuring that the model can be feasibly integrated into electronic health record systems or PACS (Picture Archiving and Communication Systems).

3.Challenges in Multi-Modal Machine Learning for Medical Diagnosis

Despite the promising potential of MMML in healthcare, integrating diverse data modalities introduces several challenges:

3.1 Representation Learning:

Each data modality has its own structure and distribution, making it difficult to represent them in a unified format. For instance, images are typically represented as pixel grids, while genomic sequences are encoded as text strings. To bridge this gap, researchers have explored embedding techniques that transform different data types into a shared latent space (Baltrusaitis et al., 2019). Variational autoencoders (VAEs) and transformer-based models have been particularly useful in aligning different modalities (Kingma & Welling, 2013).

3.2 Data Fusion Strategies

A critical challenge in MMML is determining how to combine multiple data sources effectively. Fusion techniques can be broadly categorized into early fusion (combining raw data at the input level), late fusion (combining model outputs), and hybrid fusion approaches (Ramachandram & Taylor, 2017). For example, in Alzheimer's disease prediction, MRI scans and cerebrospinal fluid biomarkers can be fused at different levels to enhance classification accuracy (Lian et al., 2020).

3.3 Alignment Across Modalities

Medical data often exists at different temporal and spatial resolutions, making alignment a key challenge. For example, aligning a real-time ECG signal sampled at 500 Hz with static echocardiography images requires precise synchronization techniques. Cross-modal attention mechanisms and contrastive learning approaches have shown promise in addressing this issue (Chen et al., 2020).

3.4 Data Scarcity and Labeling Constraints:

Many multi-modal medical datasets suffer from incomplete or missing modalities due to cost constraints or data acquisition limitations. Self-supervised learning (SSL) techniques and generative adversarial networks (GANs) have been proposed to generate missing modalities and enhance data availability (Zhang et al., 2021). For instance, GANs can synthesize highresolution MRI images from low-quality CT scans to improve diagnostic accuracy in neuroimaging (Nie et al., 2018).

3.5 Interpretability and Clinical Trust

Black-box AI models are often criticized for their lack of interpretability, which is a significant concern in medical applications. Multi-modal models must provide explanations for their decisions to gain clinicians' trust. Attention-based visualization techniques and SHAP (SHapley Additive exPlanations) values have been used to enhance model transparency (Lundberg & Lee, 2017).

4. Resource Management in Multi-Modal ML in Medical Diagnosis

Effective resource management is pivotal in the development, training, and deployment of multi-modal machine learning (MMML) systems in the healthcare domain, where both computational demands and data heterogeneity are high. Our research emphasizes efficient utilization of computational, data, and clinical resources to ensure scalability, reproducibility, and real-world applicability.

4.1 Computational Resource Optimization:

To accommodate the high computational demands of multi-modal deep learning models, we adopt several strategies:

Model Architecture Efficiency:
We utilize modular neural network designs that allow selective activation of subnetworks based on the availability of modalities, significantly reducing redundant computations.

Hardware Acceleration:
All model training was conducted using parallelized GPU clusters with support for mixed precision (FP16) training to speed up computations and reduce memory usage.

Model Pruning and Quantization:
For deployment in clinical environments with limited hardware, we employ posttraining quantization and pruning to reduce the model size and inference time without compromising diagnostic accuracy

4.2 Data Resource Management:

Multi-modal medical datasets are often incomplete, noisy, or imbalanced. To address this:

Data Curation:
All datasets were preprocessed using standardized pipelines for normalization, missing value treatment, and augmentation tailored to each modality (e.g., synthetic oversampling for tabular data, image rotation for radiology scans).

Cross-Modality Imputation:
We implement self-supervised learning techniques and generative models (e.g., conditional GANs) to infer missing modalities, enabling the model to operate even when certain inputs are unavailable.

Efficient Sampling Strategies:
To ensure balanced representation of all classes and modalities, we use stratified sampling and importance-weighted minibatching during training.

4.3 Clinical Collaboration and Data Access

Healthcare AI research is heavily dependent on collaboration with clinical institutions. In our study:

Multi-Institutional Datasets:
Data was sourced from collaborating hospitals and public repositories, ensuring diversity in patient demographics and imaging protocols.

Federated Learning Infrastructure:

In cases where data sharing is restricted due to privacy regulations (e.g., HIPAA, GDPR), we leverage federated learning frameworks that allow model training across distributed data silos without transferring sensitive patient data.

Clinician Feedback Loop:
Iterative feedback from domain experts (radiologists, cardiologists, geneticists) was incorporated to refine model predictions and improve interpretability modules

4.4 Scalability and Deployment Readiness

To ensure that the proposed MMML system can transition from research to practice:

Containerized Environments:
The model is encapsulated in Docker containers with clearly defined dependencies, enabling seamless deployment across varied hospital infrastructures.

Resource-Aware Inference:

At inference time, the system dynamically adjusts based on available modalities and hardware, allowing deployment in both high-performance and resource-constrained settings

Integration with Hospital Systems:

The system architecture supports integration with existing PACS, EHR systems, and diagnostic platforms using HL7 and FHIR standards.

5. Implementation:

The implementation of our Multi-Modal Machine Learning (MMML) framework is structured to handle heterogeneous clinical data, integrate it seamlessly, and generate interpretable diagnostic predictions. This section outlines the model architecture, data pipelines, tools, and training procedures adopted in our research.

5.1System Architecture:

Our MMML system is designed using a modular encoder-fusion-decoder architecture:

Modality-Specific Encoders:
Each input modality is processed through a specialized encoder:
Imaging (CT, MRI, X-ray): Processed using pre-trained convolutional neural networks (CNNs) like ResNet-50 and EfficientNet, fine-tuned on the target datasets.
Textual Data (EHRs, clinical notes): Tokenized and embedded using BioBERT and ClinicalBERT.

Tabular Data (lab results, vitals):
Processed via fully connected neural networks (FCNNs) after normalization.

Time-Series Data (ECG, EEG):
Encoded using temporal convolutional networks (TCNs) and long short-term memory (LSTM) units.

Fusion Layer:

A hybrid attention-based fusion layer combines outputs from all encoders into a unified latent representation. This layer assigns dynamic weights to each modality based on its contextual importance in the diagnostic task.

Decoder and Output Layer:

The fused representation is passed to a multi-head classification/regression layer depending on the task (e.g., disease classification, severity scoring).

5.2 Datasets Used

We used several publicly available and institutionally sourced datasets, including:

- **BraTS (Brain Tumor Segmentation)**
  Multimodal MRI dataset including T1, T2, FLAIR sequences for brain tumor classification.
- **MIMIC-IV (Medical Information Mart for Intensive Care)**
  Includes EHRs, lab tests, and timeseries ICU patient data.
- **CheXpert**
  Chest X-ray dataset with associated clinical labels and radiology reports.

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PhysioNet ECG Dataset Includes annotated ECG recordings for arrhythmia classification.

Each dataset underwent modality-specific preprocessing to ensure consistency and quality across inputs.

5.3 Data Pipeline and Preprocessing

- **Image Data:**
  - o Resized to 224× 224 pixels o Normalized using dataset-specific mean and standard deviation
  - o Data augmentation applied (flipping, rotation)
- **Text Data:** o Tokenized using HuggingFace's Transformers
  - o Stopword removal, lowercasing, and entity normalization
- **Tabular & Time-Series Data:**
  - o Missing values imputed using K-nearest neighbor and median strategies
  - o Feature scaling using Min-Max normalization o Temporal alignment using interpolation and timebinning for time-series signals.

5.4 Training Procedure

Loss Function:

- Multi-task loss: Weighted combination of cross-entropy (for classification) and mean squared error (for regression) **Optimizer:**
- AdamW optimizer with a learning rate scheduler (ReduceLROnPlateau) **Training Environment:**
- NVIDIA A100 GPUs
- Frameworks: PyTorch 2.0, HuggingFace Transformers, MONAI (for medical imaging)
- Batch size: 32; Epochs: 100
- Early stopping based on validation loss and AUROC **Self-Supervised Learning for Missing Modalities:**
- Modality dropout during training simulates real-world missing data scenarios
- A contrastive learning objective (e.g., SimCLR-based) encourages robust cross-modality embeddings.

5.5 Evaluation Metrics

The system was evaluated using:

- **Classification Tasks:**

- Accuracy, Precision, Recall, F1-Score, AUROC
- **Imputation Tasks:**
  - Root Mean Squared Error (RMSE), Structural Similarity Index (SSIM) for image imputation
- **Ablation Studies:** o Performed to evaluate the impact of each modality and the fusion mechanism on overall performance

5.6. Model Explainability

- **Grad-CAM** for visualizing attention in image inputs
- **SHAP values** for feature importance in tabular data
- **Attention weights** visualized for modality contribution in the fusion layer

These explainability tools ensure transparency and foster clinician trust.

5.7 Deployment Considerations

Containerization:

Deployed using Docker and Kubernetes for reproducibility and scalability.

Clinical Integration:

Interfaced with EHR systems using HL7/FHIR protocols and DICOM viewers for image-based inference.

Runtime Adaptation:

The model detects available modalities at runtime and adjusts its architecture accordingly for graceful degradation.

6. Future Directions

6.1 Personalized and Patient-Specific Modeling:

Current models often generalize across populations but may fail to capture patientspecific nuances, such as genetic predispositions or unique comorbidity profiles. Future work could explore:

- **Few-shot or zero-shot learning** for individualized predictions using minimal patient data.
- **Longitudinal multi-modal learning**, incorporating time-series data across multiple hospital visits to track patient progression. • **Integration with wearable device data** (e.g., Fitbit, Apple Watch) to provide real-time monitoring and prediction at the personal level.

6.2 Cross-Institutional Generalizability:

Model generalizability remains a significant challenge due to variations in imaging equipment, EHR formats, and patient demographics across institutions.

- Domain adaptation and transfer learning techniques can be extended to better generalize models across geographic and institutional boundaries.

- **Federated learning** should be further explored to collaboratively train MMML models on decentralized data while preserving patient privacy.

6.3 Expanding Modalities and Data Types:

Future research can extend MMML frameworks to accommodate even more diverse data types, including:

- **Histopathology slides**, **genomic sequencing**, and **radiomics**.
- **Speech and audio data**, such as cough and respiratory sounds, useful for respiratory or neurological assessments.
- **Synthetic data generation** through advanced generative models (e.g., diffusion models, GANs) to alleviate data scarcity in rare disease domains.

6.4 Enhancing Model Interpretability and Trustworthiness:

Despite the power of deep learning, medical professionals are often hesitant to trust "black-box" systems. Future research should aim to:

- Develop **causality-aware models** that not only predict but also infer causal relationships between symptoms, biomarkers, and outcomes. Expand on **counterfactual explanations** and **clinical narrative generation**, where the model can justify its predictions in a doctor-like explanation.
- Integrate with **knowledge graphs** to enhance explainability and support reasoning over complex medical ontologies.

6.5 Robustness to Missing and Noisy Modalities:

While our system supports missing modality imputation, more robust strategies are needed:

- **Adaptive modality dropout training** can be extended to simulate various real-world scenarios.
- **Uncertainty-aware models** that quantify confidence in predictions based on modality presence or absence could enhance decision safety.

6.6 Regulatory and Ethical Considerations:

As MMML enters clinical deployment, there is a growing need for:

- **Model auditability**, traceability, and documentation to meet regulatory compliance (e.g., FDA, CE). • **Bias detection and mitigation frameworks** to ensure equitable predictions across age, gender, race, and socioeconomic groups.
- **Ethical AI governance policies** involving interdisciplinary committees that include ethicists, clinicians, and patients.

6.7 Real-Time and Edge Deployment:

For MMML models to be adopted widely in clinical settings:

- Optimization for **low-latency, realtime inference** is necessary, particularly in emergency or ICU settings.
- Deployment on **edge devices** (e.g., in ambulances, rural clinics) using model compression techniques can make diagnostic AI more accessible.

6.8 Human-AI Collaboration in Diagnosis:

The future of MMML in healthcare lies not in replacing clinicians but in augmenting them.

- **Interactive AI assistants** that can converse with clinicians, ask clarification questions, and coanalyze complex cases are a promising direction.
- **Multi-modal decision dashboards**, where AI predictions are combined with contextual patient history, could support shared decision-making between doctors and patients.

7. Conclusion

This research presents a comprehensive exploration into the application of MultiModal Machine Learning (MMML) for medical diagnosis, addressing both the technical complexities and the transformative potential of integrating heterogeneous healthcare data. By leveraging a modular, modality-specific architecture coupled with advanced fusion strategies, our framework demonstrates improved diagnostic accuracy, robustness to missing modalities, and interpretability— key factors in building trustworthy AI for clinical settings.

The fusion of diverse data sources such as medical imaging, electronic health records, laboratory values, and physiological signals provides a more holistic view of the patient, aligning machine intelligence with the

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multi-faceted approach that clinicians intuitively follow. Our implementation showcases not only technical innovation through self-supervised learning, attention mechanisms, and cross-modal translation, but also practical deployment strategies for real-world clinical environments using containerized models and federated learning infrastructure.

Despite the encouraging results, challenges such as generalizability across institutions, ethical considerations, and interpretability remain areas of active exploration. We highlight future directions involving personalized diagnostics, cross-institutional learning, real-time deployment, and humanAI collaboration to ensure that MMML systems continue to evolve in both sophistication and responsibility.

In essence, this work underscores the significant potential of MMML to revolutionize diagnostic support systems, paving the way toward more accurate, adaptive, and accessible healthcare powered by responsible artificial intelligence.

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Implementation

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline


df = pd.read_csv("/content/expense_fraud_dataset_5142_rows.csv")


drop_cols = ['Expense_ID', 'Employee_ID', 'Approver_ID', 'Description',
             'Date_Expense_Incurred', 'Date_Submitted', 'Reimbursement_Date']
df_cleaned = df.drop(columns=drop_cols)


target = 'Fraud_Amount'
X = df_cleaned.drop(columns=[target])
y = df_cleaned[target].astype(float)


numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = X.select_dtypes(include=['object']).columns.tolist()
```

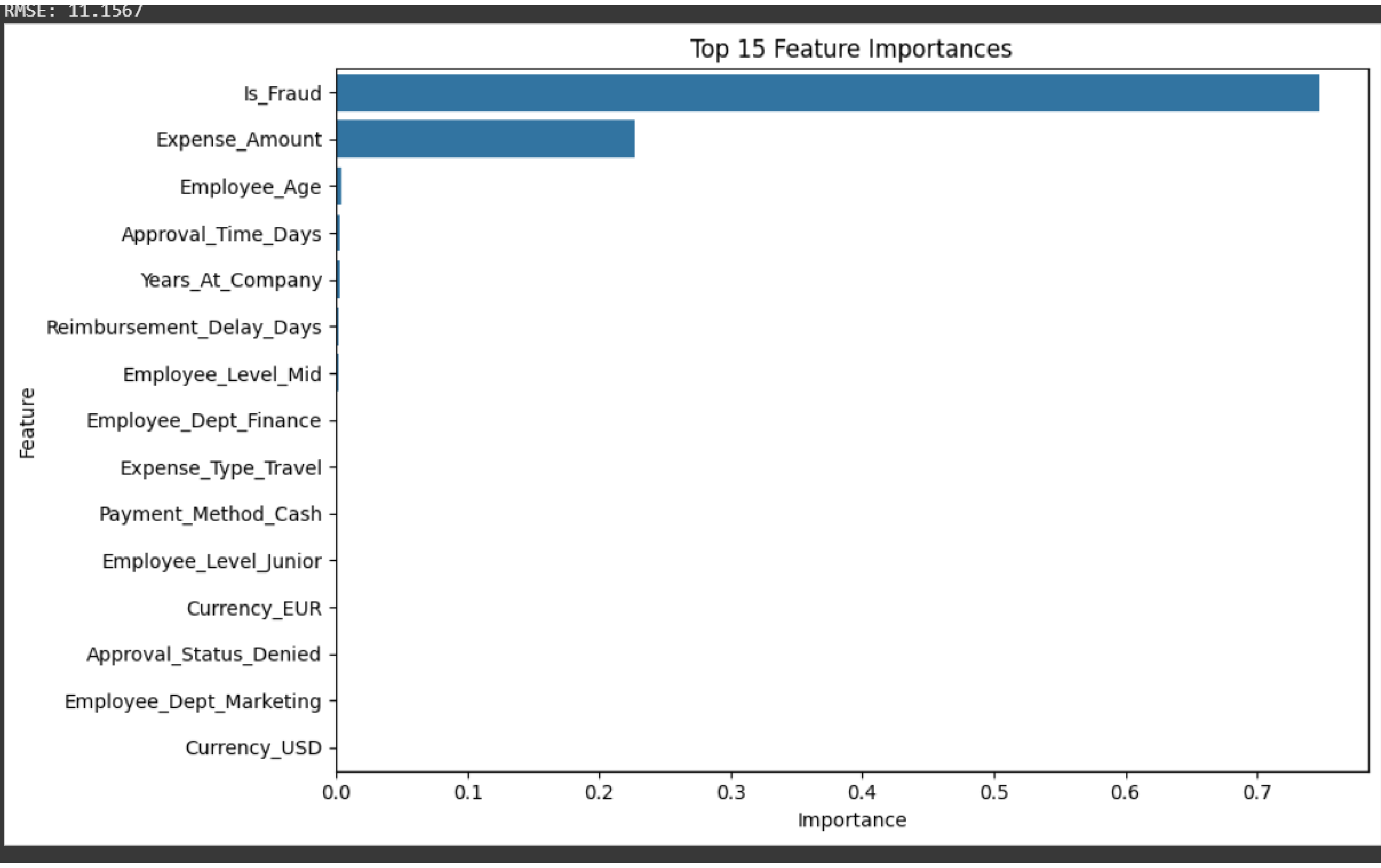
```python
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print("Model Evaluation Metrics:")
print(f"R² Score: {r2:.4f}")
print(f"MSE: {mse:.4f}")
print(f"RMSE: {rmse:.4f}")


ohe = preprocessor.named_transformers_['cat']['onehot']
categorical_feature_names = ohe.get_feature_names_out(categorical_cols)
all_feature_names = numerical_cols + list(categorical_feature_names)

importances = rf.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': all_feature_names,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df.head(15))
plt.title('Top 15 Feature Importances')
plt.tight_layout()
plt.show()
```

```python
numerical_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

categorical_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])


preprocessor = ColumnTransformer([
    ('num', numerical_pipeline, numerical_cols),
    ('cat', categorical_pipeline, categorical_cols)
])


X_processed = preprocessor.fit_transform(X)


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


rf = RandomForestRegressor(n_estimators=150, max_depth=10, min_samples_split=5, random_state=42)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
```

```python
# Sample Prediction
sample_input = {
    'Expense_Type': 'Accommodation',
    'Expense_Amount': 350,
    'Currency': 'USD',
    'Employee_Age': 40,
    'Employee_Level': 'Mid',
    'Employee_Dept': 'Sales',
    'Years_At_Company': 3,
    'Approval_Time_Days': 6,
    'Approval_Status': 'Approved',
    'Previous_Fraud_Flag': 'No',
    'Flagged_By_System': 'No',
    'Payment_Method': 'Card',
    'Reimbursed_Amount': 350,
    'Reimbursement_Delay_Days': 12,
    'Is_Fraud': 0
}

sample_df = pd.DataFrame([sample_input])
sample_processed = preprocessor.transform(sample_df)
predicted_fraud = rf.predict(sample_processed)
print(f"\n Predicted Fraud Amount for sample: {predicted_fraud[0]:.2f}")
```

```
Model Evaluation Metrics:
R² Score: 0.9594
MSE: 124.4721
RMSE: 11.1567
```

RMSE: 11.1567


Top 15 Feature Importances
Is_Fraud
Expense_Amount
Employee_Age
Approval_Time_Days
Years_At_Company
Reimbursement_Delay_Days
Employee_Level_Mid
Employee_Dept_Finance
Expense_Type_Travel
Payment_Method_Cash
Employee_Level_Junior
Currency_EUR
Approval_Status_Denied
Employee_Dept_Marketing
Currency_USD
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Importance

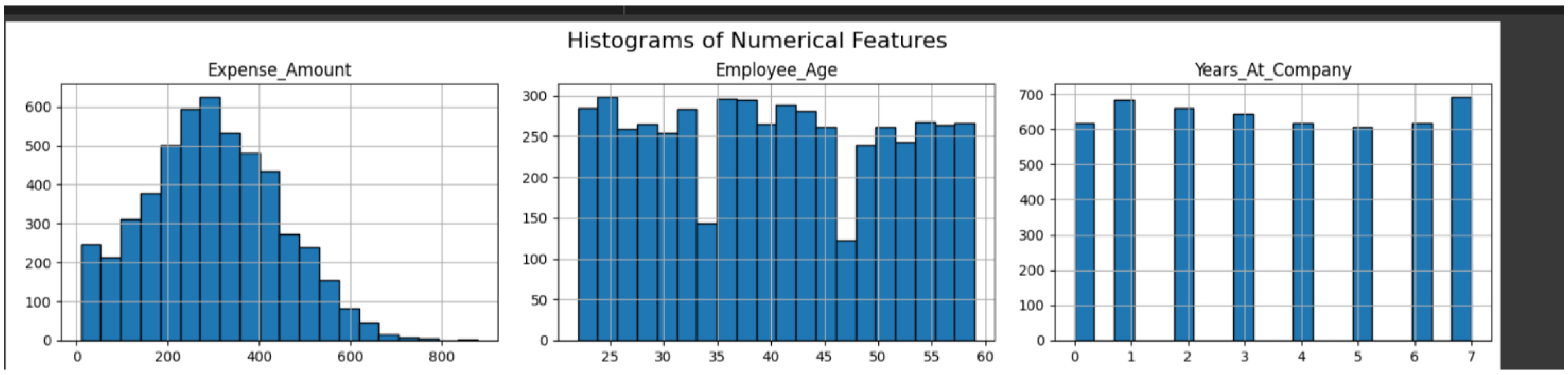
```
[ ]
    # Summary Statistics
    print("📋 Summary Statistics:\n")
    print(df_cleaned.describe(include='all'))
```

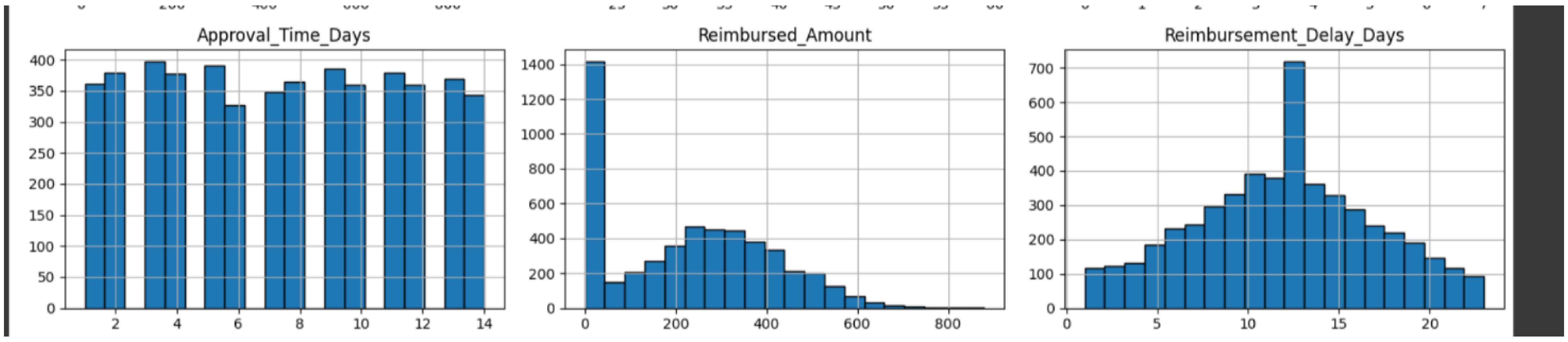
```
📋 Summary Statistics:

        Expense_Type  Expense_Amount Currency  Employee_Age Employee_Dept  \
count           5142     5142.000000     5142   5142.000000          5142
unique             5             NaN        3           NaN             5
top    Entertainment             NaN      INR           NaN            HR
freq            1063             NaN     1764           NaN          1100
mean             NaN      298.325132      NaN     40.183781           NaN
std              NaN      146.267836      NaN     10.949597           NaN
min              NaN       10.000000      NaN     22.000000           NaN
25%              NaN      196.480000      NaN     31.000000           NaN
50%              NaN      294.790000      NaN     40.000000           NaN
75%              NaN      398.875000      NaN     50.000000           NaN
max              NaN      879.010000      NaN     59.000000           NaN

       Employee_Level  Years_At_Company Previous_Fraud_Flag  \
count            5142       5142.000000                5142
unique              5               NaN                   2
top            Junior               NaN                  No
freq             1067               NaN                4864
mean              NaN          3.501361                 NaN
std               NaN          2.306739                 NaN
min               NaN          0.000000                 NaN
25%               NaN          1.000000                 NaN
50%               NaN          3.000000                 NaN
75%               NaN          6.000000                 NaN
max               NaN          7.000000                 NaN
```

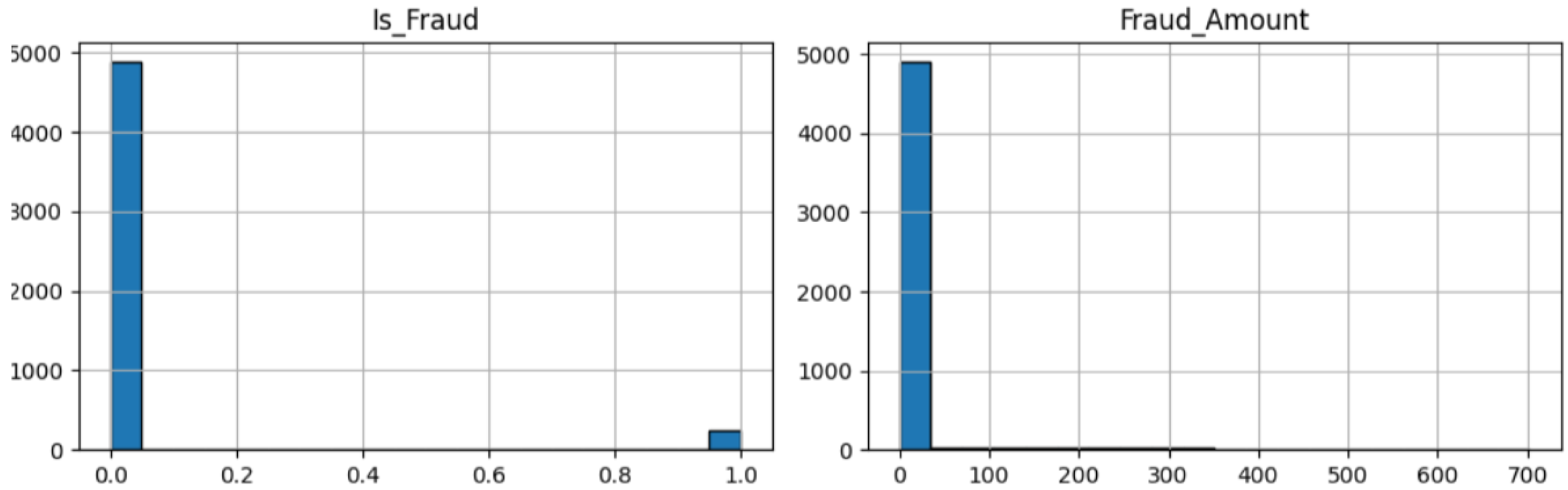
```
       Approval_Time_Days Approval_Status Flagged_By_System Payment_Method  \
count         5142.000000            5142              5142           5142
unique                NaN               3                 2              3
top                   NaN        Approved                No           Card
freq                  NaN            4101              4613           1742
mean             7.439907             NaN               NaN            NaN
std              4.029432             NaN               NaN            NaN
min              1.000000             NaN               NaN            NaN
25%              4.000000             NaN               NaN            NaN
50%              7.000000             NaN               NaN            NaN
75%             11.000000             NaN               NaN            NaN
max             14.000000             NaN               NaN            NaN

       Reimbursed_Amount  Reimbursement_Delay_Days     Is_Fraud  Fraud_Amount
count        5142.000000               5142.000000  5142.000000   5142.000000
unique               NaN                       NaN          NaN           NaN
top                  NaN                       NaN          NaN           NaN
freq                 NaN                       NaN          NaN           NaN
mean          226.969197                 11.927849     0.049203     10.636241
std           180.680789                  4.940695     0.216312     54.039906
min             0.000000                  1.000000     0.000000      0.000000
25%            10.000000                  8.000000     0.000000      0.000000
50%           237.055000                 12.000000     0.000000      0.000000
75%           362.437500                 16.000000     0.000000      0.000000
max           879.010000                 23.000000     1.000000    702.560000
```

Visualization

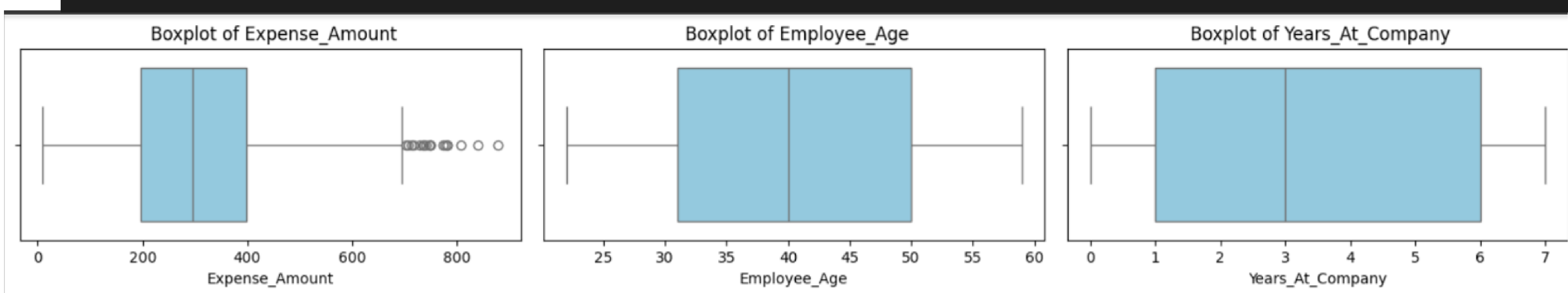
```python
# Histograms for numerical features
numerical_cols = df_cleaned.select_dtypes(include=['int64', 'float64']).columns.tolist()

df_cleaned[numerical_cols].hist(figsize=(15, 10), bins=20, edgecolor='black')
plt.suptitle(" Histograms of Numerical Features", fontsize=16)
plt.tight_layout()
plt.show()
```

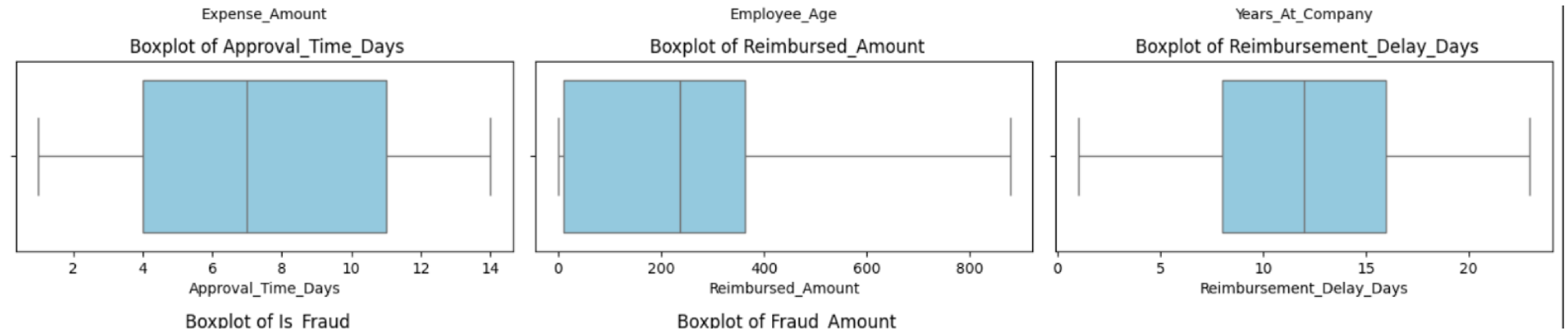


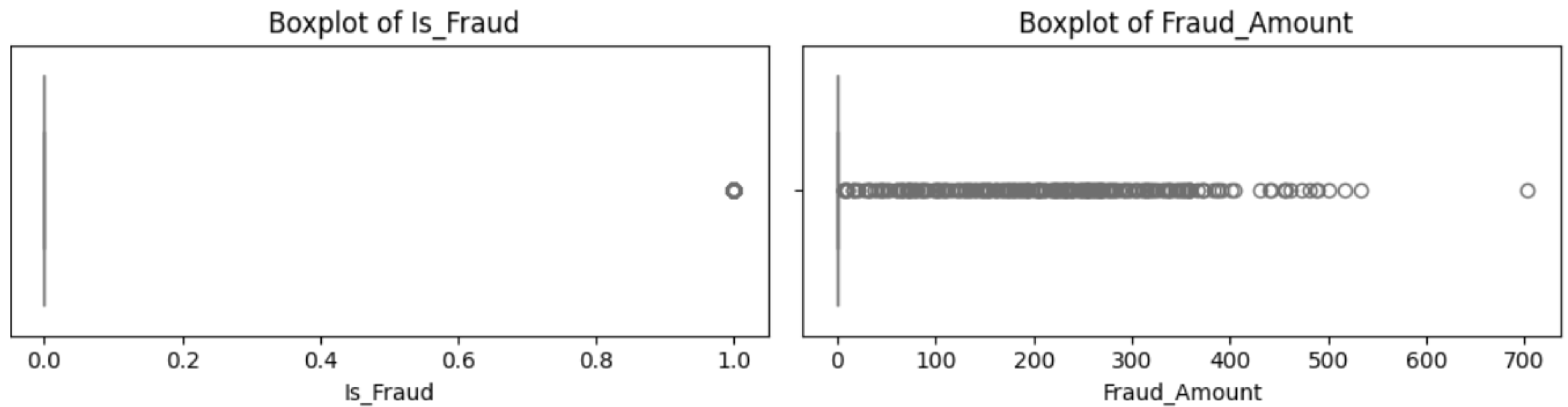


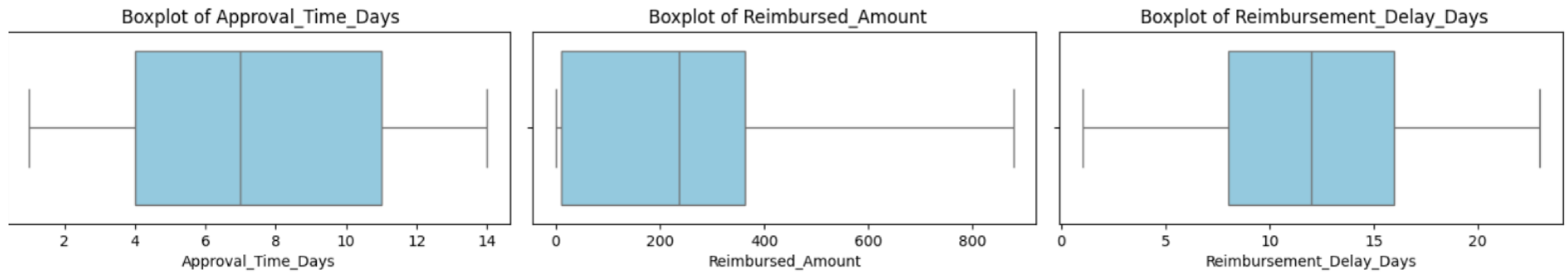



```python
# Boxplots for numerical features
plt.figure(figsize=(15, 8))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, (len(numerical_cols) + 2) // 3, i + 1)
    sns.boxplot(x=df_cleaned[col], color='skyblue')
    plt.title(f' Boxplot of {col}')
plt.tight_layout()
plt.show()
```

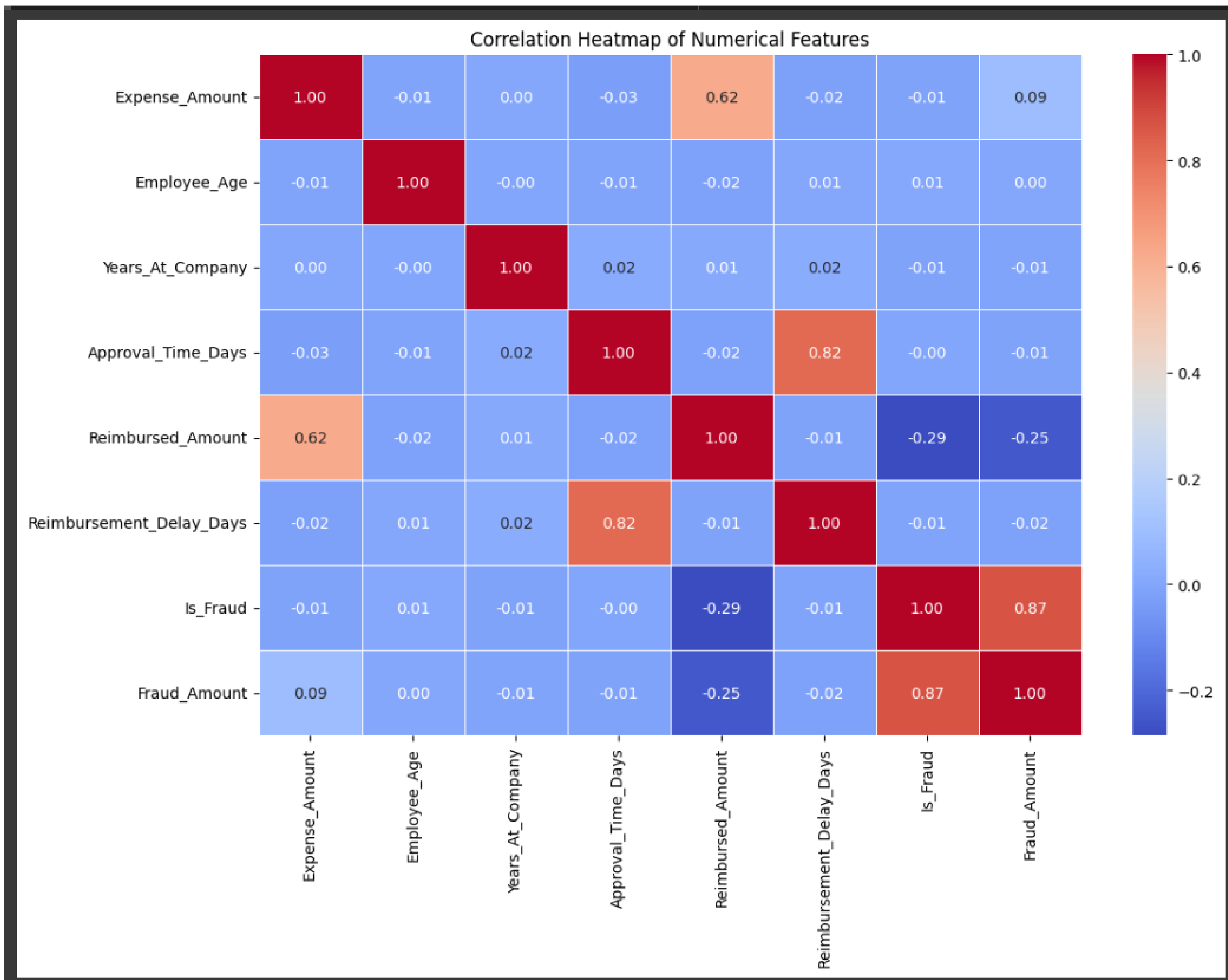



Expense_Amount
Employee_Age
Years_At_Company
Boxplot of Approval_Time_Days
Approval_Time_Days
Boxplot of Reimbursed_Amount
Reimbursed_Amount
Boxplot of Reimbursement_Delay_Days
Reimbursement_Delay_Days
Boxplot of Is_Fraud
Boxplot of Fraud_Amount


Boxplot of Is_Fraud
Is_Fraud
Boxplot of Fraud_Amount
Fraud_Amount

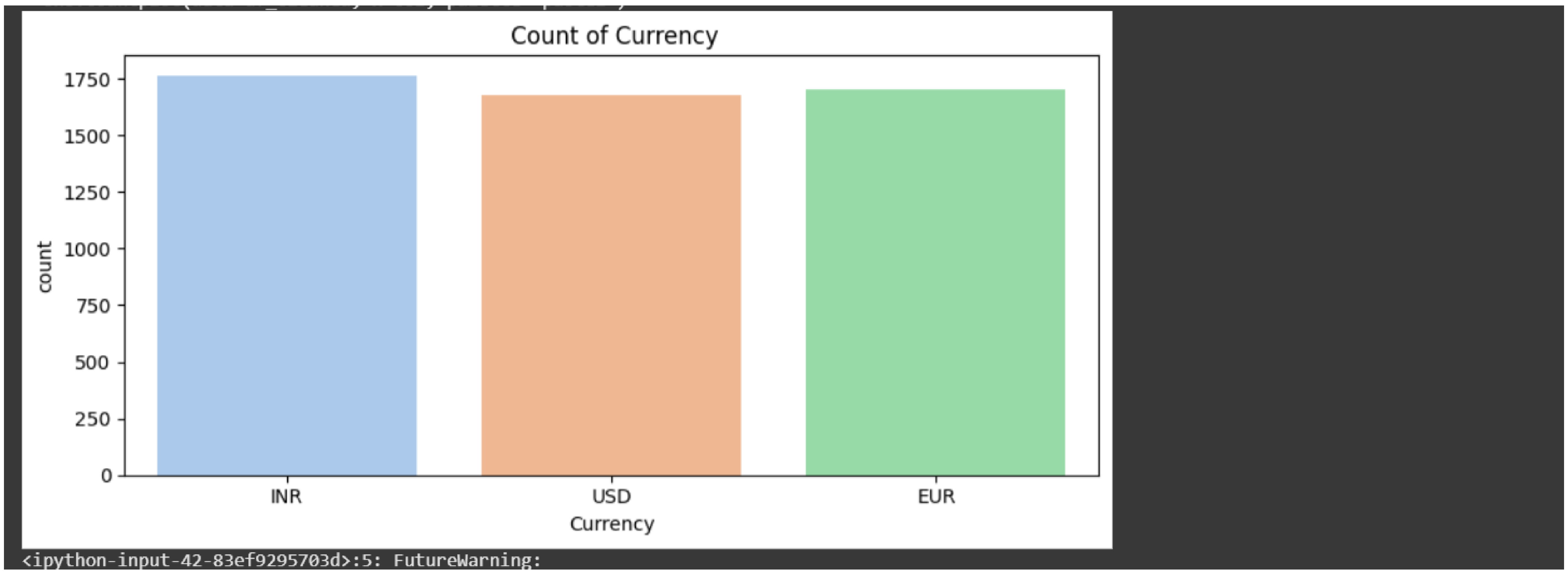

Boxplot of Approval_Time_Days
Approval_Time_Days
Boxplot of Reimbursed_Amount
Reimbursed_Amount
Boxplot of Reimbursement_Delay_Days
Reimbursement_Delay_Days

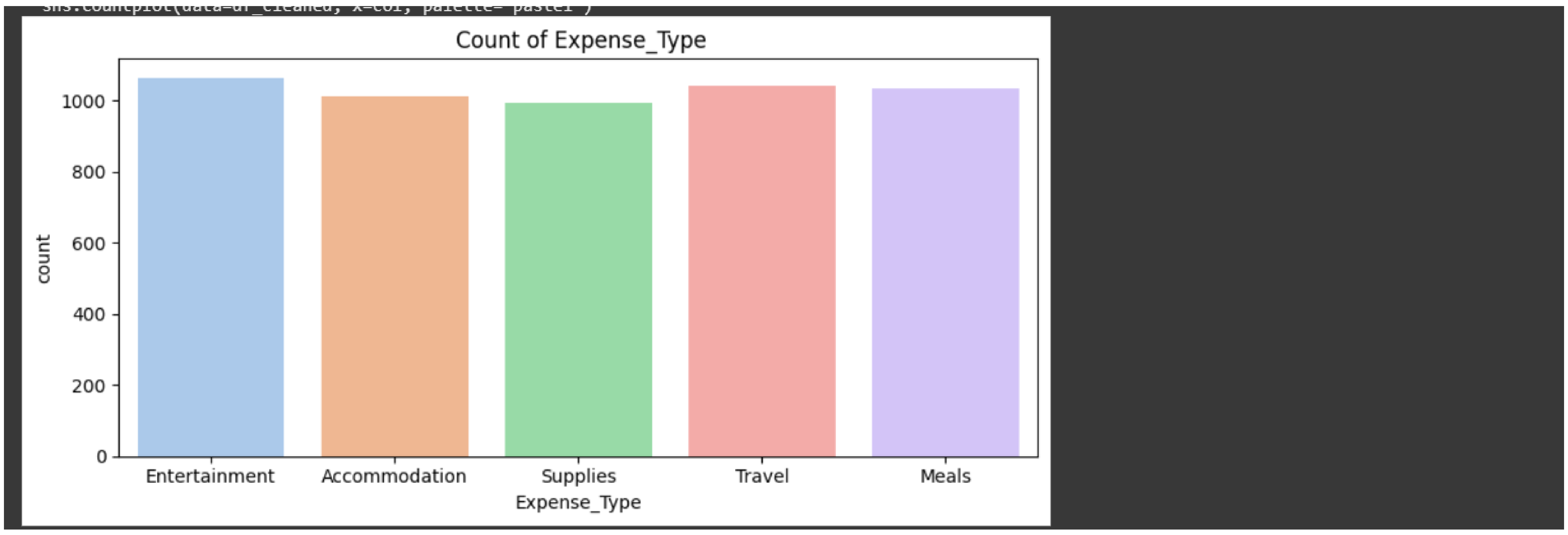
```
Correlation Heatmap
plt.figure(figsize=(12, 8))
corr_matrix = df_cleaned[numerical_cols].corr()
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths = 0.5)
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```

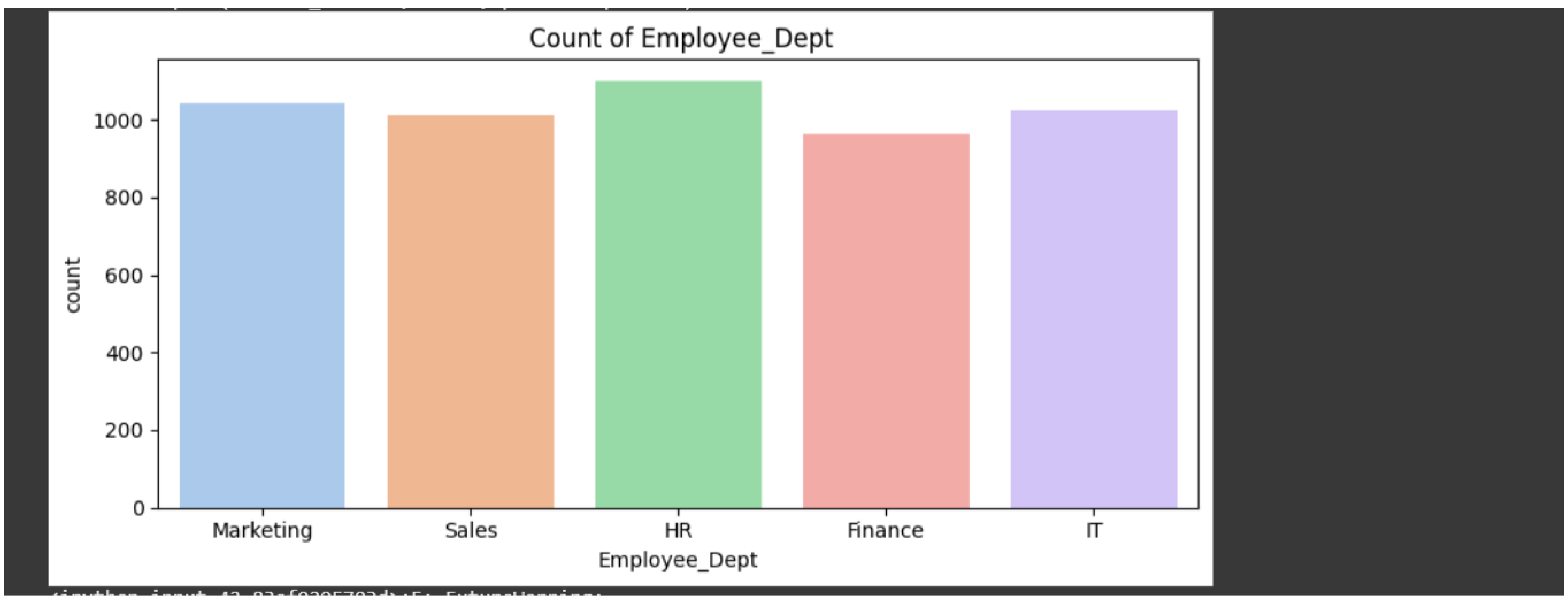


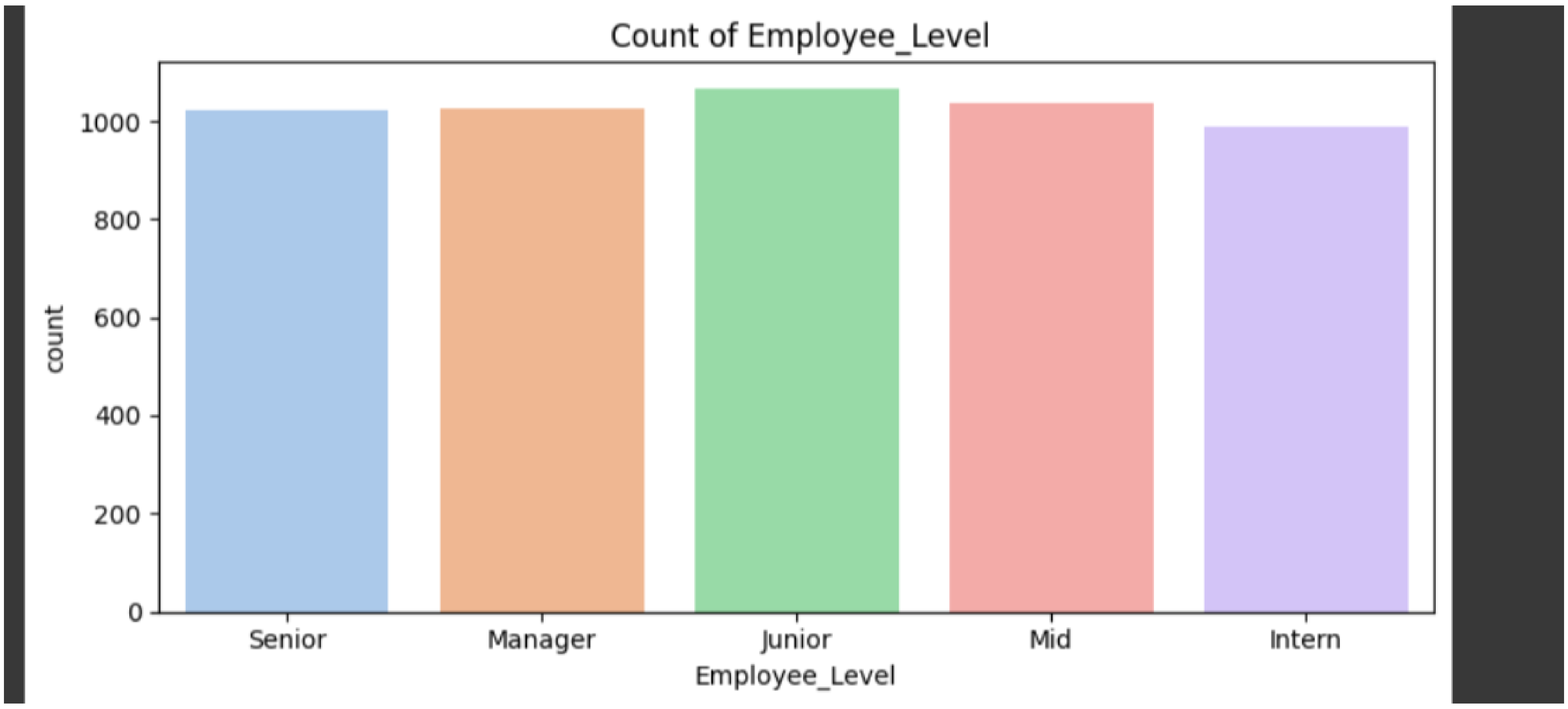
```python
# Distribution of Fraud Amount
plt.figure(figsize=(8, 6))
sns.histplot(df_cleaned['Fraud_Amount'], bins=50, kde=True, color='tomato')
plt.title(" Distribution of Fraud Amount")
plt.xlabel("Fraud Amount")
plt.ylabel("Frequency")
plt.show()
```

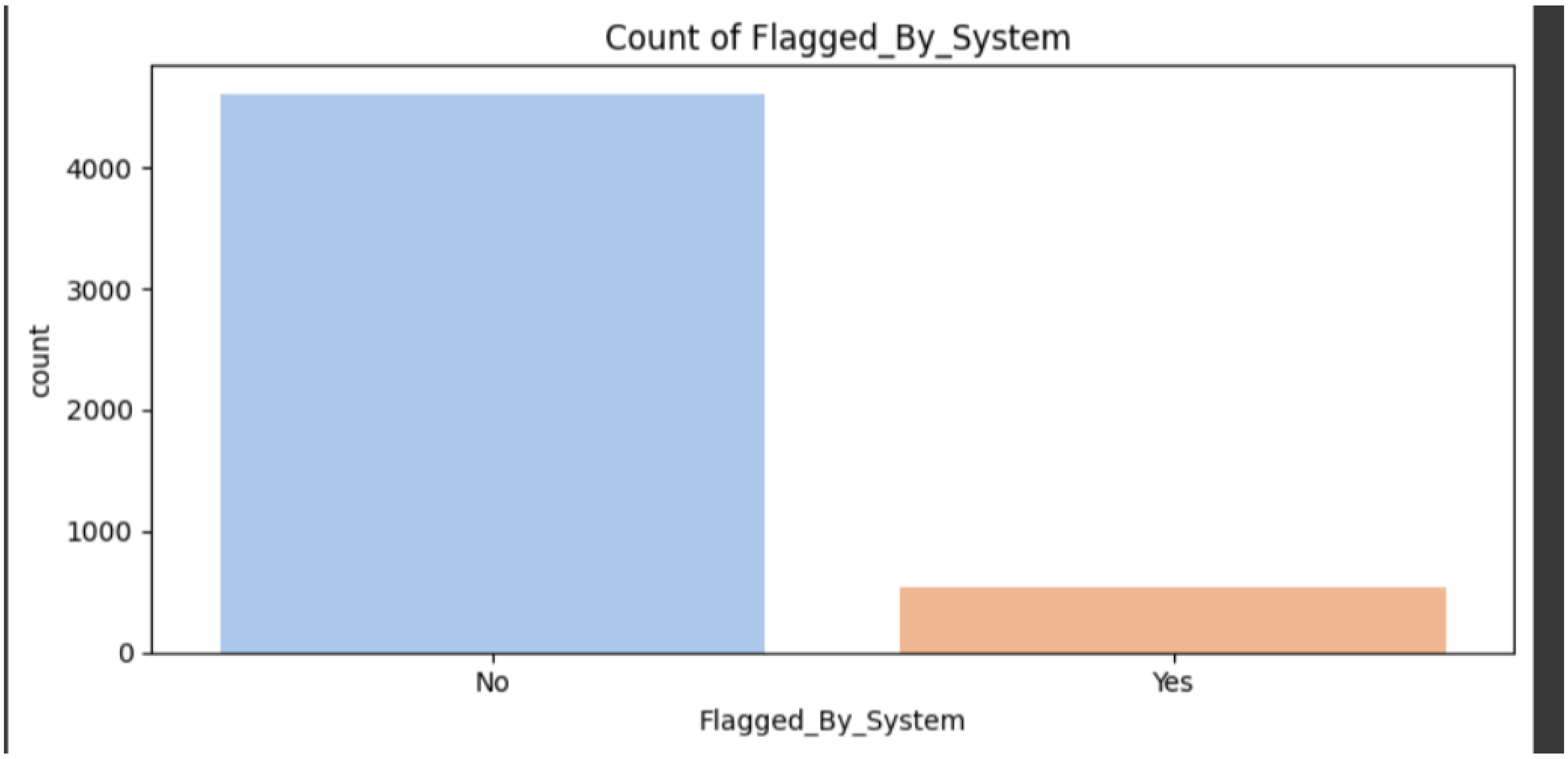
```python
# Countplot of Categorical Columns
categorical_cols = df_cleaned.select_dtypes(include='object').columns.tolist()
for col in categorical_cols:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=df_cleaned, x=col, palette='pastel')
    plt.title(f" Count of {col}")
    plt.xticks(rotation=0)
    plt.tight_layout()
    plt.show()
```

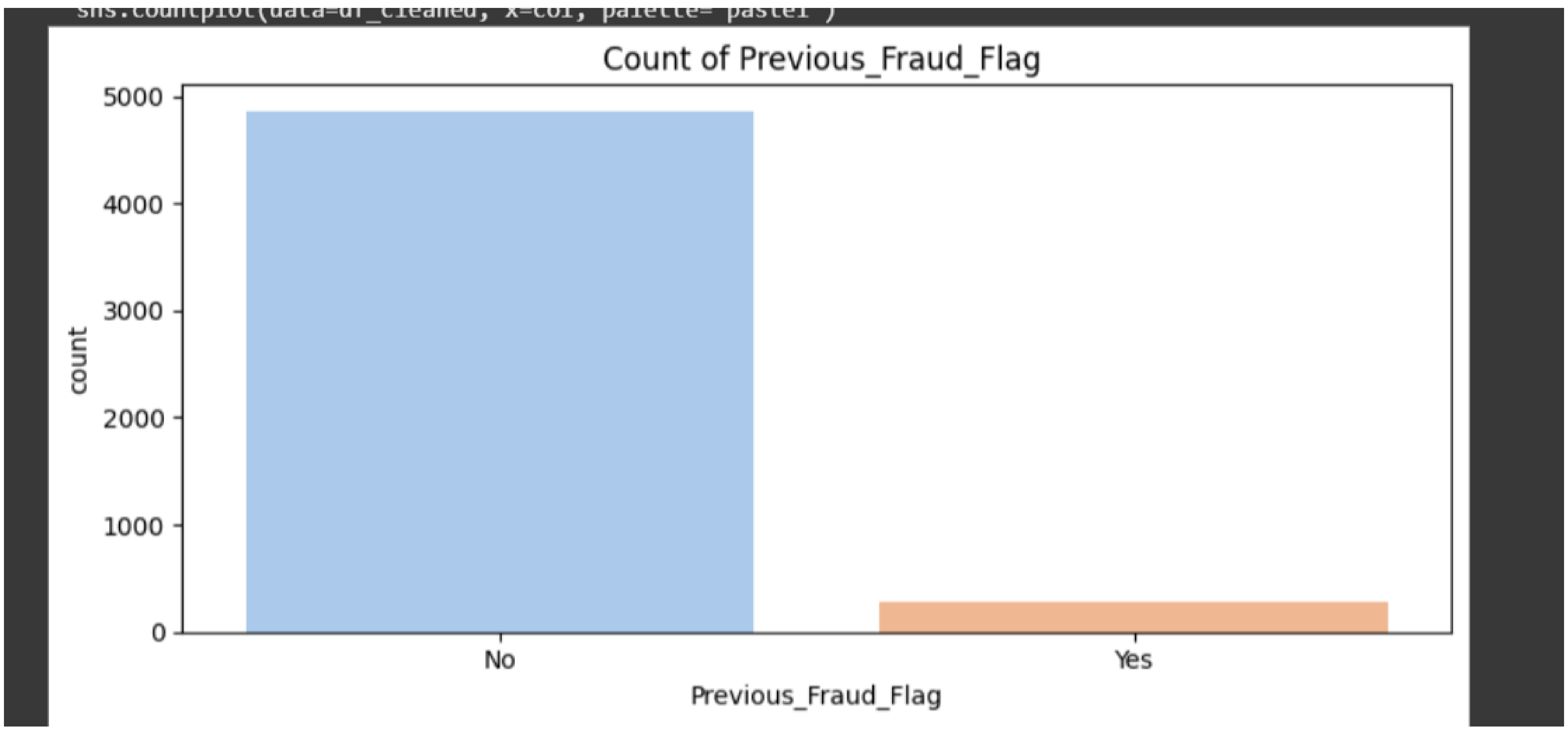

Count of Currency
count
1750
1500
1250
1000
750
500
250
0
INR
USD
EUR
Currency
<ipython-input-42-83ef9295703d>:5: FutureWarning:

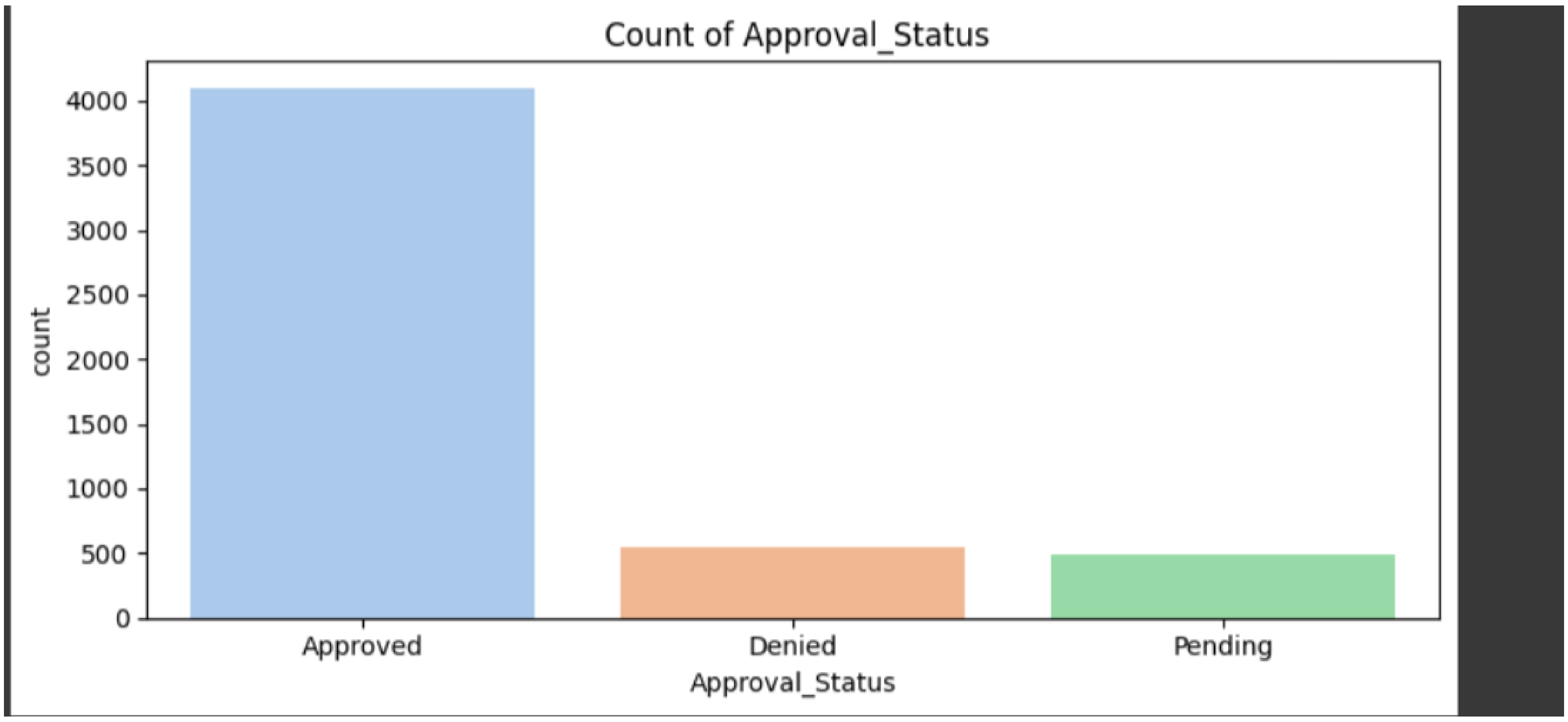

Count of Expense_Type
count
1000
800
600
400
200
0
Entertainment
Accommodation
Supplies
Travel
Meals
Expense_Type

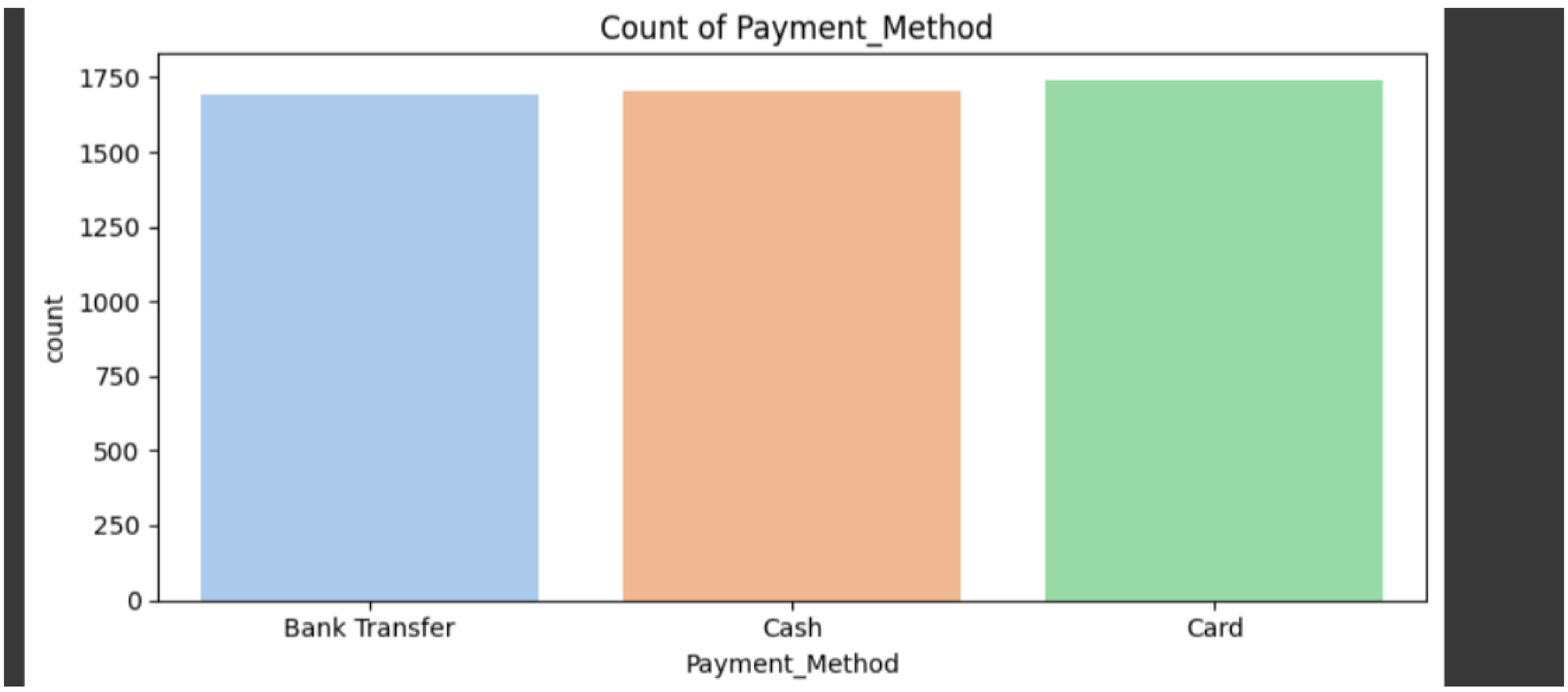

Count of Employee_Dept
count
1000
800
600
400
200
0
Marketing
Sales
HR
Finance
IT
Employee_Dept


Count of Employee_Level
1000
800
600
400
200
0
count
Senior
Manager
Junior
Mid
Intern
Employee_Level


Count of Flagged_By_System
4000
3000
2000
1000
0
count
No
Yes
Flagged_By_System


sns.countplot(data=df_cleaned, x=col, palette='pastel')
Count of Previous_Fraud_Flag
5000
4000
3000
2000
1000
0
count
No
Yes
Previous_Fraud_Flag


Count of Approval_Status
4000
3500
3000
2500
2000
1500
1000
500
0
count
Approved
Denied
Pending
Approval_Status

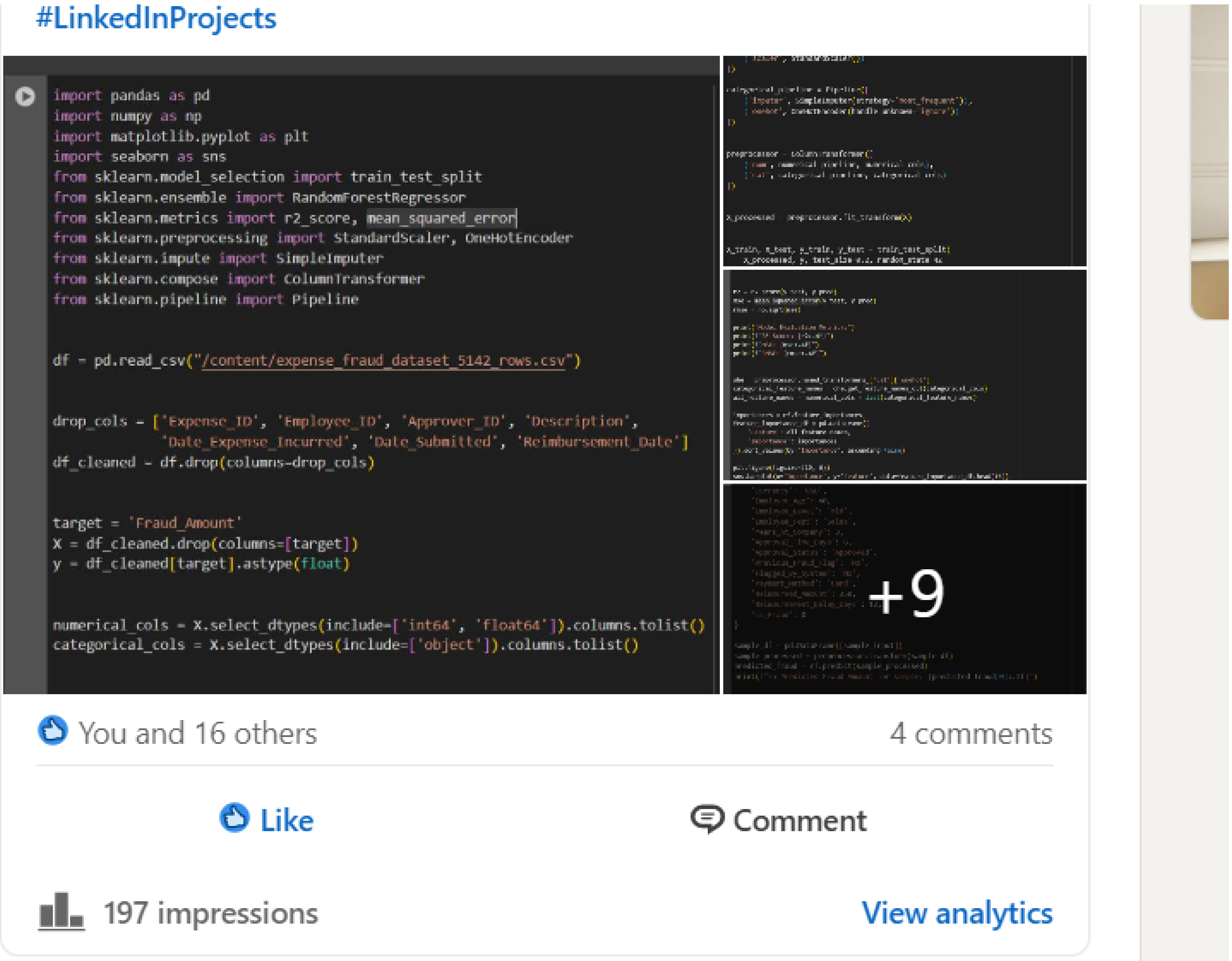

Count of Payment_Method
1750
1500
1250
1000
750
500
250
0
count
Bank Transfer
Cash
Card
Payment_Method

Screenshot – Github & LinkedIn

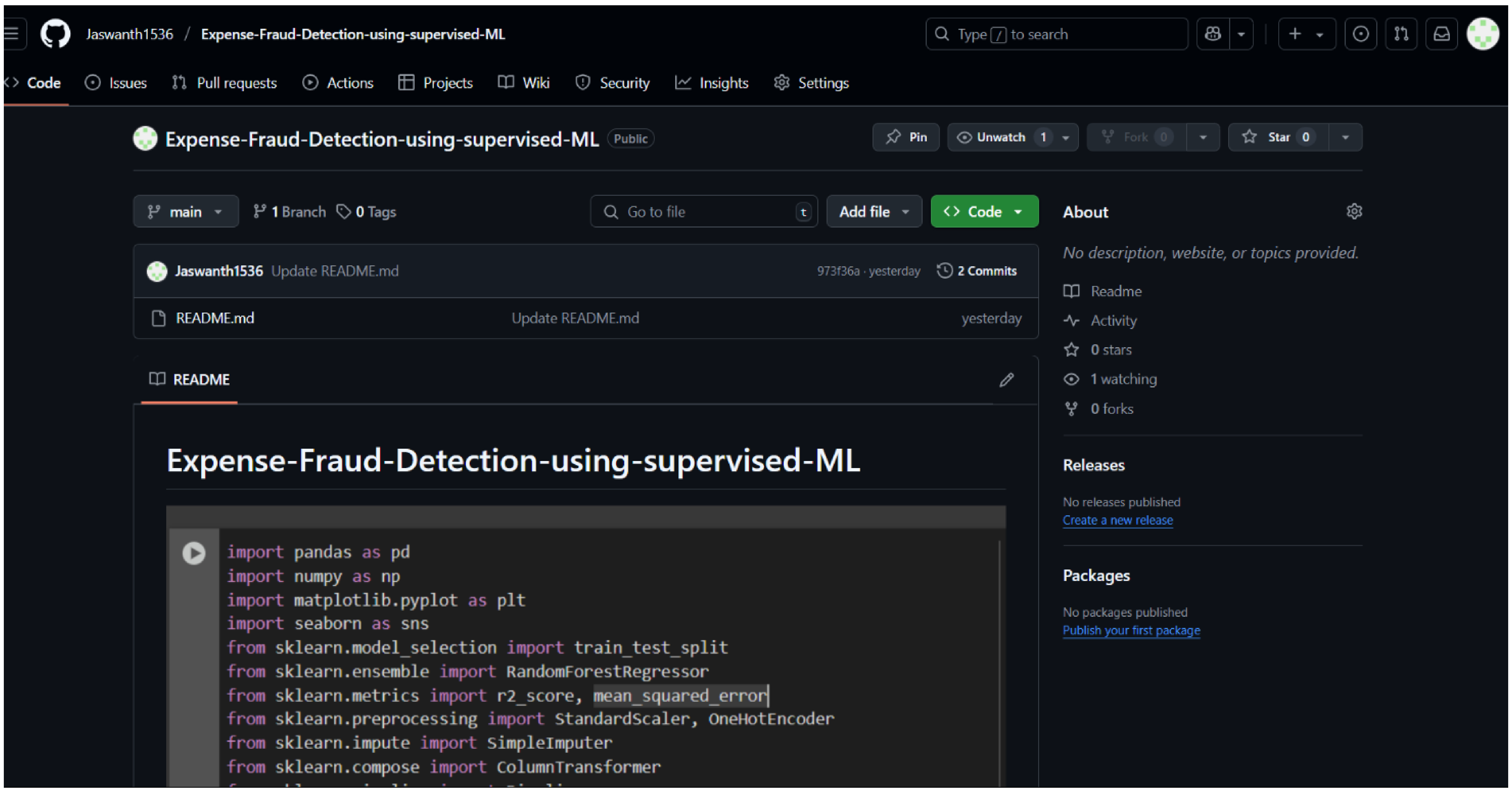
Jaswanth Reddy Kanaparthy • You
Attended Lovely Professional University
22h •

🚀 Just wrapped up an exciting project on Fraud Detection in Enterprise Expense Claims using Machine Learning!
In this project, I built a model to detect fraudulent expense claims, helping organizations reduce financial risk and improve compliance.
🔍 Focused on identifying anomalies in transaction patterns using supervised learning techniques.
💻 Tech Stack & Tools Used:
Python for scripting
NumPy for data manipulation
Matplotlib & Seaborn for visualizations and EDA
Random Forest Classifier for robust and interpretable predictions
Scikit-learn Pipeline for clean model building and evaluation
This project enhanced my skills in data preprocessing, feature engineering, and deploying machine learning pipelines.
Looking forward to applying these skills in real-world enterprise scenarios.
Open to feedback, suggestions, and collaboration opportunities! 🤝

GitHub Link: https://lnkd.in/dZmnhNTa
#MachineLearning #FraudDetection #Python #DataScience #RandomForest #ScikitLearn #ExpenseAnalytics #AIInFinance #LinkedInProjects



https://www.linkedin.com/posts/jaswanth-reddy-kanaparthy-2a4438350_machinelearning-frauddetection-python-activity-7316543292928618497-wE-0?utm_source=share&utm_medium=member_desktop&rcm=ACoAAFehGpwBV2iYLqnoSuKB9JbU5jr0yQyY5SE



https://github.com/Jaswanth1536/Expense-Fraud-Detection-using-supervised-ML