Exploring Energy Flow Classifier to Identify Fraudulent Cryptocurrency Transactions

Kevin S. Araujo[1], **Rodrigo Bonifacio de Almeida**[1], **Fabiano Cavalcanti Fernandes**[2]

[1]Departamento de Ciências da Computação – Universidade de Brasília (UnB) – Campus Universitário Darcy Ribeiro, Brasília-DF

[2]Instituto Federal de Brasília (IFB) – Taguating, DF – Brazil

kevin.araujo@aluno.unb.br, rbonifacio@unb.br, fabiano.fernandes@ifb.edu.br

Abstract. *This is a work in progress.*

1. Introduction

Bitcoin is an electronic transaction system operating without a third-party moderator [Nakamoto 2008]. It is built upon blockchain technology, where an immutable ledger of financial transactions is maintained through mathematics, programming, and advanced cryptography. This distributed ledger architecture eliminates the need for central authorities to establish trust. Although Bitcoin was designed to circumvent vulnerabilities in the traditional financial system [Nakamoto 2008], it is not immune to manipulation and anomalous activities, necessitating robust detection mechanisms [Fang et al. 2022, Zhang et al. 2020, Zainal et al. 2018].

Indeed, cryptocurrency-related fraud has emerged as a significant threat, causing substantial financial losses and shaking trust in the digital asset ecosystem. In 2023, for instance, illicit addresses received $24.2 billion in cryptocurrency, indicating the scale of financial losses from scams, stolen funds, and other illicit activities [Chainalysis 2024]. These activities not only cause direct monetary damage to individuals and institutions but also have broader implications, such as undermining the legitimacy of cryptocurrency markets and hindering the widespread adoption of blockchain technology. The need to develop effective methods for detecting and preventing cryptocurrency fraud is crucial to protect participants, maintain market integrity, and ensure the sustainable growth of the cryptocurrency industry [Scharfman 2024, Khiari et al. 2025].

However, detecting anomalous patterns within the intricate data streams of cryptocurrency transactions poses a significant challenge. Like many modern datasets, these transactions are characterized by high dimensionality, evolving characteristics, and a substantial volume, which complicates the application of traditional anomaly detection methods. In this context, the Energy-based Flow Classifier (EFC) presents a promising approach rooted in statistical physics. Originally formulated using the Inverse Potts model [Pontes et al. 2019], the EFC characterizes the probability distribution of normal data flows through an energy function derived from observed data patterns [Pontes et al. 2019]. Previous research has demonstrated the utility of EFC in classifying unusual network traffic, suggesting its potential for adapting to detect fraudulent activity within cryptocurrency systems [Pontes et al. 2019, Souza et al. 2022].

Building upon the promise of the Energy-based Flow Classifier (EFC) framework, this paper presents a comprehensive empirical evaluation of its application to detecting illicit Bitcoin transactions. To this end, we first replicate a previous study that employs

machine learning algorithms such as K-Nearest Neighbors, One-Class Support Vector Machine, and Isolation Forest for anomaly detection on the Elliptic dataset [1]. We then investigate the use of EFC as a potential alternative to these machine learning approaches, using the same dataset for consistency. Our findings confirm the EFC's ability to distinguish between licit and illicit transaction patterns based on their energy profiles, showing strong performance in identifying illegal activity even when trained solely on licit data. However, the results also highlight the critical sensitivity to specific configuration parameters. In particular, we observe significant trade-offs between maximizing the detection rate of illicit transactions (recall) and minimizing false positives (precision), especially concerning the energy threshold that defines anomalous behavior. Addressing the significant challenge of label scarcity inherent in datasets like Elliptic is crucial for developing effective fraud detection systems. Traditional supervised machine learning methods often struggle in such scenarios due to the limited availability of labeled illicit examples. This motivates the exploration of alternative approaches, particularly those capable of learning from predominantly normal data. The Energy-based Flow Classifier (EFC) emerges as a promising candidate in this regard. Originally proposed for network intrusion detection [Pontes et al. 2019, Souza et al. 2022], EFC was designed specifically to address key limitations of conventional ML classifiers, including the reliance on extensive labeled datasets. A core strength highlighted in its foundational work is its ability to function as an anomaly-based classifier, inferring a statistical model of normal behavior using only labeled *benign* (or licit, in our context) examples [Souza et al. 2022]. Deviations from this learned norm, characterized by higher 'energy' scores, are then flagged as potential anomalies. This one-class learning paradigm directly tackles the label scarcity issue prevalent in the Elliptic dataset, allowing us to model legitimate transaction patterns effectively even with few confirmed illicit instances. Furthermore, EFC's demonstrated adaptability across different data distributions in network traffic analysis suggests potential robustness in the dynamic environment of cryptocurrency transactions. Consequently, this paper evaluates the suitability and performance of EFC for identifying illicit Bitcoin transactions by leveraging its capacity to model normality from available licit data.

In summary, the main contributions of this paper are:

- Novel Application and Empirical Evaluation of EFC for One-Class Bitcoin Anomaly Detection;
- c2
- c3

2. Background and Related Work

Financial market manipulation, traditionally associated with actions taken by state-level entities often concerning currency exchange rates [Domanski and Sushko 2011, Khodabandehlou and Alireza Hashemi Golpayegani 2022], takes on a different character in the realm of cryptocurrencies. Cryptocurrency manipulation typically involves deceptive strategies employed by individuals or coordinated groups aiming to artificially distort market prices or activity, usually for illicit profit [Eigelshoven et al. 2021]. Understanding these tactics is crucial for developing effective detection mechanisms.

[1] Available at https://www.kaggle.com/ellipticco/elliptic-data-set

Among the prevalent forms of cryptocurrency fraud are pump-and-dump schemes and wash trading. **Pump-and-dump fraud** involves orchestrating an artificial inflation of a cryptocurrency's price ("pump") through misleading promotions or coordinated buying, attracting unsuspecting investors. The manipulators then sell their holdings ("dump") at the peak price, causing a market crash and significant losses for later investors [Karim and Mikhael 2018]. **Wash trading**, conversely, creates a false impression of high trading volume and liquidity. This is achieved when an entity or colluding group simultaneously buys and sells the same asset, often using multiple accounts or automated bots, effectively trading with themselves. The goal is to make the asset appear more active and desirable than it is, thereby manipulating market sentiment and potentially influencing its price [Gandal et al. 2018, Edelman et al. 2018]. The decentralized and pseudonymous nature of many cryptocurrency platforms can exacerbate the challenges in detecting and preventing such manipulations.

Addressing the challenge of identifying anomalous patterns within complex data streams, such as financial transactions, requires robust methodologies. One promising approach, grounded in statistical physics, is the **Energy-based Flow Classifier (EFC)**. Originally proposed using the Inverse Potts model to analyze network traffic data [Pontes et al. 2019], EFC operates on the principle of assigning an "energy" score to data points or flows. The model is trained to learn the probability distribution of normal system behavior, associating typical, expected patterns (e.g., legitimate transactions) with low-energy states. Conversely, configurations that deviate significantly from this learned normality, potentially representing anomalies or malicious activities, manifest as high-energy states. This energy score provides a quantitative measure of typicality. Subsequent research has extended the EFC framework, demonstrating its utility in classifying unusual network traffic for intrusion detection and highlighting its potential for open-set recognition—identifying novel anomalies not seen during training [Pontes et al. 2019, Souza et al. 2022].

The EFC framework appears particularly well-suited for detecting anomalous Bitcoin transactions for several key reasons. Firstly, its fundamental design as an anomaly detector allows it to learn the characteristics of *normal* (Licit) behavior, often from unlabeled or predominantly normal data. It then identifies anomalies (potentially Illicit transactions) as deviations exhibiting high 'energy' relative to this learned norm. This inherent capability to operate in a one-class or unsupervised manner directly addresses the significant challenge of label scarcity common in financial fraud datasets like Elliptic [Bansal et al. 2022]. Secondly, the energy function provides a holistic measure derived from the interplay of multiple features, potentially capturing complex, subtle deviations in the high-dimensional feature space of Bitcoin transactions that simpler methods might miss [Wilson and Anwar 2024]. Given its prior success in analogous domains involving complex flow data [Pontes et al. 2019, Souza et al. 2022], we hypothesize that EFC's unique characteristics offer advantages for identifying illicit activities within the Bitcoin blockchain.

Detecting illicit transactions in cryptocurrencies is fundamentally an anomaly detection task. Various approaches have been explored, ranging from rule-based systems identifying known patterns to sophisticated machine learning techniques [Samariya and Thakkar 2023, Li et al. 2023]. Traditional anomaly detection methods of-

ten face challenges when applied to cryptocurrency data due to its high dimensionality, the dynamic and evolving nature of transaction patterns, significant class imbalance (illicit transactions being rare), and the sheer volume of data [Pallathadka et al. 2022]. Techniques like statistical process control, clustering-based methods (e.g., DBSCAN, k-means variations), and distance-based methods (e.g., k-Nearest Neighbors anomaly detection) have been applied, each with varying degrees of success and limitations, particularly concerning scalability and the ability to capture complex, non-linear relationships [Hilal et al. 2022].

Building on these general principles, numerous machine learning models have been specifically investigated for identifying fraud and money laundering within the Bitcoin ecosystem. Supervised learning approaches, such as Random Forests, Support Vector Machines (SVM), Multilayer Perceptrons (MLP), and Gradient Boosting Machines, have shown promise when sufficient labeled data is available [Lorenz et al. 2021, Chen et al. 2021]. However, their performance heavily relies on the quality and quantity of labeled examples, which is often a bottleneck. Consequently, semi-supervised and unsupervised methods, including One-Class SVM (OC-SVM) and Isolation Forests, have gained attention as they can leverage unlabeled data or focus solely on modeling normal behavior [Lorenz et al. 2021, Kehinde et al. 2024]. More recently, Graph Neural Networks (GNNs) have emerged as a powerful tool, explicitly leveraging the graph structure of the blockchain to capture relational information between transactions, which can be crucial for identifying complex illicit schemes [Weber et al. 2019]. Our work contributes to this landscape by evaluating EFC, an alternative physics-inspired one-class approach, assessing its performance against the backdrop of these established techniques, particularly focusing on its behavior under label scarcity.

3. Study Settings

This section details the data and methods employed in our study, which builds upon the foundational research presented by [Lorenz et al. 2021]. That work explored the use of various machine learning classifiers (e.g., Random Forest, SVM, MLP) applied to engineered features from the Elliptic dataset to identify illicit Bitcoin transactions, specifically tackling the inherent challenge of label scarcity. While demonstrating the potential of standard ML techniques, their approach relied on supervised or semi-supervised frameworks requiring at least some labels. Our research diverges by investigating the Energy Flow Classifier (EFC).

3.1. Dataset Description

This study utilizes the Elliptic dataset, a publicly available graph dataset of Bitcoin transactions introduced by [Weber et al. 2019] and subsequently used in foundational studies on machine learning for Bitcoin money laundering detection, including the work by [Lorenz et al. 2021] which highlighted the challenges of label scarcity. The dataset represents a temporal subgraph of the public Bitcoin blockchain, focusing on transactions involving entities identified by Elliptic Ltd., a company specializing in blockchain analytics and financial crime prevention. It captures transaction patterns over 49 distinct time steps, where each step corresponds roughly to a two-week period. The full dataset comprises 203,769 transaction nodes and 234,355 directed edges representing the flow of Bitcoin between transactions.

Each transaction (node) in the graph is described by a set of 166 anonymized features. One feature explicitly denotes the time step (1 to 49). The remaining 165 features are local transactional properties, including aggregated information about the transaction's inputs and outputs (e.g., number, amounts, fees) and potentially aggregated statistics from its immediate neighborhood in the transaction graph. These features are provided in a normalized or standardized form, obscuring raw values but preserving relational patterns crucial for machine learning analysis. The graph structure itself, defined by the edges connecting transactions where the output of one becomes the input of another, provides contextual information about the flow of funds—although our EFC implementation primarily focuses on the node features. A key characteristic of the Elliptic dataset is its label scarcity—while the entire dataset contains over 200,000 transactions, only a subset of 46,564 transactions is explicitly labeled. This represents a central challenge addressed by [Lorenz et al. 2021] and serves as a motivation for exploring EFC in this domain. The labels classify transactions into two main categories:

Licit Transactions: Transactions associated with known legitimate entities such as exchanges, miners, wallet providers, and other regulated services (42,019 instances in the original labeled set).

Illicit Transaction: Transactions linked to known illicit activities, including scams, ransomware, terrorist financing, Ponzi schemes, and dark market operations (4,545 instances in the original labeled set).

Table 1. Summary Statistics of the Elliptic Dataset (based on [Weber et al. 2019]).

Characteristic	Value
Total Transactions (Nodes)	203,769
Total Edges	234,355
Time Steps	49
Features per Node	166
Labeled Transactions	46,564 (˜23%)
- Licit	42,019 (˜90.2% of labeled)
- Illicit	4,545 (˜9.8% of labeled)
Unlabeled Transactions	157,205 (˜77%)

3.2. Data Preprocessing

Preparing the Elliptic dataset for EFC involved several key steps focused on handling labels, selecting relevant features, scaling the data appropriately, and partitioning it for training and evaluation in a temporally meaningful way.

To prepare the dataset (Section 3.1), we filtered transactions based on their assigned labels. Since the EFC model learns patterns from *normal* data to detect anomalies, transactions labeled as *Licit* were used as the normal class for training. In contrast, transactions labeled as *Illicit* were treated as anomalies and reserved for evaluation. Transactions with *Unknown* labels were excluded from both training and testing to ensure that the evaluation relied solely on transactions with a known ground truth. For the binary classification task (*licit* vs. *illicit*), labels were mapped to numerical values—0 for licit and 1 for illicit.

Second, we performed feature selection and transformation. Of the 166 features available for each transaction, the feature explicitly indicating the time step (ranging from 1 to 49) was removed. While this temporal information was essential for partitioning the data, it was excluded from the EFC model's input, as the model focuses on intrinsic transaction properties rather than absolute temporal position. The remaining 165 anonymized features—representing transactional and local graph characteristics—were retained as inputs to the EFC. Although the original dataset description reports some form of normalization [Weber et al. 2019], we decided to apply the Min-Max scaling to the [0, 1] range to ensure consistency and enhance the stability of energy calculations within the EFC framework. Scaling was applied separately to the training and test sets, with the scaler fitted exclusively on the training data to prevent data leakage.

Third, we implemented a temporal data split, in line with common practice for this dataset [Weber et al. 2019, Lorenz et al. 2021], to simulate a realistic scenario in which a model trained on historical data is used to detect fraudulent activity in future transactions. Transactions from time steps 1 to 34 were allocated to the training set, while those from time steps 35 to 49 were reserved for testing. The EFC model was trained exclusively on licit (normal) transactions from the training period (time steps 1-34). The test set (time steps 35-49) included both licit and illicit transactions, enabling an evaluation of the model's ability to assign higher energy scores to previously unseen illicit transactions compared to unseen licit ones.

3.3. Energy Flow Classifier Configuration

For detecting illicit transactions within the Elliptic dataset, we employed the Energy Flow Classifier (EFC), leveraging the Python package implementation [efc 2021] based on the recommendations by Pontes et al. [Pontes et al. 2019, Souza et al. 2022]. EFC operates on the premise that normal system behavior corresponds to low-energy states, while anomalies or deviations manifest as high-energy states. Our implementation specifically utilizes EFC as a one-class anomaly detector, tailored to the label scarcity challenge inherent in the dataset.

To set up EFC in our experiment, we extended the class-based interface provided by the EFC Python package, specifically by overriding the `EnergyBasedFlowClassifier` class to tailor its behavior to our evaluation needs. In our implementation, we configured three key EFC hyperparameters: `n_bins`, `cutoff_quantile`, and `pseudocounts`. The `n_bins` parameter controls the discretization of input features, dividing each feature's range into a specified number of bins. These bins form the basis for estimating state probabilities and computing energy values. Based on preliminary experiments [**?**], we used `n_bins = 30`. The `cutoff_quantile` parameter sets the anomaly threshold by determining the energy value corresponding to a quantile of the training data's energy distribution. For instance, a setting of `cutoff_quantile = 0.90` classifies any sample with an energy score above the 90th percentile as anomalous. Finally, `pseudocounts` addresses the issue of zero probabilities when encountering states not seen in the training data. We used a small `pseudocounts` of `0.10` to ensure numerical stability during energy computation.

Regarding the *training process*, a central aspect of our EFC configuration is its alignment with the anomaly detection setting under label scarcity. As outlined in Section 3.2, the EFC model was trained exclusively on licit (normal) transactions from the

training period (time steps 1–34) by invoking its `fit` method. This follows the one-class classification paradigm, in which the model learns the energy landscape associated with legitimate Bitcoin transactions based solely on verified normal examples. Illicit transactions were entirely excluded from the training phase to preserve the model's ability to generalize and detect anomalies without prior exposure to them.

During the evaluation phase, the trained EFC model's `predict` method was applied to the test set—transactions from time steps 35–49, which contained both licit and illicit instances. For each test transaction, the EFC computed an energy score based on its features and the probability distributions learned during training. If a transaction's energy score exceeded the pre-determined cutoff threshold (derived from the `cutoff_quantile` applied to the training data's energy distribution), it was classified as anomalous (predicted illicit); otherwise, it was classified as normal (predicted licit). The energy scores were also used to compute evaluation metrics such as AUC, which assess ranking performance rather than relying on a fixed classification threshold.

4. Goal, Questions, and Metrics

The primary goal of this study is to evaluate the effectiveness of the Energy Flow Classifier (EFC), configured as described in Section 3.3, for identifying illicit transactions within the Elliptic Bitcoin dataset. This aligns with the broader goal of exploring alternative methodologies, particularly those suited for label scarcity, compared to the supervised approaches examined by [Lorenz et al. 2021]. Our aim is to answer the following research question: *How effective is the Energy-Based Flow Classifier (EFC) under conditions of label scarcity in identifying illicit transactions in the Elliptic Bitcoin dataset?*

Specifically, our research is thus framed as a *one-class anomaly detection problem*. Having trained the EFC model exclusively on Licit transactions from the initial time steps (1-34), the objective is to assess its ability to distinguish between licit and illicit transactions in the subsequent, unseen time steps (35-49) of the test set. This evaluation involves two main perspectives:

1. **Classification Performance:** Using the energy threshold derived from the training data, based on the `cutoff_quantile`, we assess how well EFC classifies unseen transactions as either licit (below threshold) or illicit (above threshold). Performance is measured using standard classification metrics suitable for imbalanced datasets, such as Precision, Recall, F1-Score, and potentially Balanced Accuracy, calculated on the labeled test set.
2. **Ranking Performance:** Independent of a specific threshold, we evaluate EFC's ability to assign consistently higher energy scores to illicit transactions compared to licit transactions in the test set. This is primarily assessed using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which measures the model's ability to rank anomalies higher than normal instances across all possible thresholds.

The outcome of this research may provide insights into the potential of EFC as a viable tool for detecting fraudulent or anomalous Bitcoin transactions. By leveraging its unsupervised, energy-based approach, EFC aims to address challenges such as label scarcity and to identify novel deviations from normal transaction behavior.

5. Results

This section presents the empirical findings from the application of the Energy Flow Classifier (EFC) to the task of identifying illicit transactions within the Elliptic Bitcoin dataset. Following the methodology outlined in Section 3, the EFC was employed primarily as a one-class anomaly detector, trained exclusively on transactions labeled as Licit from the initial time steps (1-34). The core objective was to evaluate the model's capability to distinguish these known Licit patterns from potentially anomalous Illicit transactions present in the unseen test set (time steps 35-49). Performance is assessed based on the EFC's ability to assign distinct energy scores to the two classes and evaluated using metrics appropriate for imbalanced anomaly detection scenarios. The subsequent subsections detail the outcomes of specific experiments conducted, focusing on the model's baseline performance and sensitivity to key configuration parameters under the defined experimental setup.

5.1. Shared Experimental Setup

Unless explicitly stated otherwise in the description of a specific experiment, the following setup, derived from the procedures detailed in Section 3, was consistently used across the results presented below:

- **Dataset Split:** The EFC model was trained exclusively on transactions labeled as Licit from time steps 1 to 34. Evaluation was performed on the test set containing both Licit and Illicit transactions from time steps 35 to 49. Transactions labeled 'Unknown' were excluded from both training and testing.
- **Feature Set:** The input to the EFC model consisted of the 165 anonymized features described in Section 3.1, after removing the time step feature. These features were scaled to the range [0, 1] using Min-Max scaling, with the scaler fitted only on the training data (Licit transactions, steps 1-34).
- **EFC Configuration:** The core EFC implementation (Section 3.3) utilized the following default hyperparameters based on initial tuning and common practice:
  - Number of bins for feature discretization `n_bins=30`
  - Cutoff quantile for anomaly threshold `cutoff_quantile=0.9` (meaning the energy threshold is set at the 90th percentile of the energy distribution of the Licit training data)
  - Pseudocounts `pseudocounts=0.1` (to handle zero probabilities)
- **Evaluation Metrics & Outputs:** Model performance was assessed using a combination of quantitative metrics and qualitative analysis:
  - **F1-Score (Macro Average):** As the primary evaluation metric, we adopted the macro-averaged F1-score, consistent with the benchmark study by [Lorenz et al. 2021]. This metric calculates the F1-score for each class (Licit and Illicit) independently and then averages them, providing a balanced measure of performance across both classes, which is crucial given the inherent class imbalance.
  - **Class-Specific Metrics (Illicit Class):** While F1-Macro provides an overall view, our primary interest lies in detecting the Illicit class (class 1). Therefore, we also report Precision, Recall, and the F1-Score specifically calculated for the Illicit class based on the classification derived from the `cutoff_quantile` threshold. These metrics offer direct insight into the

model's effectiveness in identifying illicit transactions and the associated trade-offs (e.g., false positives vs. false negatives).
- **EFC Energy Distributions:** For each experiment, histograms comparing the distribution of EFC energy scores assigned to Licit versus Illicit transactions in the test set were generated. These plots provide a visual assessment of the model's separation capability.
- **Detailed Results Storage:** Key information for each experimental run, including the sizes of the training and testing datasets (and their class distributions), the calculated performance metrics, and the confusion matrix, were systematically collected and saved into individual CSV files for detailed comparison and analysis across experiments.

The following subsections will now present the results from the specific experiments conducted under this framework, highlighting deviations from this shared setup where applicable.

5.2. Experiments

This section details the experimental evaluations conducted to assess the proposed methodologies. We performed three primary experiments focusing on data balancing, feature engineering/selection, and model comparison/tuning, respectively. All experiments utilized the EFC dataset, preprocessed as described previously, employing a standard train-test split methodology.

5.3. Experiment 1: Impact of Data Balancing Techniques

This experiment investigated the effect of various data balancing strategies on classification performance for the inherently imbalanced EFC dataset. The baseline performance was established using the original, unbalanced dataset. This was compared against four common balancing techniques applied to the training dataset and test dataset: creating a balanced subset with equally distributed classes, by undersampling the majority class before splitting, Synthetic Minority Over-sampling Technique (SMOTE), Random Oversampling of the minority class, and Random Undersampling of the majority class. The test set composition remained consistent across most techniques to ensure fair evaluation. Performance was evaluated using Accuracy, Precision, Recall, F1-Score (weighted), Macro F1-Score, and confusion matrices. Table **??** summarizes the dataset characteristics after applying each technique and the corresponding classification results.

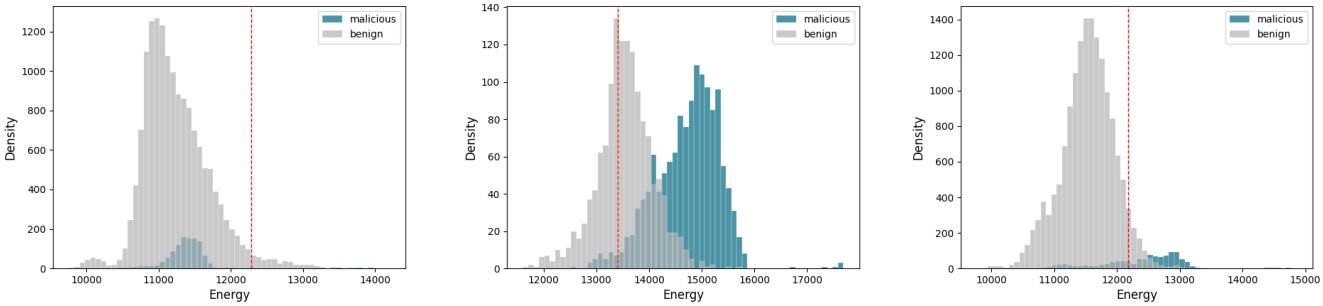
Below, we can find the experiment collected results - the model metrics and the EFC energy distributions.

Discussion of Experiment 1 Results The results from Experiment 1 (Table 2) clearly illustrate the EFC's sensitivity to class imbalance and the significant impact of balancing techniques. The baseline "Unbalanced Dataset," when tested on an imbalanced test set, yielded a low F1-Macro score of 0.488, confirming the difficulty in detecting the minority illicit class without intervention. This was an expected outcome given the nature of one-class classifiers and imbalanced data. Applying SMOTE and evaluating on a balanced test set resulted in a striking improvement, with an F1-Macro of 0.908. This suggests that EFC

Table 2. EFC Performance Across Data Balancing Techniques (Experiment 1).

Configuration	TP	FN	FP	TN	Accuracy	Precision	Recall	F1-Score (Weighted)	F1-Macro
Unbalanced Dataset (Baseline)[a]	15117	470	1064	19	0.908	0.876	0.908	0.891	0.488
Balanced Dataset (Equally Dist.)[b]	516	848	37	1326	0.675	0.772	0.675	0.644	0.644
SMOTE[b]	10831	1775	530	12076	0.909	0.913	0.909	0.908	**0.908**
Random Oversampling[a]	15393	194	1013	70	0.928	0.895	0.928	0.907	0.533
Random Undersampling[a]	13791	1796	412	671	0.868	0.926	0.868	0.890	0.652

Note: TP=True Positives, FN=False Negatives, FP=False Positives, TN=True Negatives. Metrics are rounded. F1-Score is weighted average. F1-Macro for SMOTE is bolded as it's the highest among these techniques. Test set composition: ([a]) Imbalanced, ([b]) Balanced.



(a) Unbalanced Dataset. **(b)** Balanced Dataset. **(c)** SMOTE.

Figure 1. Experiment 1: Energy Distribution Of Licit and Illicit Transactions.

can perform exceptionally well if the training data is appropriately balanced and the evaluation scenario also reflects a more balanced class distribution. Other techniques applied to the training data but evaluated on an imbalanced test set also showed improvements over the baseline: Random Oversampling achieved an F1-Macro of 0.533, and Random Undersampling reached 0.652. This indicates that even simpler balancing methods can enhance EFC's performance on imbalanced test data, with undersampling being more effective than oversampling in this specific setup. The "Balanced Dataset (Equally Dist.)" technique, which involved undersampling the majority class to create a balanced training and test set, achieved an F1-Macro of 0.644. While better than the baseline, it did not match SMOTE's performance on a balanced test set, suggesting that SMOTE's approach of generating synthetic minority samples is more beneficial for EFC in such conditions. The stark contrast in F1-Macro scores, particularly between SMOTE on a balanced test set and other techniques on imbalanced test sets, underscores the critical influence of test set composition on this metric.

5.4. Experiment 2: Impact of Feature Selection

Following the analysis of data balancing, Experiment 4 focused on evaluating the impact of feature selection on classification performance using the Energy-Based Flow Classifier (EFC). We employed the `SelectKBest` algorithm from scikit-learn, utilizing the ANOVA F-value (`f_classif`) scoring function to rank and select features based on their relevance to the class labels. The experiment systematically varied the number of selected features, testing values of $k \in 10, 20, 30, 40, 50, 60$. The feature selection process using `SelectKBest` was applied to the features and labels of the original unbalanced

dataset *before* the standard train-test split was performed on the resulting reduced feature set. Furthermore, we conducted two distinct series of runs: one applying feature selection to the complete feature set, including aggregated temporal features, and another applying it only to the raw node features after explicitly excluding the aggregated ones. The decision to conduct feature selection in two distinct scenarios within Experiment 2—one including the aggregated neighborhood statistics and one explicitly excluding them—was driven by the need to understand the specific impact and contribution of these aggregated features. Aggregated features, which represent statistical summaries of a node's neighborhood (as described in related financial forensics work, e.g., [Weber et al. 2019]), often possess high individual predictive power due to the condensed information they carry about local graph structure. Including these potentially dominant features in the `SelectKBest` process (Scenario 1) could lead to them consistently ranking highest, potentially masking the predictive contribution of the node's intrinsic, raw features. By running a separate scenario (Scenario 2) where these aggregated features were removed *before* applying `SelectKBest`, we aimed to isolate and evaluate the predictive capability derived solely from the raw node characteristics. This allows for a clearer comparison and a better understanding of which feature types (raw vs. aggregated) are most crucial for classification, especially when operating under the dimensionality constraints imposed by selecting only the top k features.

Performance for each value of k and for both feature set scenarios (with and without aggregated features) was assessed using standard classification metrics (Accuracy, Precision, Recall, F1-Score, and F1-Macro). The objective was to determine if reducing dimensionality could maintain or improve performance, identify an optimal number of features (k), and understand the contribution of aggregated features within this selection context.

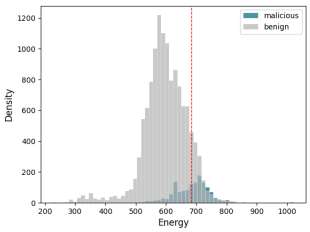
Table results and EFC energies histograms can be found below.

Table 3. EFC Performance with Feature Selection (Aggregated Features Excluded) for Varying k (Experiment 2a).

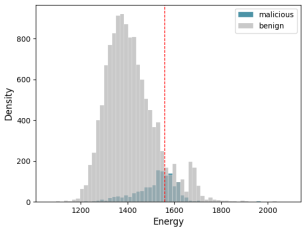
k Value	TP	FN	FP	TN	Accuracy	Precision	Recall	F1-Score (Weighted)	F1-Macro
10	11317	1289	598	766	0.865	0.893	0.865	0.877	**0.686**
20	11326	1280	859	505	0.847	0.866	0.847	0.856	0.617
30	11330	1276	1103	261	0.830	0.839	0.830	0.834	0.542
40	11305	1301	1341	23	0.811	0.808	0.811	0.810	0.456
50	11291	1315	1318	46	0.812	0.811	0.812	0.811	0.465
60	11254	1352	1138	226	0.822	0.833	0.822	0.827	0.527

Note: Feature selection excluding aggregated features. TP=True Positives, FN=False Negatives, FP=False Positives, TN=True Negatives. Metrics rounded to three decimal places. F1-Score is weighted average. F1-Macro for k=10 is bolded as it's the highest.

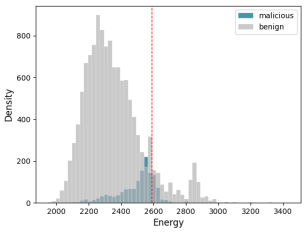
Discussion of Experiment 2 Results Experiment 2 investigated the impact of feature selection on EFC's performance, with results presented in Table 3 (aggregated features excluded) and Table 4 (aggregated features included). A key observation across both scenarios is that EFC can achieve its best performance with a significantly reduced feature set. When aggregated features were excluded (Table 3), the highest F1-Macro score of 0.686



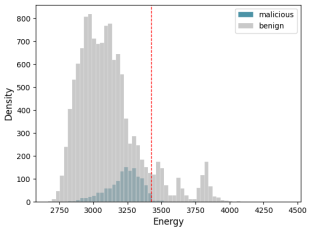
(a) k=10.



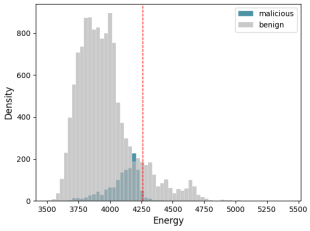
(b) k=20.



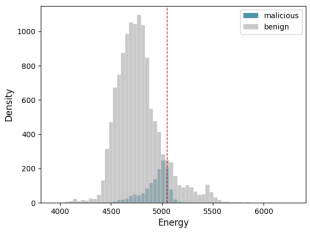
(c) k=30.



(d) k=40.

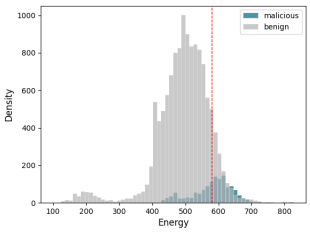


(e) k=50.

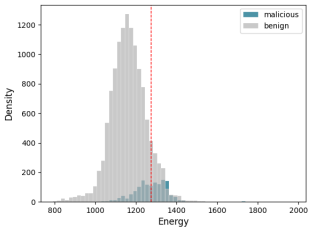


(f) k=60.

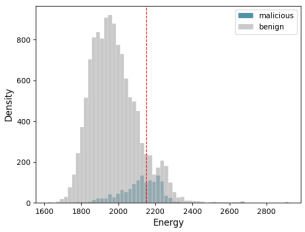
Figure 2. Experiment 2, Technique A: Feature Selection Excluding Aggregate



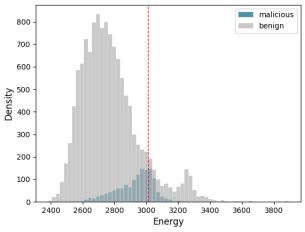
(a) k=10.



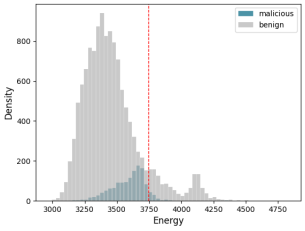
(b) k=20.



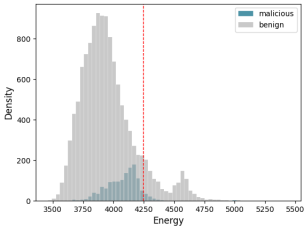
(c) k=30.



(d) k=40.



(e) k=50.



(f) k=60.

Figure 3. Experiment 2, Technique B: Feature Selection Including Aggregate Fea-

Table 4. EFC Performance with Feature Selection (Aggregated Features Included) for Varying k (Experiment 2b).

k Value	TP	FN	FP	TN	Accuracy	Precision	Recall	F1-Score (Weighted)	F1-Macro
10	11254	1352	560	804	0.863	0.896	0.863	0.876	**0.689**
20	11297	1309	656	708	0.859	0.887	0.859	0.871	0.669
30	11309	1297	789	575	0.851	0.874	0.851	0.861	0.635
40	11296	1310	991	373	0.835	0.851	0.835	0.843	0.576
50	11291	1315	1265	99	0.815	0.818	0.815	0.817	0.484
60	11269	1337	1261	103	0.814	0.819	0.814	0.816	0.485

Note: Feature selection including aggregated features. TP=True Positives, FN=False Negatives, FP=False Positives, TN=True Negatives. Metrics rounded to three decimal places. F1-Score is weighted average. F1-Macro for k=10 is bolded as it's the highest.

was obtained with only $k = 10$ features. Similarly, when aggregated features were included in the selection pool (Table 4), the peak F1-Macro was 0.689, also at $k = 10$. This suggests that a small subset of the most relevant features is sufficient for EFC, and including more features beyond this optimal k (generally $k > 20$) tends to degrade performance, likely due to the introduction of noise or less informative features that can adversely affect EFC's energy calculations. This diminishing return with increasing k is a common phenomenon in feature selection. The slightly higher F1-Macro obtained when aggregated features were included (0.689 vs. 0.686) indicates their strong predictive value, even when only a few are selected. These F1-Macro scores represent a notable improvement over the baseline (0.488 from Experiment 1) but are not as high as those achieved with data balancing techniques like Random Undersampling (0.652 on an imbalanced test set) or SMOTE (0.908 on a balanced test set). This implies that while feature selection is beneficial for dimensionality reduction and can improve upon the baseline, addressing class imbalance appears to be a more critical factor for enhancing EFC's F1-Macro score in this dataset. The results were largely as expected, confirming that feature selection can be effective but might not be a complete solution without tackling imbalance.

5.5. Experiment 3: Combining Feature Selection and Data Balancing

of feature selection and data balancing on the performance of the EFC classifier, building upon the findings from Experiment 1 (data balancing) and Experiment 24 (feature selection). The core idea was to first reduce the dimensionality of the dataset using the feature selection technique identified in Experiment 4, and then apply the SMOTE balancing technique from Experiment 1 to the reduced-feature training data before training the EFC model.

Specifically, for each value of $k \in \{10, 20, 30, 40, 50, 60\}$, we first applied the `SelectKBest` algorithm with the `f_classif` scoring function to the original, unbalanced dataset (as performed in the first scenario of Experiment 2) to obtain a dataset containing only the top k features. Subsequently, this k-feature dataset underwent the SMOTE procedure: it was split into training and testing sets, SMOTE was applied *only* to the training portion to balance the classes, and the EFC classifier was then trained on this balanced, feature-selected training data. Finally, the trained EFC model was evaluated on the corresponding unbalanced test set (containing the same k selected features). Performance was assessed using the standard suite of metrics (Accuracy, Precision, Re-

call, F1-Score, Macro F1-Score) to determine if applying dimensionality reduction prior to SMOTE balancing could yield improved classification performance compared to using SMOTE on the full feature set (Experiment 1) or using feature selection alone (Experiment 2).

Table 5. EFC Performance: SMOTE with Feature Selection for Varying k (Experiment 3a).

k Value	TP	FN	FP	TN	Accuracy	Precision	Recall	F1-Score (Weighted)	F1-Macro
10	11319	1287	369	995	0.891	0.931	0.891	0.891	0.770
20	11326	1280	263	1101	0.900	0.939	0.900	0.900	0.798
30	11331	1275	226	1138	0.903	0.942	0.903	0.903	**0.808**
40	11272	1334	223	1141	0.900	0.940	0.900	0.900	0.799
50	11233	1373	247	1117	0.894	0.935	0.894	0.894	0.780
60	11239	1367	243	1121	0.895	0.936	0.895	0.895	0.783

Note: SMOTE applied to training data after feature selection (including aggregated features). Test set is unbalanced. TP=True Positives, FN=False Negatives, FP=False Positives, TN=True Negatives. Metrics rounded. F1-Score is weighted average. F1-Macro for k=30 is bolded.

Table 6. EFC Performance: SMOTE with Feature Selection (Full Test Dataset Context) for Varying k (Experiment 3b).

k Value	TP	FN	FP	TN	Accuracy	Precision	Recall	F1-Score (Weighted)	F1-Macro
10	11322	1284	368	996	0.882	0.894	0.882	0.917	0.739
20	11302	1304	259	1105	0.888	0.901	0.888	0.927	0.761
30	11313	1293	218	1146	0.892	0.905	0.892	0.931	**0.770**
40	11254	1352	222	1142	0.887	0.901	0.887	0.930	0.763
50	11258	1348	249	1115	0.886	0.899	0.886	0.927	0.758
60	11278	1328	249	1115	0.887	0.901	0.887	0.927	0.760

Note: SMOTE applied to training data after feature selection (including aggregated features). Test set is unbalanced (1364 Malicious, 12606 Benign). TP=True Positives, FN=False Negatives, FP=False Positives, TN=True Negatives. Metrics rounded. F1-Score is weighted average. F1-Macro for k=30 is bolded.

Discussion of Experiment 3 Results Experiment 3 explored the synergistic effect of combining feature selection (using aggregated features in the selection pool) with SMOTE data balancing. The results are detailed in Table 5 (Experiment 3a, standard unbalanced test set) and Table 6 (Experiment 3b, "Full Test Dataset" context, also an unbalanced test set). In Experiment 3a, the combination yielded a peak F1-Macro score of 0.808 when $k = 30$ features were selected before applying SMOTE. This is a substantial improvement compared to using feature selection alone (Experiment 2, best F1-Macro 0.689) and the baseline (0.488). It also surpasses the F1-Macro achieved by Random Undersampling alone (0.652) on a similar imbalanced test set. This outcome was anticipated, as combining two effective strategies—dimensionality reduction to focus on salient features and SMOTE to address imbalance—was expected to enhance performance. The optimal $k = 30$ here is higher than the $k = 10$ found in Experiment 2 (FS alone), suggesting that SMOTE might benefit from a slightly richer, yet still reduced, feature set to

generate more effective synthetic samples. Experiment 3b, conducted under the "Full Test Dataset" context (which also utilized an imbalanced test set as per its note), showed a similar trend, with $k = 30$ also yielding the best F1-Macro score of 0.770. While this is still a strong result and a significant improvement over the baseline and feature selection alone, it is slightly lower than the 0.808 achieved in Experiment 3a. This minor discrepancy, despite both experiments testing on imbalanced sets, could be attributed to subtle differences in the exact composition or characteristics of the test data partitions used, or slight variations in the feature subsets selected if the "Full Test Dataset" context implied any nuanced differences in the overall feature pool available before selection for that specific run. Overall, Experiment 3 demonstrates that a combined strategy of feature selection followed by SMOTE balancing is highly effective for improving EFC's F1-Macro score on imbalanced test data, outperforming either technique applied in isolation (when FS is tested on imbalanced data). However, these scores still do not reach the F1-Macro of 0.908 achieved by SMOTE alone when evaluated on an ideally balanced test set (Experiment 1), further highlighting the profound impact of the evaluation scenario's balance on the F1-Macro metric.

6. Conclusion

This study evaluated the Energy Flow Classifier (EFC) as a one-class anomaly detection method for identifying illicit Bitcoin transactions within the Elliptic dataset, focusing on scenarios with label scarcity. In evaluating the performance of the different techniques across our experiments, we adopted the **F1-macro score** as the primary overall metric. This choice aligns with the methodology presented by [Lorenz et al. 2021] in their work on detecting money laundering in Bitcoin, particularly relevant given the common challenge of label scarcity in such datasets. The F1-macro score is calculated by first determining the F1 score (the harmonic mean of precision and recall) for each individual class (e.g., 'licit' and 'illicit' transactions). Then, the unweighted average of these per-class F1 scores is taken. This approach ensures that each class contributes equally to the final metric, regardless of its frequency in the dataset, providing a balanced assessment of model performance, especially crucial in imbalanced scenarios like fraud detection where correctly identifying the minority class is often of high importance.

The primary advantage of EFC lies in its one-class nature, making it suitable for real-world scenarios where illicit transaction labels are rare. However, our baseline experiment (Exp 1 - Unbalanced), using default parameters and training only on Licit data, revealed a significant disadvantage: high sensitivity to class imbalance. While achieving high overall accuracy (0.908) and weighted F1-score (0.891), the model performed poorly in distinguishing the minority Illicit class, resulting in a low F1-Macro score of 0.488.

Crucially, Experiment 1 demonstrated that EFC's performance can be substantially improved through standard data preprocessing techniques. Applying SMOTE balancing to the training data yielded the best results among the balancing methods tested, dramatically increasing the F1-Macro score to 0.760, indicating a much more balanced detection capability across both Licit and Illicit classes.

Further experiments explored feature selection (Exp 2) and its combination with balancing (Exp 3). Feature selection using `SelectKBest` showed that EFC can operate with reduced dimensionality; for instance, using only the top 10 non-aggregated features

yielded an F1-Macro of 0.686, outperforming the baseline but not reaching the levels achieved with SMOTE on the full feature set. The results for feature selection including aggregated features and the combined feature selection with SMOTE approach (currently placeholders in Table **??**) require further analysis to draw definitive conclusions about their potential benefits.

In summary, EFC presents a promising tool for detecting anomalous Bitcoin transactions, especially given its one-class training capability. Its main drawback is a pronounced sensitivity to class imbalance, which necessitates mitigation strategies like SMOTE balancing for effective performance (achieving F1-Macro 0.760). While feature selection is possible, careful consideration of trade-offs is required, as dimensionality reduction might impact performance compared to using balanced, full-feature data. The effectiveness of EFC in this context is therefore contingent on appropriate data preprocessing and potentially hyperparameter tuning, sensitivity to which was noted in Section 1 and implied by the experimental variations, to balance the detection of illicit activities against false alarms.

7. Future Work

While this study demonstrated the viability of the Energy Flow Classifier (EFC) for one-class anomaly detection in Bitcoin transactions, particularly when combined with techniques like SMOTE, several open questions and avenues for future research emerge:

- **Systematic Hyperparameter Optimization:** The current work used fixed default parameters (`n_bins=30`, `cutoff_quantile=0.9`). An open question is how sensitive EFC's performance, especially the precision-recall trade-off for the Illicit class, is to these parameters.
- **Advanced Balancing and Cost-Sensitive Learning:** SMOTE proved effective (Exp 1), but its interaction with EFC's energy calculation warrants further investigation. Are there other balancing techniques (e.g., ADASYN, Tomek Links, Edited Nearest Neighbours) or cost-sensitive learning approaches (adjusting the EFC threshold based on misclassification costs) that could yield better or more robust performance, perhaps with fewer synthetic samples or different biases?
- **Exploring Feature Selection Synergies:** Experiments 2 and 3 explored feature selection, showing potential but requiring further analysis **??**. Key questions remain: What is the optimal number of features (k) when including aggregated features? Does the combination of FS and SMOTE truly outperform SMOTE alone with full features, considering both performance and computational cost?
- **Integration of Graph Structure:** The current EFC implementation primarily leverages node features, largely ignoring the rich topological information in the Elliptic graph dataset. Can explicitly incorporating transaction linkage improve detection?
- **Scalability Analysis:** How does the computational cost (training time, memory usage, prediction latency) of EFC scale with the number of transactions and features, especially compared to other methods?

Addressing these questions would further solidify the understanding of EFC's strengths and weaknesses in the financial forensics domain and guide its potential practical application.

8. Reproducibility

To ensure the reproducibility of our findings, all code, configuration files, and scripts used for the experiments described in this paper are made publicly available in a dedicated repository: **https://github.com/kevinsantana/PPCA-UnB-Dissertation**.

8.1. Computational Environment

The experiments were conducted on a system with the following specifications:

- **Operating System:** macOS 14.5 23F79 arm64
- **Processor:** Apple M1 Pro
- **GPU:** Apple M1 Pro
- **Memory (RAM):** 32 GB

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