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A New Framework for Fraud Detection in Bitcoin Transactions Through Ensemble Stacking Model in Smart Cities

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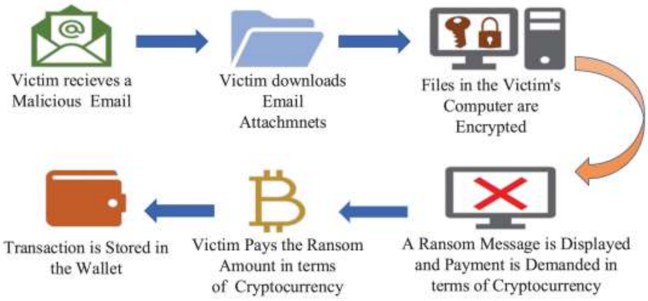
Abstract - *Fraudulent activities within Bitcoin transactions present a pressing concern for the integrity of financial systems, particularly in the context of smart cities where digital currencies are increasingly prevalent. In response to this challenge, we propose a pioneering framework for fraud detection that harnesses the power of machine learning, specifically leveraging the XGBoost algorithm. Our framework integrates the robust security features of blockchain technology to combat illegal transactions such as money laundering, dark web transactions, and ransomware payments.While blockchain technology offers a decentralized and secure ledger for recording transactions, it falls short in detecting fraudulent patterns within legitimate transactions. To address this limitation, our solution introduces a novel approach by incorporating ensemble stacking models. These models combine the strengths of various machine learning algorithms to enhance the accuracy and reliability of fraud identification.*

By integrating machine learning with blockchain technology, our framework aims to provide a comprehensive solution for detecting and preventing fraudulent activities in Bitcoin transactions within the dynamic landscape of smart cities. Our system is designed to proactively identify anomalies and deviations from normal transaction behavior, enabling timely intervention to prevent fraudulent activities.This proposed framework represents a significant advancement in bolstering the security of smart cities' financial ecosystems. By capitalizing on the transparency and immutability of blockchain technology and harnessing the sophisticated pattern recognition capabilities of machine learning, our solution offers a comprehensive and adaptive approach to combating the evolving landscape of fraudulent activities within Bitcoin transactions.

KEYWORDS: *Fraud Detection, Bitcoin, Smart Cities, Machine Learning, XGBoost, Blockchain Technology, Ensemble Stacking Models, Anomaly Detection.*

1. INTRODUCTION

With the escalating prevalence of fraudulent activities in Bitcoin transactions within the framework of smart cities, there arises a pressing need for a robust solution. While blockchain technology provides a foundation for security, its limitations in actively identifying fraudulent patterns within legitimate transactions are evident. Moreover, the surge in illegal transactions, encompassing money laundering, dark web transactions, and ransomware payments, underscores the urgency for a comprehensive approach.



To address this challenge, this project proposes a pioneering framework that amalgamates the power of machine learning, particularly the XGBoost algorithm, with the security features of blockchain. By integrating these technologies, the framework aims to not only prevent unauthorized transactions but also proactively detect and mitigate fraudulent activities.

Central to the proposed solution is the utilization of ensemble stacking models, which combine multiple machine learning algorithms to enhance the accuracy of fraud detection. This approach enables the system to identify anomalies and deviations from normal transaction behavior, thereby bolstering the resilience of the financial ecosystem within smart cities.

In essence, this project endeavors to bridge the gap between machine learning and blockchain technology to provide a holistic solution for detecting and preventing fraudulent activities in Bitcoin transactions. By doing so, it aims to contribute to the establishment of a more secure and resilient financial infrastructure within the dynamic landscape of smart cities.

1.1 Addressing the Challenge:

This project endeavors to confront these challenges head-on by proposing an innovative framework that seamlessly integrates the power of machine learning, specifically leveraging the XGBoost algorithm, with the inherent security features of blockchain. By synergizing these cutting-edge technologies, the aim is not only to fortify the defenses against unauthorized transactions but also to proactively identify and mitigate fraudulent activities before they escalate.

1.2 Advancing Financial Ecosystems:

Beyond mere detection, the envisioned framework aspires to contribute to the establishment of a more secure and resilient financial ecosystem within smart cities. By instilling confidence among users and stakeholders alike, it fosters trust in the integrity of digital transactions, thus laying the groundwork for sustained growth and innovation in the digital economy.

1.3 Advantages

1. The integration of blockchain technology ensures a secure and transparent environment for financial transactions, preventing illegal activities and ensuring the integrity of the transaction history.

2. Anomaly detection techniques, a fundamental aspect of recognizing potential fraud, to identify irregular patterns in Bitcoin transactions.

3. In the real-time monitoring of transactions, enabling swift responses to potential fraud and minimizing the impact of illicit activities.

4. The automated nature of the ensemble stacking model, combined with blockchain's efficiency in transaction processing, contributes to a cost-effective solution for fraud detection in Bitcoin transactions.

1.4 Applications

1. Fraud Detection in Bitcoin Transactions: The project's primary application is the detection of fraudulent activities within Bitcoin transactions, including money laundering, dark web transactions, and ransomware payments.
2. Smart City Security: It enhances security within smart cities by proactively identifying and mitigating potential instances of fraud, thus safeguarding the integrity of digital transactions.
3. Financial Ecosystem Resilience: By fortifying the financial ecosystem against illicit transactions, the project contributes to its resilience and stability, fostering trust among users and stakeholders.
4. Real-Time Detection: The system enables real-time detection of anomalies and deviations from normal transaction behavior, allowing for timely intervention to prevent fraudulent activities from escalating.
5. Adaptability to Evolving Threats: Its adaptability ensures effectiveness against evolving fraud tactics, ensuring continued relevance and efficacy in combating emerging threats.
6. Promotion of Economic Growth: By fostering a secure and trustworthy environment for digital transactions, the project promotes economic growth and innovation within smart cities.

2. METHODOLOGY

2.1.Overview

The proposed framework for fraud detection in Bitcoin transactions within the context of smart cities leverages a robust combination of machine learning, specifically the XGBoost algorithm, and blockchain technology.
In response to the inherent limitations of blockchain in detecting fraudulent transactions, our system introduces a novel approach by integrating anomaly detection techniques.
The ensemble stacking model, a fusion of various machine learning algorithms, serves as the cornerstone of our system, enhancing the accuracy and reliability of fraud identification.

The strengths of XGBoost and blockchain, our framework aims to proactively address challenges associated with money laundering, dark web transactions, and ransomware payments.
The system capitalizes on the transparency and immutability of blockchain while employing the sophisticated pattern recognition capabilities of machine learning to identify irregularities indicative of potential fraud.

This proposed system represents a pioneering step towards bolstering the security of smart cities' financial ecosystems, offering a comprehensive and adaptive solution to the evolving landscape of fraudulent activities within Bitcoin transactions.

2.2.Work Flow

The following are the proceedings :
Dataset
•Gather a diverse and representative dataset containing information on various fault scenarios and normal operating conditions of tail ropes.
•Annotate the dataset to label instances of different fault types and normal behavior for supervised learning.
Preprocessing
Address missing values, outliers, and inconsistencies in the dataset to ensure the quality of training data.
Normalize or scale the input features to ensure uniformity and facilitate convergence during training.
Divide the dataset into training and testing sets, ensuring an appropriate balance to prevent over fitting or under fitting.
For preprocessing , we have used here is scikit-learn (sklearn) since we could do the following
Text Processing , Feature Selection , Missing Data Imputation etc.
Data Labelling :
Labelbox allows teams to efficiently label large datasets, iterate on labeling tasks, and manage labeling projects at scale. Its features include customizable labeling workflows, automation options, and support for multiple data types.

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Feature extraction

•Utilize **signal processing techniques** to extract relevant features from the raw data, capturing patterns indicative of faults in tail ropes because of **Noise Reduction , Feature Extraction , Dimensionality Reduction , Pattern Recognition** etc.

•Design the input layer to accommodate the extracted features, considering the temporal and spectral aspects of tail rope data.

Data Base

•Establish a database to store the preprocessed and feature-extracted data. Consider using a relational database for efficient data retrieval during training and testing.

•We are using **postgres** for database storage due to high capability of storing information.

Training

Employ a suitable loss function, such as categorical cross-entropy, to measure the difference between predicted and actual fault labels during training.

Train the model on the training set, monitoring performance on a separate validation set to prevent over fitting

Testing

Evaluate the trained model on the reserved testing set to assess its generalization performance and identify any issues.

Evaluate the model using metrics such as accuracy, precision, recall, and F1-score for both normal and faulty class predictions.

We use **Backtesting** and **Threshold Selection** usually as testing methods in specific.

2.3.Depth understanding of XGBoost

XGBoost, or eXtreme Gradient Boosting, is a machine learning algorithm under ensemble learning. It is trendy for supervised learning tasks, such as regression and classification. XGBoost builds a predictive model by combining the predictions of multiple individual models, often decision trees, in an iterative manner. The algorithm works by sequentially adding weak learners to the ensemble, with each new learner focusing on correcting the errors made by the existing ones. It uses a gradient descent optimization technique to minimize a predefined loss function during training.

Key features of XGBoost Algorithm include its ability to handle complex relationships in data, regularization techniques to prevent overfitting and incorporation of parallel processing for efficient computation. XGBoost is widely used in various domains due to its high predictive performance and versatility across different datasets.

2.3.1 **Ensemble Learning**

XGBoost is an ensemble learning method. Sometimes, it may not be sufficient to rely upon the results of just one machine learning model. Ensemble learning offers a systematic solution to combine the predictive power of multiple learners. The resultant is a single model which gives the aggregated output from several models.

The models that form the ensemble, also known as base learners, could be either from the same learning algorithm or different learning algorithms. Bagging and boosting are two widely used ensemble learners. Though these two techniques can be used with several statistical models, the most predominant usage has been with decision trees.

Let's briefly discuss bagging before taking a more detailed look at the concept of gradient boosting.

1. Bagging

While decision trees are one of the most easily interpretable models, they exhibit highly variable behavior. Consider a single training dataset that we randomly split into two parts. Now, let's use each part to train a decision tree in order to obtain two models.

When we fit both these models, they would yield different results. Decision trees are said to be associated with high variance due to this behavior. Bagging or boosting aggregation helps to reduce the variance in any learner. Several decision trees which are generated in parallel, form the base learners of bagging technique. Data sampled with replacement is fed to these learners for training. The final prediction is the averaged output from all the learners.

2. Boosting

In boosting, the trees are built sequentially such that each subsequent tree aims to reduce the errors of the previous tree. Each tree learns from its predecessors and updates the residual errors. Hence, the tree that grows next in the sequence will learn from an updated version of the residuals.

The base learners in boosting are weak learners in which the bias is high, and the predictive power is just a tad better than random guessing. Each of these weak learners contributes some vital information for prediction, enabling the boosting technique to produce a strong learner by effectively combining these weak learners. The final strong learner brings down both the bias and the variance.

In contrast to bagging techniques like Random Forest, in which trees are grown to their maximum extent, boosting makes use of trees with fewer splits. Such small trees, which are not very deep, are highly interpretable. Parameters like the number of trees or iterations, the rate at which the gradient boosting learns, and the depth of the tree, could be optimally selected through validation techniques like k-fold cross validation. **Having a large number of trees might lead to overfitting. So, it is necessary to carefully choose the stopping criteria for boosting.**

The gradient boosting ensemble technique consists of three simple steps:

An initial model F0 is defined to predict the target variable y. This model will be associated with a residual (y – F0)

A new model h1 is fit to the residuals from the previous step

Now, F0 and h1 are combined to give F1, the boosted version of F0. The mean squared error from F1 will be lower than that from F0:

$$F_1(x) <- F_0(x) + h_1(x)$$

To improve the performance of F1, we could model after the residuals of F1 and create a new model F2:

$$F_2(x) <- F_1(x) + h_2(x)$$

This can be done for *'m'* iterations, until residuals have been minimized as much as possible:

$$F_m(x) \leftarrow F_{m-1}(x) + h_m(x)$$

Here, the additive learners do not disturb the functions created in the previous steps. Instead, they impart information of their own to bring down the errors

2.3.2.Demonstration

Consider the following data where the years of experience is predictor variable and salary (in thousand dollars) is the target. Using regression trees as base learners, we can create an ensemble model to predict the salary. For the sake of simplicity, we can choose square loss as our loss function and our objective would be to minimize the square error. As the first step, the model should be initialized with a function F0(x). F0(x) should be a function which minimizes the loss function or MSE (mean squared error), in this case:

$$F_0(x) = argmin_\gamma \sum_{i=1}^{n} L(y_i, \gamma)$$

$$argmin_\gamma \sum_{i=1}^{n} L(y_i, \gamma) = argmin_\gamma \sum_{i=1}^{n} (y_i - \gamma)^2$$

Taking the first differential of the above equation with respect to γ, it is seen that the function minimizes at the mean i=1nyin. So, the boosting model could be initiated with:

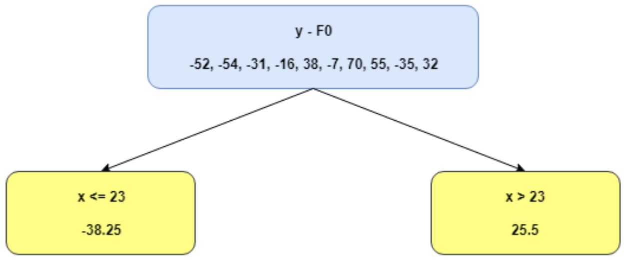
$$F_0(x) = \frac{\sum_{i=1}^{n} y_i}{n}$$

F0(x) gives the predictions from the first stage of our model. Now, the residual error for each instance is (yi – F0(x)).

Years	Salary
5	82
7	80
12	103
23	118
25	172
28	127
29	204
34	189
35	99
40	166

x	y	F0	y - F0
5	82	134	-52
7	80	134	-54
12	103	134	-31
23	118	134	-16
25	172	134	38
28	127	134	-7
29	204	134	70
34	189	134	55
35	99	134	-35
40	166	134	32

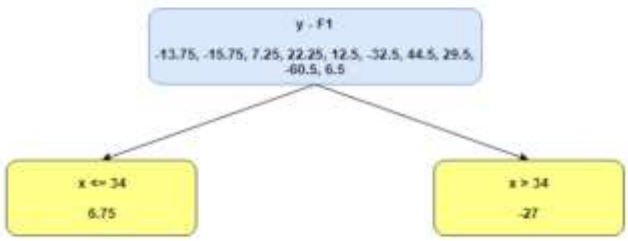
h1(x)

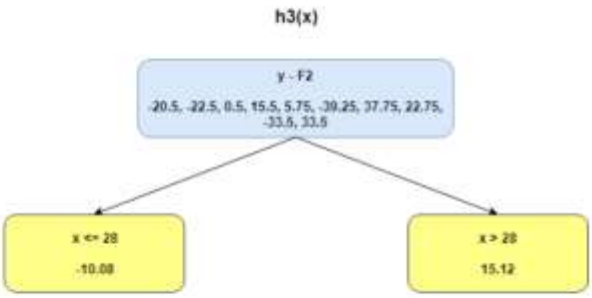


The additive model h1(x) computes the mean of the residuals (y – F0) at each leaf of the tree. The boosted function F1(x) is obtained by summing F0(x) and h1(x). This way h1(x) learns from the residuals of F0(x) and suppresses it in F1(x).

x	y	F0	y-F0	h1	F1
5	82	134	-52	-38.25	95.75
7	80	134	-54	-38.25	95.75
12	103	134	-31	-38.25	95.75
23	118	134	-16	-38.25	95.75
25	172	134	38	25.50	159.50
28	127	134	-7	25.50	159.50
29	204	134	70	25.50	159.50
34	189	134	55	25.50	159.50
35	99	134	-35	25.50	159.50
40	166	134	32	25.50	159.50

h2(x)

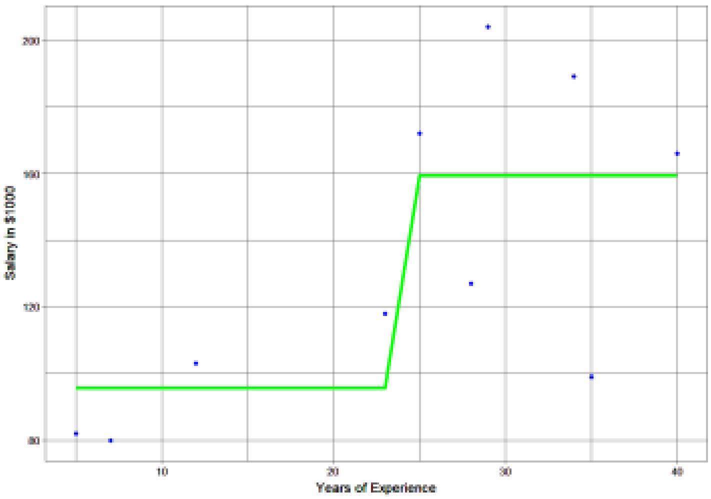




x	y	F0	y-F0	h1	F1	y-F1	h2	F2	y-F2	h3	F3
5	82	134	-52	-38.25	95.75	-13.75	6.75	102.50	-20.50	-10.08333	92.41667
7	80	134	-54	-38.25	95.75	-15.75	6.75	102.50	-22.50	-10.08333	92.41667
12	103	134	-31	-38.25	95.75	7.25	6.75	102.50	0.50	-10.08333	92.41667
23	118	134	-16	-38.25	95.75	22.25	6.75	102.50	15.50	-10.08333	92.41667
25	172	134	38	25.50	159.50	12.50	6.75	166.25	5.75	-10.08333	156.16667
28	127	134	-7	25.50	159.50	-32.50	6.75	166.25	-39.25	-10.08333	156.16667
29	204	134	70	25.50	159.50	44.50	6.75	166.25	37.75	15.12500	181.37500
34	188	134	55	25.50	159.50	29.50	6.75	166.25	22.75	15.12500	181.37500
35	99	134	-35	25.50	159.50	-60.50	-27.00	132.50	-33.50	15.12500	147.62500
40	166	134	32	25.50	159.50	6.50	-27.00	132.50	33.50	15.12500	147.62500

The MSEs for F0(x), F1(x) and F2(x) are 875, 692 and 540. It's amazing how these simple weak learners can bring about a huge reduction in error!

Note that each learner, hm(x), is trained on the residuals. All the additive learners in boosting are modeled after the residual errors at each step. Intuitively, it could be observed that the boosting learners make use of the patterns in residual errors. At the stage where maximum accuracy is reached by boosting, the residuals appear to be randomly distributed without any pattern.



Using Gradient d=Descent for Optimizing the Loss Function

In the case discussed above, MSE was the loss function. The mean minimized the error here. When MAE (mean absolute error) is the loss function, the median would be used as F0(x) to initialize the model. A unit change in y would cause a unit change in MAE as well.

For MSE, the change observed would be roughly exponential. Instead of fitting hm(x) on the residuals, fitting it on the gradient of loss function, or the step along which loss occurs, would make this process generic and applicable across all loss functions.

Gradient descent helps us minimize any differentiable function. Earlier, the regression tree for hm(x) predicted the mean residual at each terminal node of the tree. In gradient boosting, the average gradient component would be computed.

For each node, there is a factor γ with which hm(x) is multiplied. This accounts for the difference in impact of each branch of the split. Gradient boosting helps in predicting the optimal gradient for the additive model, unlike classical gradient descent techniques which reduce error in the output at each iteration.

The following steps are involved in gradient boosting:

F0(x) – with which we initialize the boosting algorithm – is to be defined:

$$F_0(x) = argmin_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma)$$

The gradient of the loss function is computed iteratively:

$$r_{im} = -\alpha\left[\frac{\partial(L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}, \text{ where } \alpha \text{ is the learning rate}$$

Each hm(x) is fit on the gradient obtained at each step

The multiplicative factor γm for each terminal node is derived and the boosted model Fm(x) is defined:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

2.3.3. Unique Features of XGBoost

XGBoost is a popular implementation of gradient boosting. Let's discuss some features of XGBoost that make it so interesting:

Regularization: XGBoost has an option to penalize complex models through both L1 and L2 regularization. Regularization helps in preventing overfitting

Handling sparse data: Missing values or data processing steps like one-hot encoding make data sparse. XGBoost incorporates a sparsity-aware split finding algorithm to handle different types of sparsity patterns in the data

Weighted quantile sketch: Most existing tree based algorithms can find the split points when the data points are of equal weights (using quantile sketch algorithm). However, they are not equipped to handle weighted data. XGBoost has a distributed weighted quantile sketch algorithm to effectively handle weighted data

Block structure for parallel learning: For faster computing, XGBoost can make use of multiple cores on the CPU. This is possible because of a block structure in its system design. Data is sorted and stored in in-memory units called blocks. Unlike other algorithms, this enables the data layout to be reused by subsequent iterations, instead of computing it again. This feature also serves useful for steps like split finding and column sub-sampling

Cache awareness: In XGBoost, non-continuous memory access is required to get the gradient statistics by row index. Hence, XGBoost has been designed to make optimal use of hardware. This is done by allocating internal buffers in each thread, where the gradient statistics can be stored

Out-of-core computing: This feature optimizes the available disk space and maximizes its usage when

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handling huge datasets that do not fit into memory

High accuracy: XGBoost is known for its accuracy and has been shown to outperform other machine learning algorithms in many predictive modeling tasks.

Scalability: It is highly scalable and can handle large datasets with millions of rows and columns.

Efficiency: It is designed to be computationally efficient and can quickly train models on large datasets.

Flexibility: It supports a variety of data types and objectives, including regression, classification, and ranking problems.

Regularization: It incorporates regularization techniques to avoid overfitting and improve generalization performance.

Interpretability: It provides feature importance scores that can help users understand which features are most important for making predictions.

Open-source: XGBoost is an open-source library that is widely used and supported by the data science community.

2.3.4.Implementation

```
# importing required libraries
import pandas as pd
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score

# read the train and test dataset
train_data = pd.read_csv('train-data.csv')
test_data = pd.read_csv('test-data.csv')

# shape of the dataset
print('Shape of training data :',train_data.shape)
print('Shape of testing data :',test_data.shape)

# Now, we need to predict the missing target variable in the test data
# target variable - Survived

# seperate the independent and target variable on training data
train_x = train_data.drop(columns=['Survived'],axis=1)
train_y = train_data['Survived']

# seperate the independent and target variable on testing data
test_x = test_data.drop(columns=['Survived'],axis=1)
test_y = test_data['Survived']
```

Now , Create the object of the XGBoost model
You can also add other parameters and test your code here
Some parameters are : max_depth and n_estimators

```
model = XGBClassifier()

# fit the model with the training data
model.fit(train_x,train_y)


# predict the target on the train dataset
predict_train = model.predict(train_x)
print('\nTarget on train data',predict_train)

# Accuray Score on train dataset
accuracy_train = accuracy_score(train_y,predict_train)
print('\naccuracy_score on train dataset : ', accuracy_train)

# predict the target on the test dataset
predict_test = model.predict(test_x)
print('\nTarget on test data',predict_test)
```

To check the Accuracy Score on test dataset,

```
accuracy_test = accuracy_score(test_y,predict_test)
print('\naccuracy_score on test dataset : ', accuracy_test)
```

4.CONCLUSION

In conclusion, the presented framework for fraud detection in Bitcoin transactions within smart cities represents a pivotal stride towards fortifying the security and integrity of digital financial ecosystems.

This security features of blockchain technology with the sophisticated anomaly detection capabilities of the XGBoost algorithm within an ensemble stacking model, this framework offers a comprehensive solution to the evolving challenges posed by illicit activities such as money laundering, dark web transactions, and ransomware payments.

The integration of real-time monitoring, alerting systems, and adaptability mechanisms ensures a proactive approach to fraud prevention, allowing for swift responses to potential threats.
In the system's ability to provide a tamper-resistant and transparent record of transactions, coupled with its cost-effective and user-friendly design, makes it well-suited for the complex and dynamic landscape of smart cities.

As smart cities continue to advance, the proposed framework stands as a robust defence mechanism, promoting the secure and trustworthy evolution of digital financial transactions within urban environments.

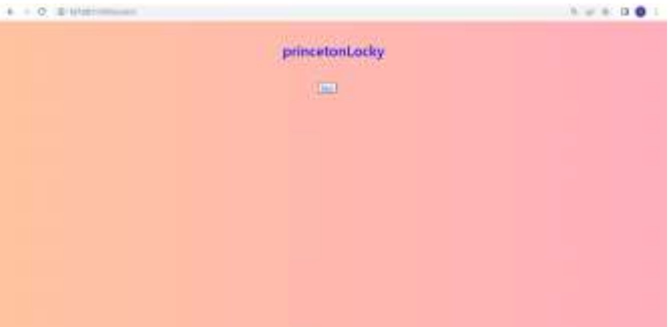
4. RESULTS AND DISCUSSION

Admin page:It specifies the user to log in via admin page for authentication purpose

Once the user pass through the admin page, the user is asked a few questions regarding the transactions.

According to the inputs, xgboost algorithm is carried in the backend.Type of fraud is found and the results accordingly are produced as output.

Similarly, we could classify the type of fraud in bitcoin transaction



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