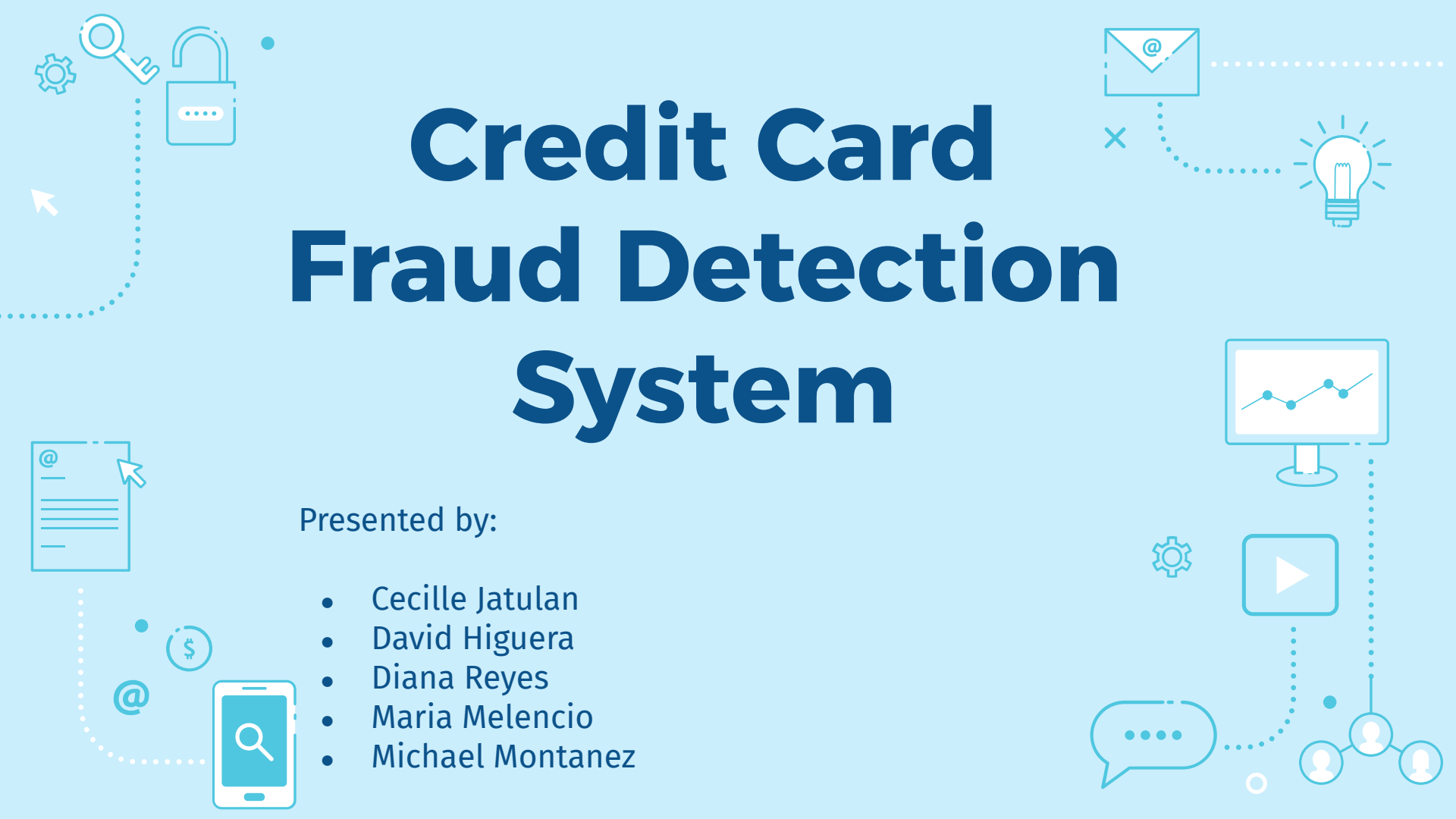


# Credit Card Fraud Detection System

Presented by:

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- Maria Melencio
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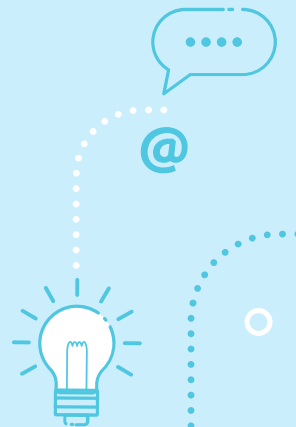
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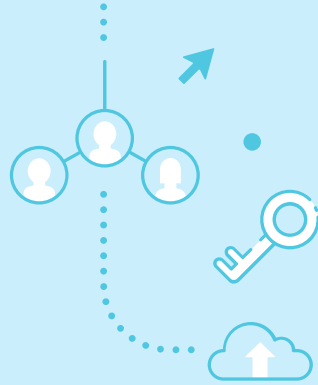
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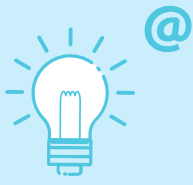
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# 01 Introduction





# Problem Statement

Project develops advanced Credit Card Fraud Detection Model to proactively identify and prevent fraud in real-time, addressing increasing sophistication in transactions





## Significance and Relevance of the Project



### Fraud Response

Project addresses sophisticated credit card fraud with effective detection methods to safeguard financial transactions



### Security Boost

Using tech to boost fraud detection accuracy for secure financial transactions



### Scalability and Adaptability

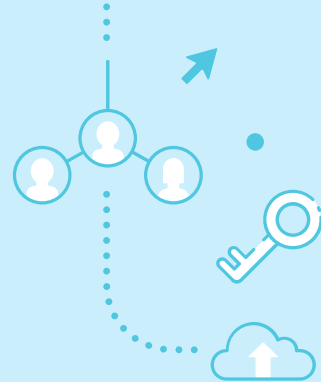
Designing scalable model for adaptable fraud detection to accommodate growing credit card transactions





# 02

## Data collection and preparation

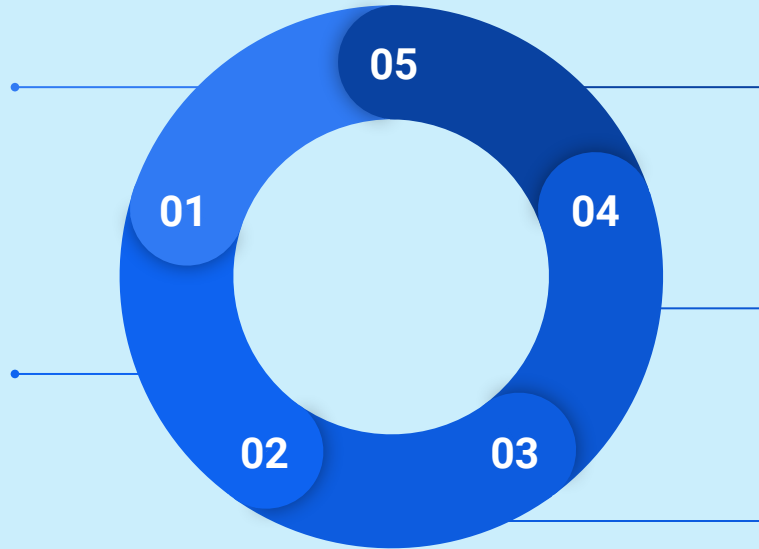


# Data collection

## Credit Card Fraud Detection Dataset

<https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud?resource=download>

Numerical input variables which are the result of a PCA transformation, due to confidentiality.



Feature Class is the response variable  
value 1 = Fraud  
Value 0 = No Fraud.

The only features which have not been transformed with PCA are Time and Amount.

Features V1, V2, ... V28 are the principal components obtained with PCA;



# Data preparation



## Data Preparation

## Data Pre-processing

## Exploratory Data Analysis(EDA)

## Feature Engineering

1. Acquiring  
Essential Libraries

2. Establishing  
Connectivity

3. Data Preparation  
Process

1. Check for missing  
values

2. Check data  
unbalance

3. Identify data types  
of the features

1. Summary  
Statistics

2. Distribution  
Analysis

3. Exploratory  
Visualizations

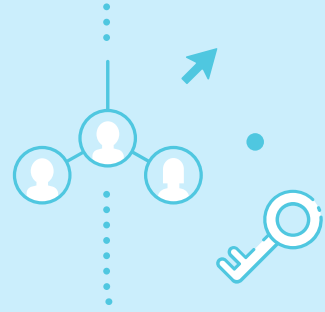
1. Time Feature Day  
Representation

2. Correlation Matrix

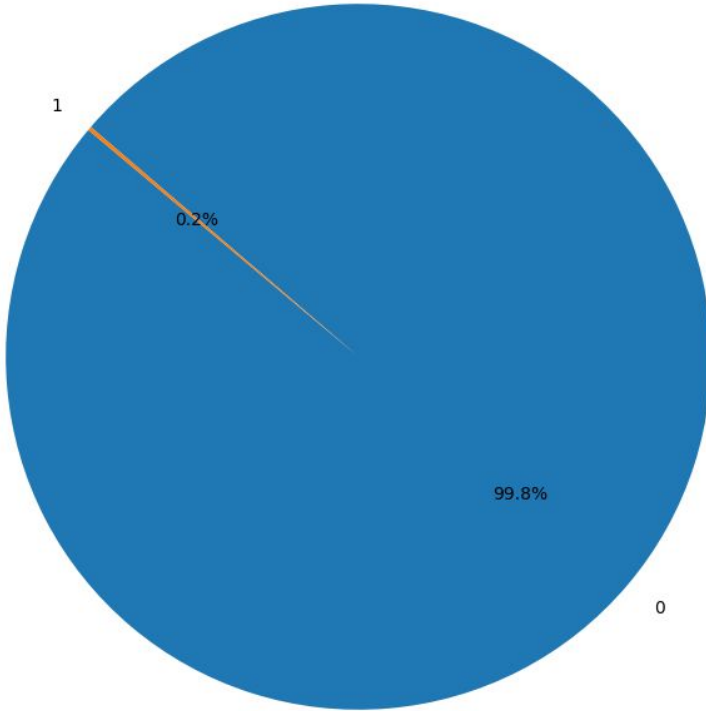




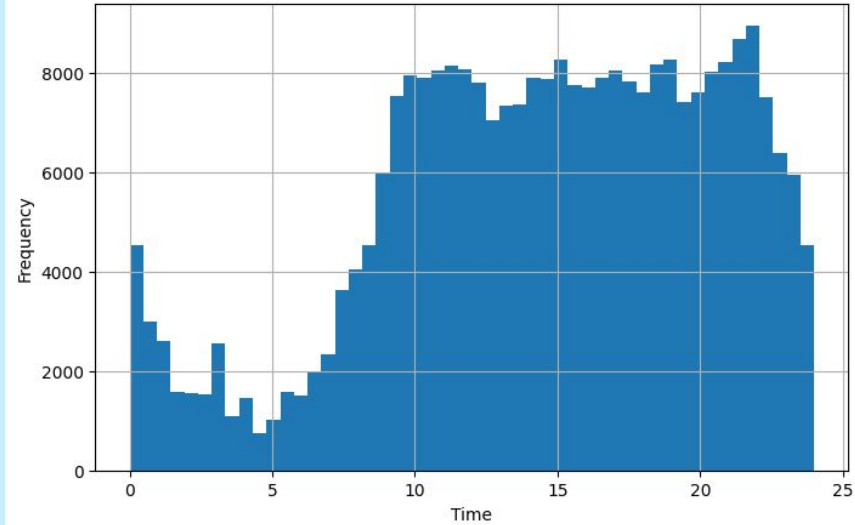
# Exploratory Data Analysis (EDA)



Proportion of Transactions by Class



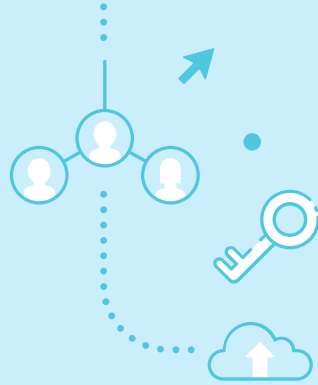
Time Distribution



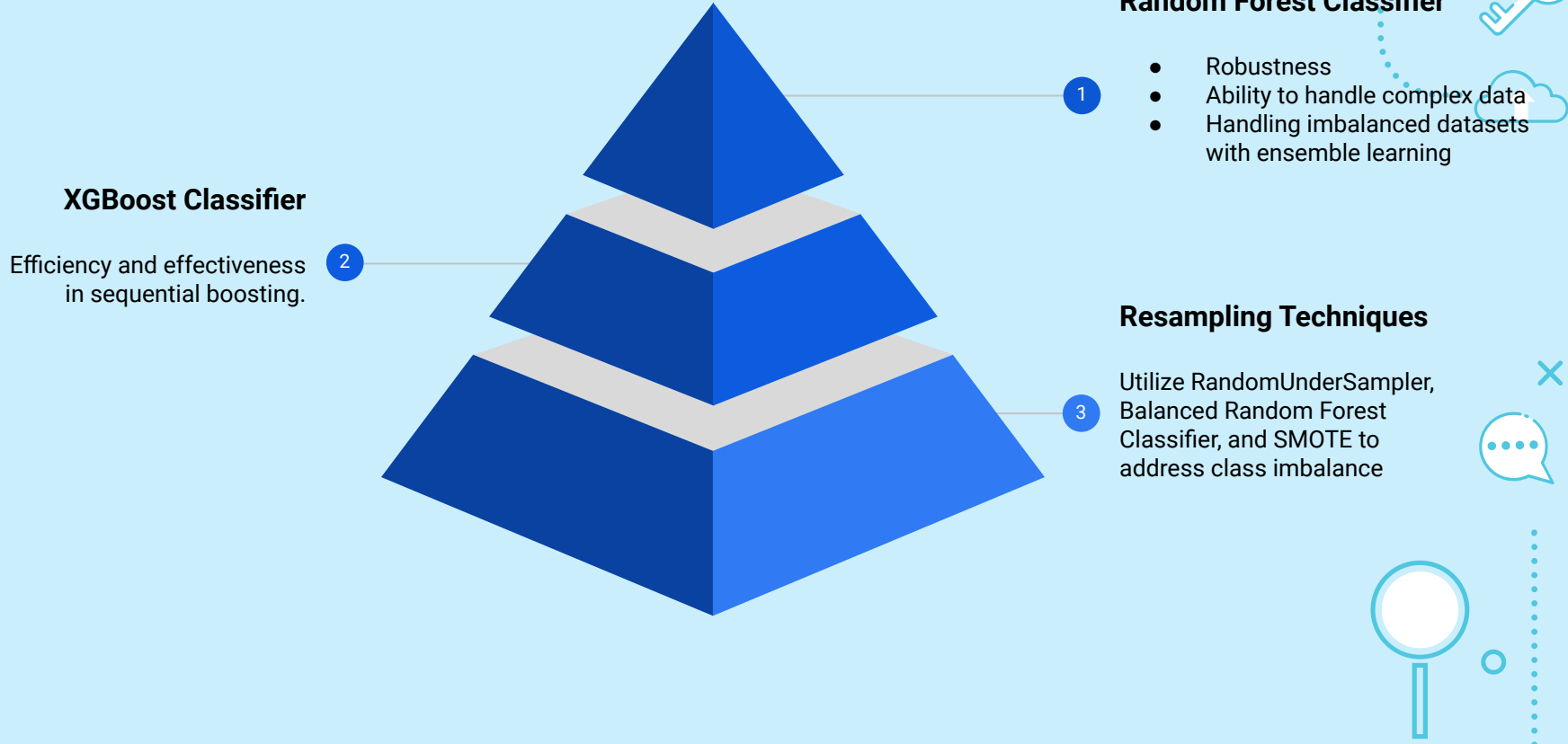


03

## Methodology



# Model Selection



# Model Training, Validation, and Evaluation

1

## Training

Train each model on the training set using default hyperparameters or after hyperparameter tuning.

2

## Validation

Validate model performance on the testing set using the chosen evaluation metric, primarily focusing on recall to minimize false negative

3

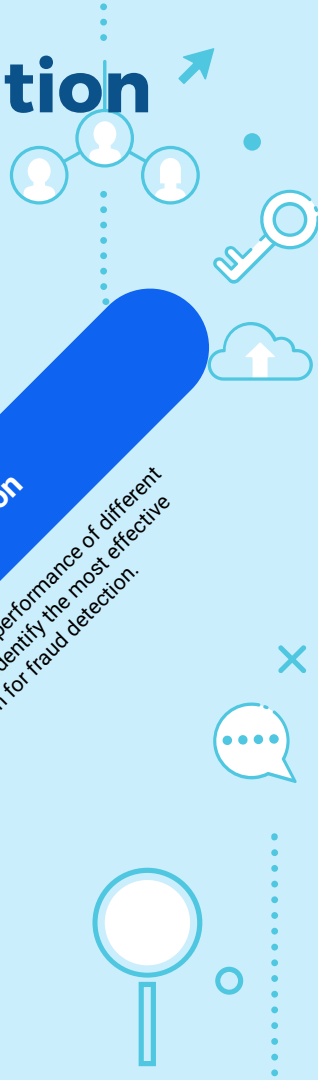
## Evaluation Metric

Use evaluation metrics such as precision, recall, F1-score, to assess model performance comprehensively.

4

## Model Comparison

Compare the performance of different models to identify the most effective approach for fraud detection.



# Hyperparameter tuning and modifications

## Grid search

Implement Grid Search to find optimal hyperparameters in models, such as the Balanced Random Forest Classifier.

## Randomized Search Cross-Validation

Apply Randomized Search CV for efficient hyperparameter sampling post-SMOTE

## Fine-Tuning

Iterate parameter tuning rounds for optimal model performance with evaluation.



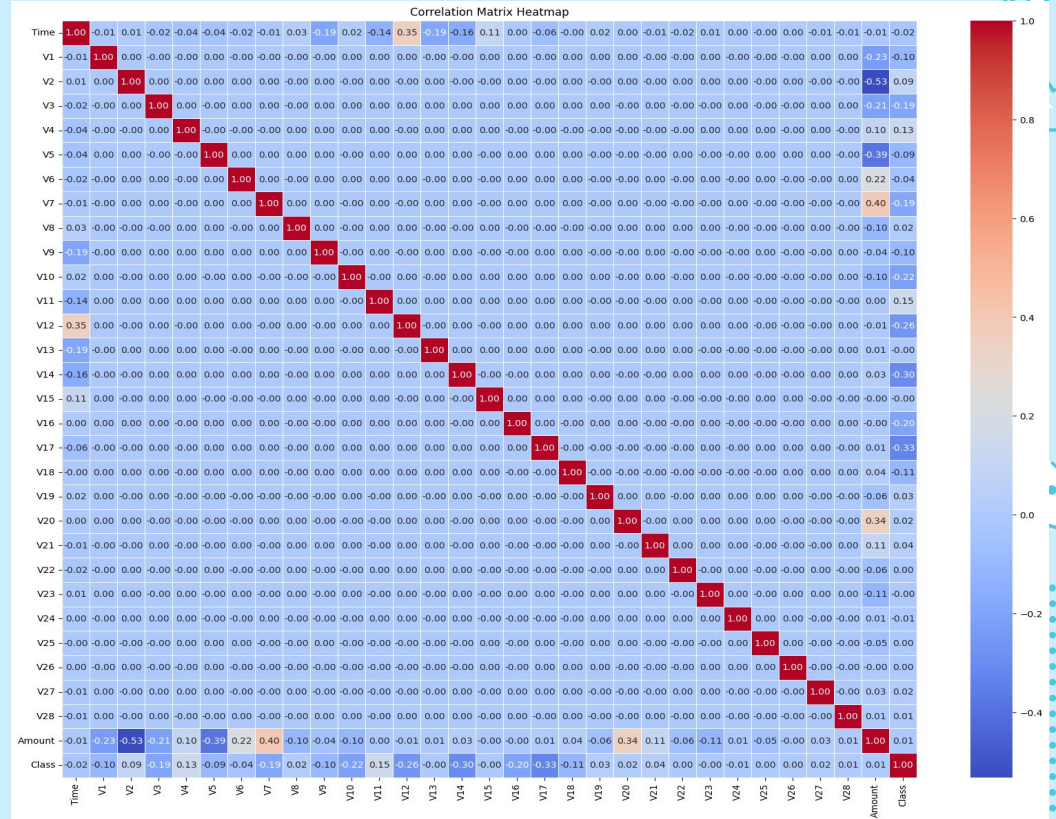
# Feature Engineering

## Time Feature Modification

Modify 'Time' feature to capture time-of-day patterns in fraud.

## Correlation Matrix

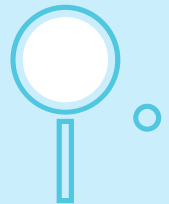
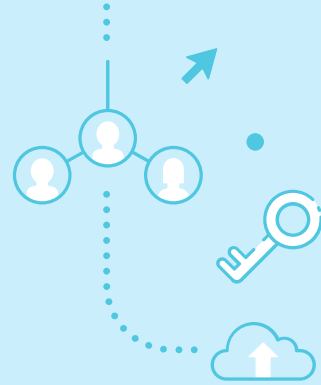
Eliminated around 50% of the features with correlation close to 0





# 04

## Analysis and Results



# Results of Models



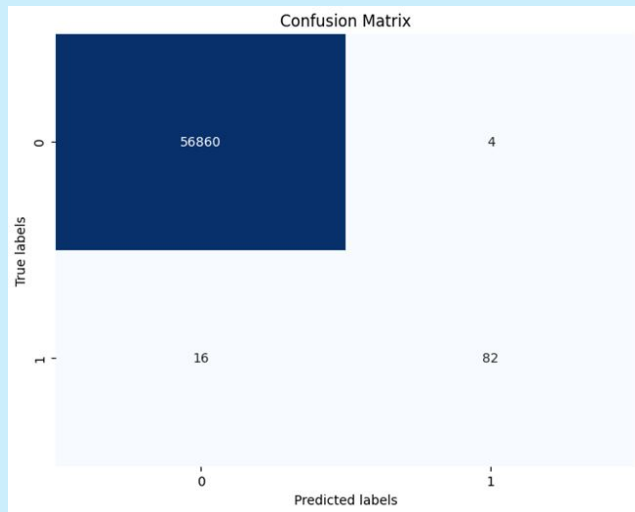
	Models	Precision	Recall
1	Random Forest Classifier	0.953488	0.836735
2	XGB classifier	0.864583	0.846939
3	Random Forest Classifier after RandomUnderSampler	0.039190	0.908163
4	Balanced Random Forest Classifier	0.048276	0.928571
5	Balanced Random Forest Classifier After SMOTE	0.625899	0.887755



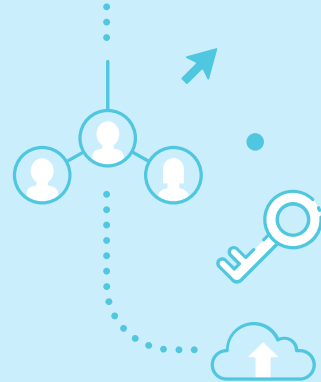
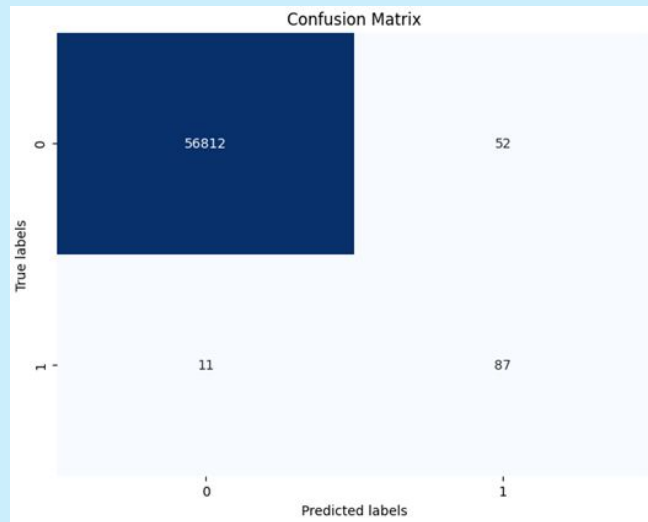


# Results of Models

## Random Forest Classifier



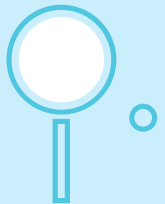
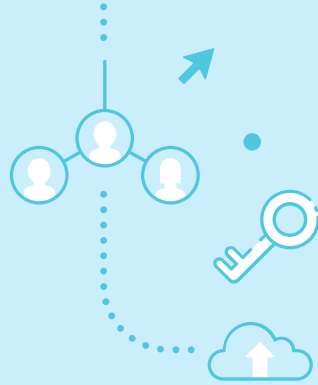
## Balanced Random Forest + SMOTE





# 05

## Discussion



# Conclusions

- Random Forest and XGB Classifiers: High precision; recall varied for fraud.
- Balanced RF and SMOTE models: Improved recall, lowered precision.
- Trade-off: Recall vs. precision; higher recall may affect precision.
- RandomUnderSampler and SMOTE enhanced recall, penalizing precision.
- Future: Explore advanced ensemble models or deep learning algorithms for better balance. Also going deep into the current models checking documentation to increase as much as possible the performance.



# References

- Mrozek, P., Panneerselvam, J., & Bagdasar, O. (2020). Efficient resampling for fraud detection during anonymised credit card transactions with unbalanced datasets. 2020 IEEE/ACM 13th International Conference on Utility and Cloud Computing (UCC). <https://doi.org/10.1109/ucc48980.2020.00067>.
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# UI DEMO



## Credit Card Fraud Detection

### About

Credit card fraud is a form of identity theft that involves an unauthorized taking of another's credit card information for the purpose of charging purchases to the account or removing funds from it.

This Streamlit application employs a Machine Learning model to identify fraudulent credit card transactions using 2 Known features and 15 PCA-transformed features.

The notebook, model and documentation are available on [GitHub](#).

#### Contributors:

- Cecille Jatulan
- David Higuera
- Diana Reyes
- Mike Montanez
- Maria Melencio

### Enter an input array

Enter your input array (separated by commas):

Make Prediction



# Thanks!

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