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Final Capstone Project

Credit Card Fraud Detection: A Machine Learning Approach

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Credit Card Fraud

- Credit Card fraud detection in a timely fashion is crucial to prevent financial losses and maintain customers trust with banks

- Increased online transactions has resulted in rising credit card fraudulent transactions

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Credit Card Fraud Statistics

Key Credit Card Fraud Statistics

- **Total value of credit card fraud**: $246 million (2023)
- **Annual global fraud losses (credit & debit card)**: $34.36 billion (2022)
- **Total volume of credit card and debit card fraud losses**: 6.81 cents per $100 (2020) & 6.78 cents per $100 (2019)
- **U.S. share of global payment card fraud**: 38.83% (payment card fraud losses) and 22.40% (transaction value)
- **Projection for total losses due to payment card fraud from 2021-2023**: $408.50 billion

Source: https://wallethub.com/edu/cc/credit-card-fraud-statistics/25725

Dataset Source

Credit Card Fraud Detection Dataset 2023

url: https://www.kaggle.com/datasets/nelgiriyewithana/credit-card-fraud-detection-dataset-2023/data

Why Credit Card Fraud Detection

"In a world where fraud is rampant, trust is the most valuable currency."
- Robert T. Kiyosaki

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Exploration & Analysis

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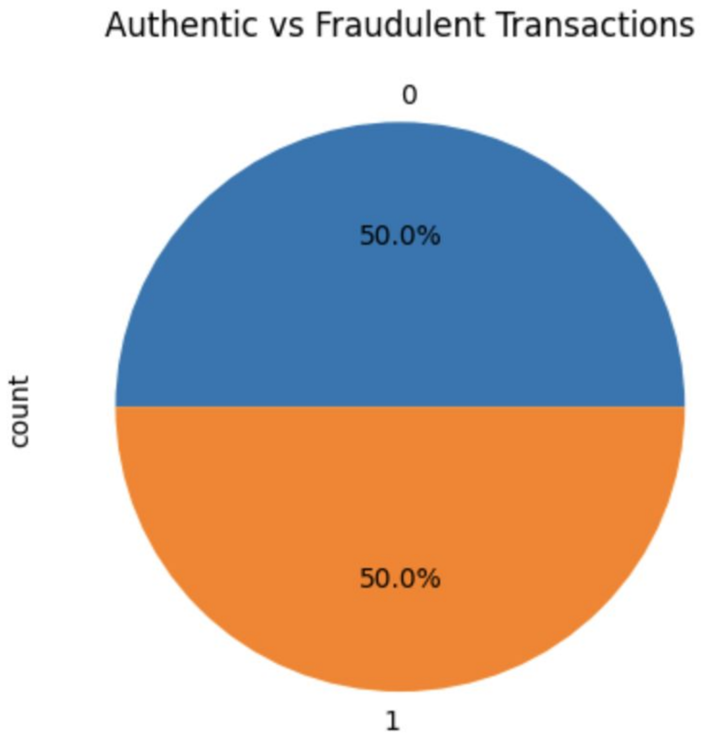
Fraudulent Transaction Proportion

- The fraudulent transaction % from the given set of data is 50%
- The dataset has 284,315 normal and 284,315 fraudulent transactions
- This in based on the 568,630 records



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Data Exploration

- The dataset has 11 columns and 568630 clean records
- Target Value is Class, which has 1 and 0 Values. It is an integer type variable.
- 1 indicates Fraud while 0 indicates normal transaction
- There are no duplicate values
- There are no null values

```
data.shape
```

```
(568630, 31)
```

```
#Identifying duplicate records
print(df.duplicated().sum())
```

```
0
```

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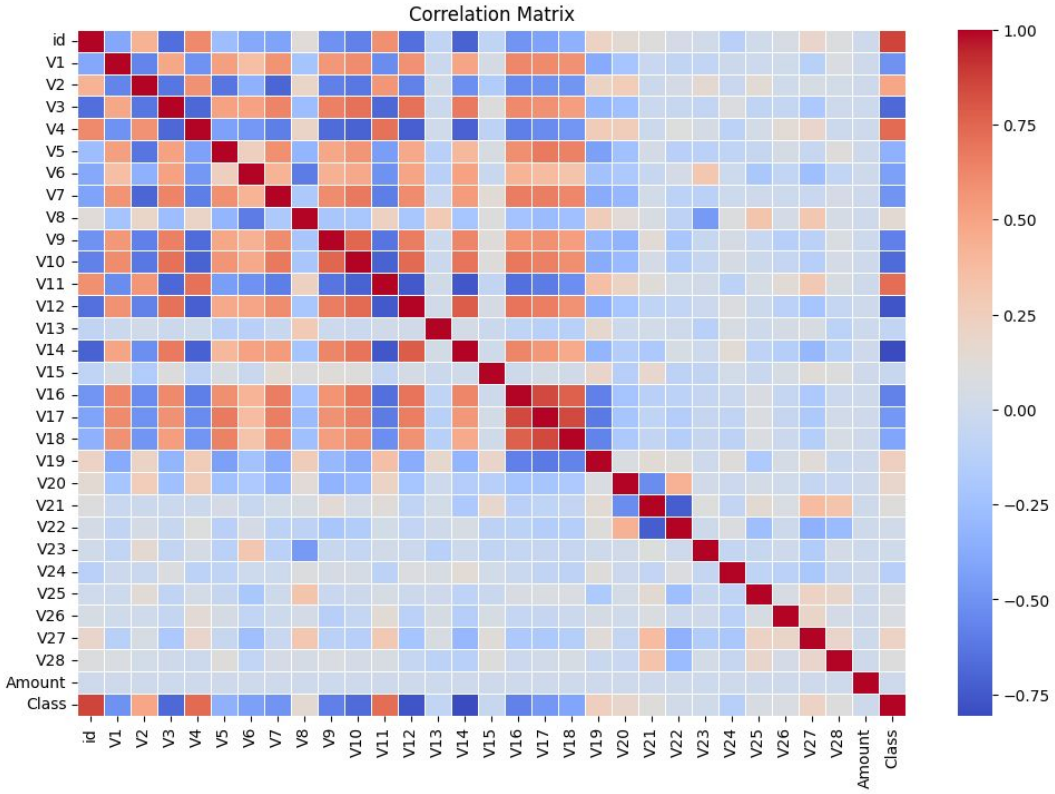
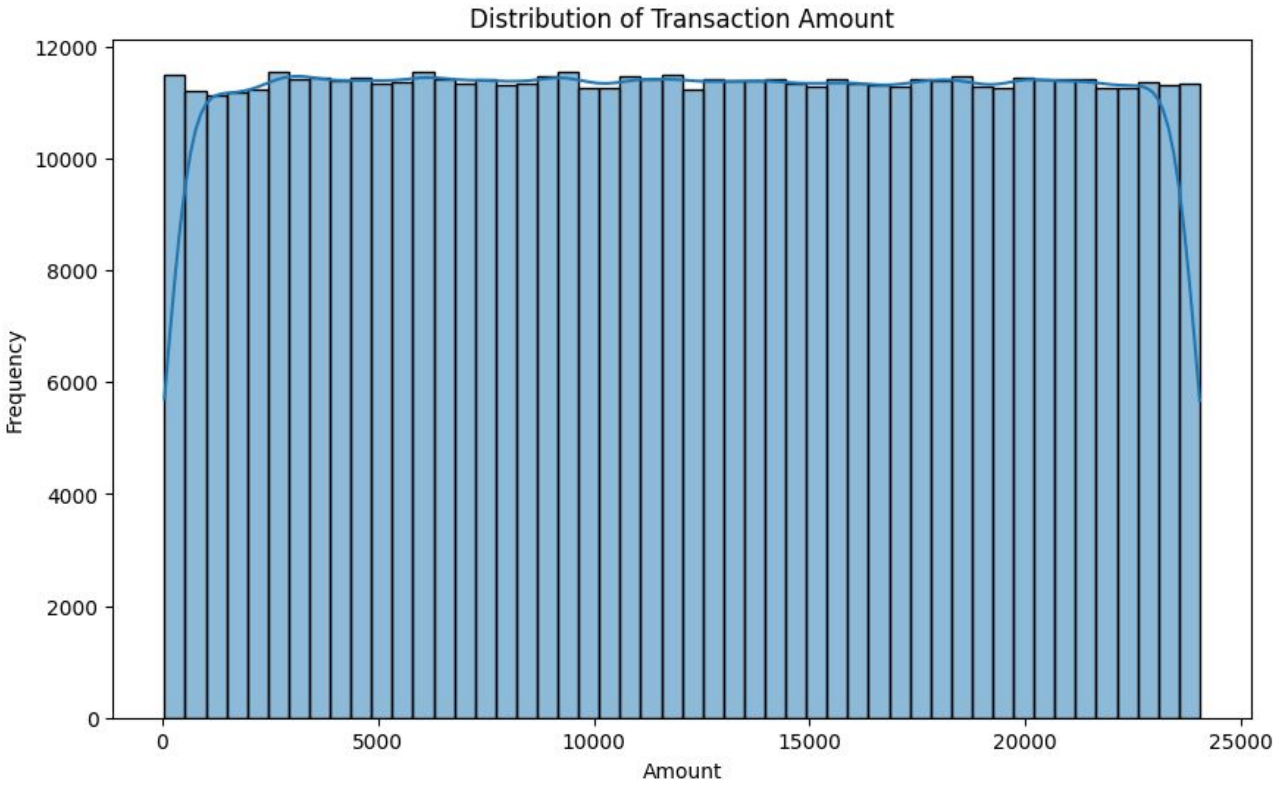
Relationship between Attributes

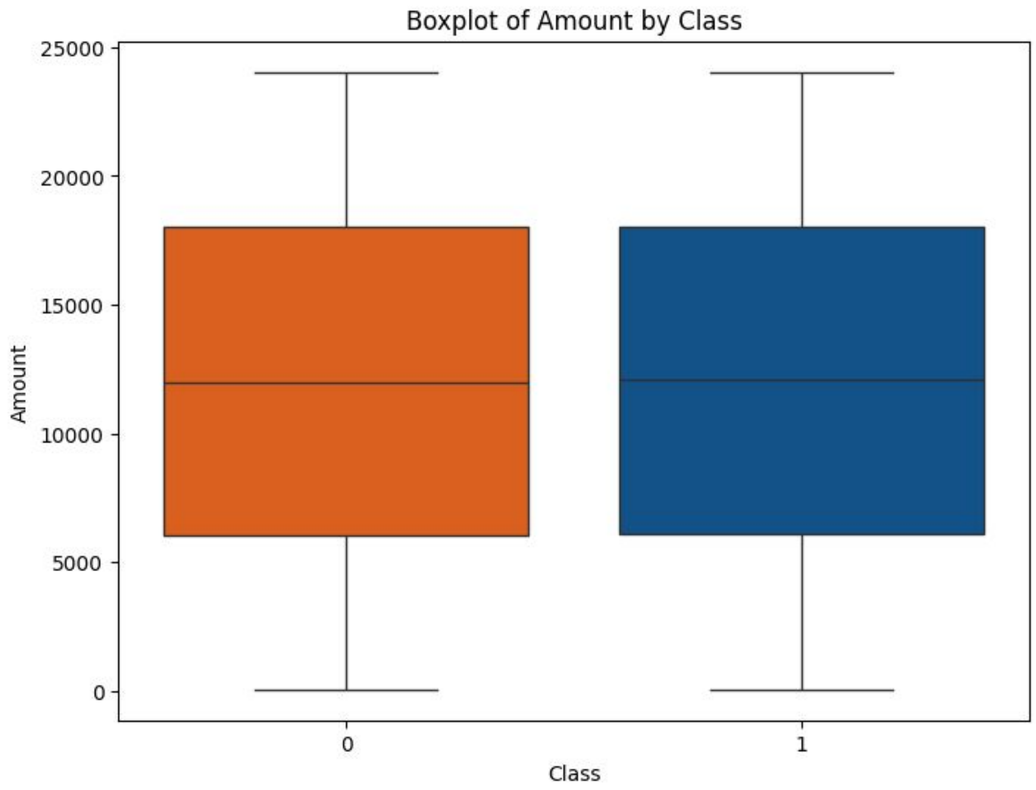


- The attributes V1-V28 are features representing anonymized transaction attributes
- They are values like time, location and PII information derived from PCA transformation
- Masked for user privacy

Distribution of transaction amount



Class with respect to amount



- Identical class separation between the amounts
- Well balanced dataset

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Supervised Machine Learning

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Targets and Features

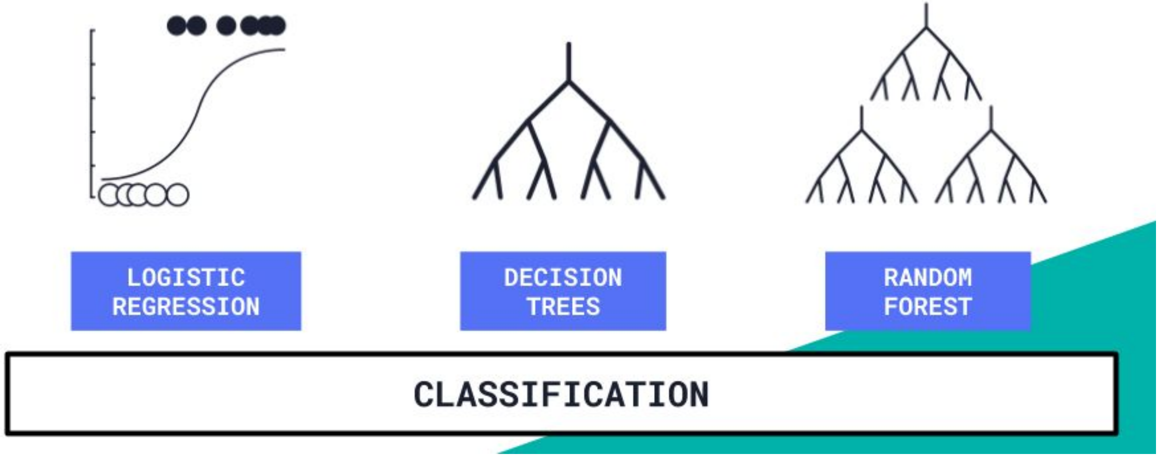
```
# Split features and target variable
X = data.drop(columns=["Class"])  # Features variable
y = data["Class"]  # Target variable
```

```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

No data processing and data wrangling needed as there are no nulls.

Supervised Machine Learning

- Decision Tree
- Random Forest
- Logistic Regression



Supervised Machine Learning Outputs

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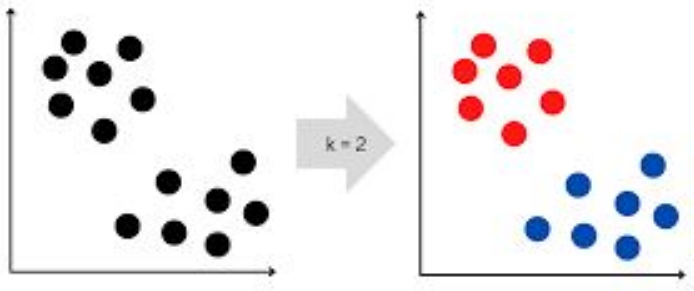
Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.8508	0.9000	0.8991	0.8662
Random Forest	0.7528	0.8348	0.8329	0.7787
Logistic Regression	0.8343	0.8167	0.8801	0.8358

Unsupervised Machine Learning

K-Means

- Data Standardization
- Applied K-Means Clustering

```
K-Means Accuracy: 0.1037827761461759
```



K-Means Clustering Algorithm

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Deep Learning

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Configurations

- Simple deep learning model-Sequential model

- Sequential model is a linear stacks of layers, where each layer has one input and output tensor

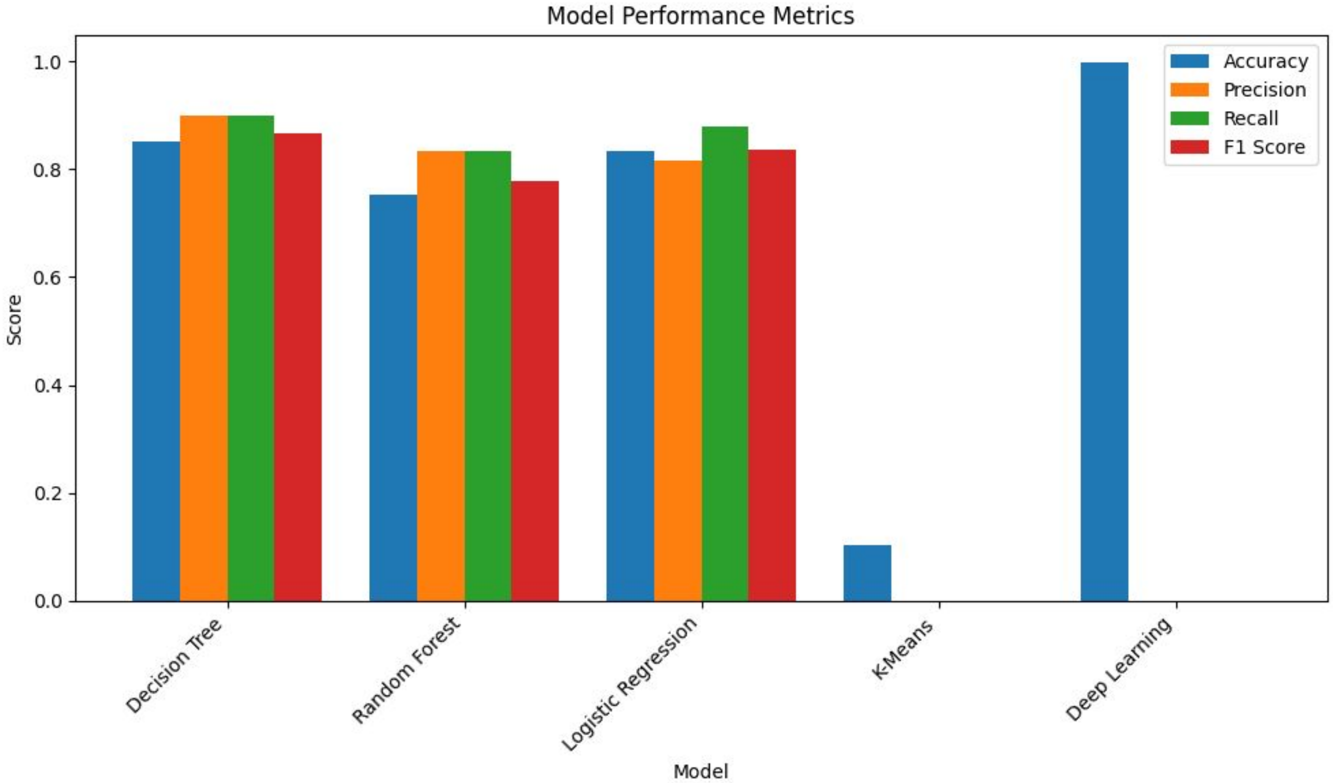
Configurations

```python
# Define a simple deep learning model
model = Sequential()
model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

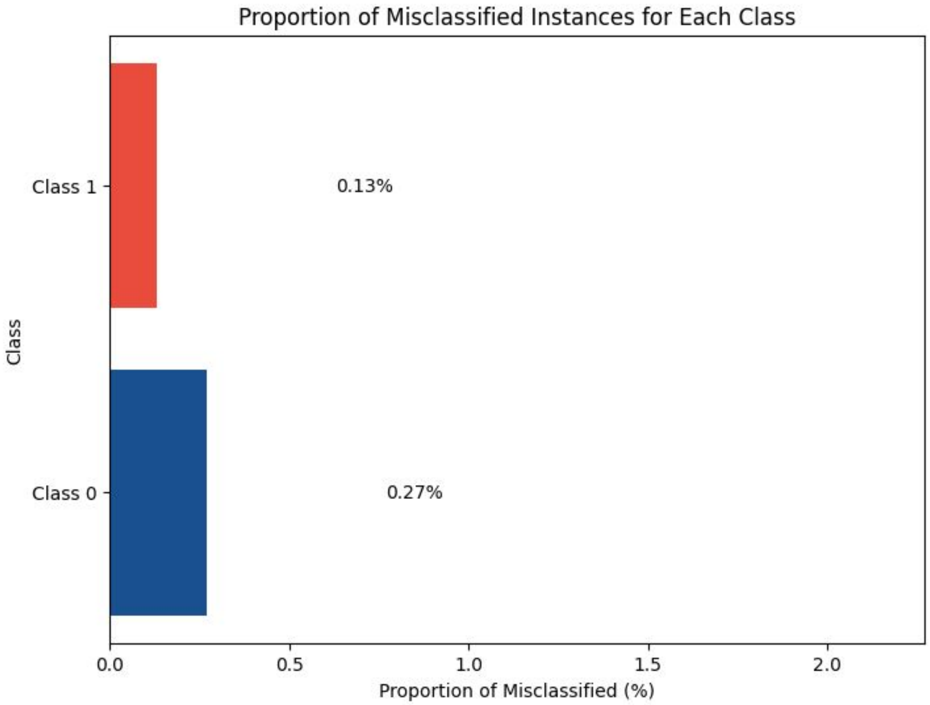
```python
# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.1, verbose=1)

# Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print("Test Accuracy:", accuracy)
```

Best Model Outcome

Model Performance Comparison



Simple Deep Learning - Outcome Analysis




```
Number of Misclassified Instances: 231
```

```
Deep Learning Mean Accuracy: 0.9979687929153442
```

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Challenges

- Feature Engineering: Identifying relevant features to improve model performance was a challenge as the feature names anonymized and difficult to interpret
- Computational Resources: Models required high GPU and faced issues with time out.
- Reduced cross validation factor from 5 to 3 to circumvent this issue. Hence hyperparameter optimization was a challenge.
- Dataset comprised of only 2023 data
    - Lack of historical context
    - Potential overfitting of 2023 trends
    - Limited diversity of fraud cases and inadequate training data

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Recommendations

- Ensemble methods such as bagging, boosting, or stacking can be utilized to aggregate the predictions of individual models, leveraging their diverse strengths and mitigating the weaknesses inherent in each model.
- Use a diverse dataset that spans over several years to get the historical context
- Continuous monitoring leveraging feedback from real-world performance for iteratively improving performance

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Conclusion

- The detection of fraud greatly helps banks and customers to take effective timely fraud prevention measures.

- Analyzing the dataset with transaction features, the project was aimed at building models to accurately predict fraudulent transactions

- Leveraging insights from the credit card transaction dataset, banks can develop and implement fraud reduction strategies thereby mitigating fraudulent transactions.

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Thank You