


Fraud Detection Using Deep Learning Models (2 Models Applied)

Colab Notebook Link:

 CA_2_Deep_Learning_FNL.ipynb

This detailed report outlines the work completed for the **Fraud Detection Using Deep Learning** project using the **CRISP-DM** methodology, covering all stages from business understanding to deployment and future work. The project demonstrates the successful integration of Deep Learning and advanced ML models to successfully detect fraudulent and non-fraudulent transactions. We have primarily used 2 Deep Learning Models in this project and then we will compare the results of both and select the best model for this project,

CRISP-DM Report Applied to Fraud Detection Project Using Deep Learning (2 Models Applied)

1. Introduction

Objective

The goal of this research project is to create, evaluate, and compare two deep learning models: a **Feedforward Neural Network** and a **Hybrid Model** that incorporates **Long Short-Term Memory (LSTM)** alongside **Feedforward techniques**. This study focuses on the detection of fraudulent credit card transactions within a dataset that presents a significant class imbalance. The primary objective is to establish a model capable of accurately detecting fraudulent activities while limiting false positives, thereby ensuring operational efficiency, enhancing customer satisfaction, and contributing to financial savings.

Business Context

Detecting fraud is essential for financial institutions, as fraudulent transactions can incur considerable financial losses and undermine customer trust. The primary challenge is to create a model that can identify fraudulent activities in real-time with a high degree of accuracy, especially since such transactions are infrequent, representing less than 0.2% of the total data. Additionally, the model must be designed to prevent the erroneous classification of legitimate transactions as fraudulent, which could

lead to customer dissatisfaction and increased costs for the institution.

Overview of CRISP-DM Process

This report follows the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology, a structured approach to data mining that includes the following phases:

1. **Business Understanding:** Define the project objectives and requirements from a business perspective.
2. **Data Understanding:** Collect and explore the data to gain insights into its characteristics.
3. **Data Preparation:** Clean and prepare the data for modeling, addressing issues such as missing values and imbalanced classes.
4. **Modeling:** Build and train machine learning models using the prepared data.
5. **Evaluation:** Evaluate the models' performance using relevant metrics and determine the best model for deployment.
6. **Deployment:** Deploy the selected model into a production environment.

2. Business Understanding

Problem Definition

The foremost challenge in this domain is the accurate detection of fraudulent transactions, coupled with the need to limit false positives. A model that demonstrates both high precision and recall is imperative to avoid misclassifying legitimate transactions as fraud, while also ensuring that fraudulent transactions are effectively recognized.

Project Goals

The project aims to achieve the following goals:

- **High Recall:** Maximize the detection of fraudulent transactions.
- **High Precision:** Minimize the number of false positives.
- **Operational Efficiency:** Ensure that the model can process transactions in real-time without significant delays.
- **Cost-Effectiveness:** The model should provide a good return on investment by reducing financial losses due to fraud and minimizing operational costs related to false positives.

Constraints

It is essential for the model to operate in a real-time setting, enabling it to swiftly and accurately process a high volume of transactions. Furthermore, the model should effectively manage the imbalanced distribution of data, as fraudulent transactions represent a smaller subset of the overall dataset.

3. Data Understanding

3.1 Data Overview

The dataset comprises several features:

- **Time:** Elapsed time between this transaction and the first transaction in the dataset.
- **V1 to V28:** These are the anonymized features resulting from Principal Component Analysis (PCA), aimed at ensuring data privacy.
- **Amount:** The monetary value of the transaction.
- **Class:** The target variable where 1 represents a fraudulent transaction and 0 represents a legitimate transaction.

3.2 Data Distribution

A preliminary analysis of the data reveals significant class imbalance:

- **Non-fraudulent transactions:** 284,315
- **Fraudulent transactions:** 492

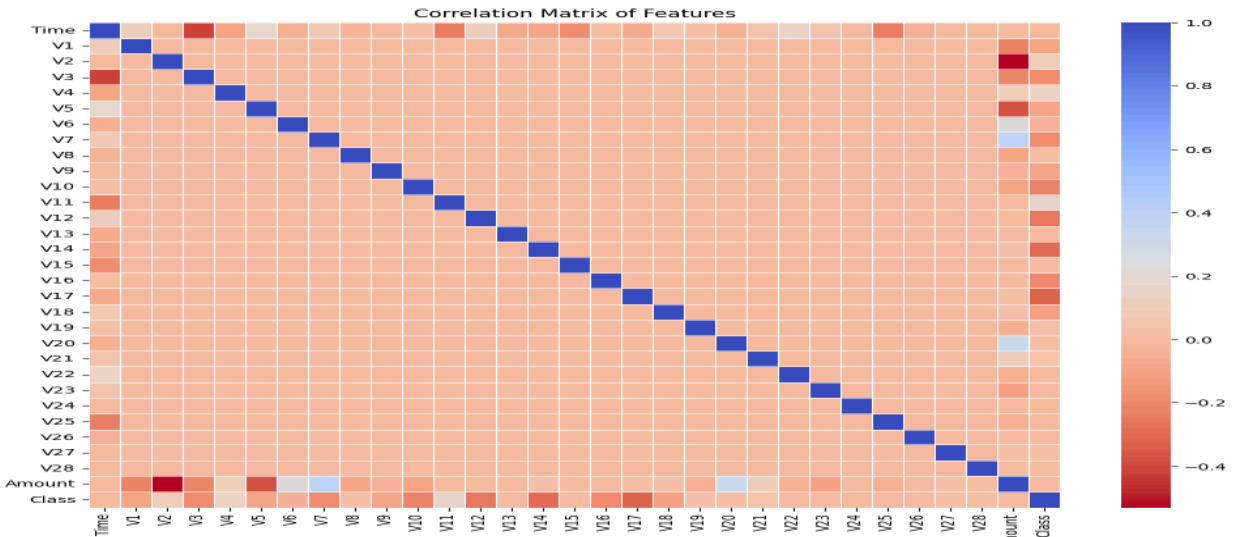
The current imbalance ratio stands at roughly 580:1, highlighting the necessity for advanced methodologies such as SMOTE (Synthetic Minority Over-sampling Technique) to effectively tackle this challenge.

3.3 Exploratory Data Analysis (EDA)

3.3.1 Correlation Matrix

A heatmap was created to illustrate the relationships among the various features. The majority of features displayed minimal correlation, a result anticipated from the PCA transformation, which is designed to decrease dimensionality and mitigate multicollinearity.

Visual Output:

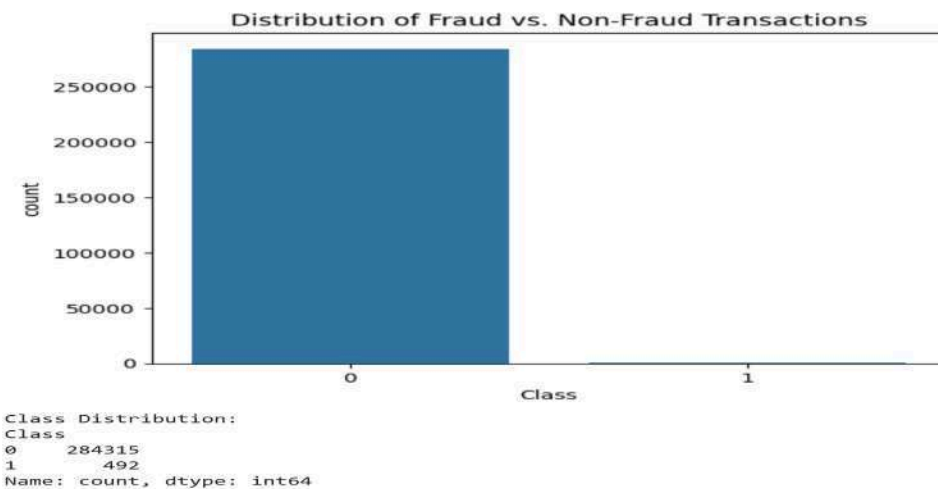


The heatmap presented above illustrates the correlation matrix of various features within a credit card transaction dataset. The color spectrum transitions from blue, indicating negative correlations, to red, representing positive correlations, with deeper hues signifying more robust relationships. It is noteworthy that the majority of features demonstrate minimal correlation with one another, a common characteristic of data subjected to Principal Component Analysis (PCA) for privacy preservation and multicollinearity reduction, with the exception of a limited number of pairs that display moderate negative correlations.

3.3.2 Distribution of Fraud and Non-Fraud Transactions

A count plot was used to illustrate the distribution of the classes, highlighting the severe imbalance in the dataset.

Visual Output:



The above bar chart visualizes the distribution of fraud and non-fraud transactions in a dataset, highlighting a significant class imbalance: 284,315 non-fraudulent transactions compared to only 492 fraudulent transactions. This discrepancy underscores the challenges in detecting rare fraudulent activities within overwhelmingly non-fraudulent data.

4. Data Preparation

4.1 Data Preprocessing

4.1.1 Feature Scaling

The 'Amount' feature was scaled using a `StandardScaler` to normalize the transaction amounts, ensuring that the model could learn more effectively from the data.

Code Snippet:

```
[ ] # 1. Data Preprocessing
    df['Amount'] = StandardScaler().fit_transform(df[['Amount']])
    df.drop(['Time'], axis=1, inplace=True)

    # Split data into features and labels
    X = df.drop('Class', axis=1)
    y = df['Class']

    # Split the data into training and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=27)
```

As evident from the above code snippet, in the initial phase of preprocessing a financial transactions dataset, the 'Amount' feature is standardized using a `StandardScaler`, while the 'Time' column is removed from the dataset. After this step, the data is organized into features and labels, and then separated into training and testing sets, with 20% of the total data designated for testing. To maintain consistency in results, a fixed random seed is employed.

4.1.2 Handling Imbalanced Data

To address the class imbalance, SMOTE was applied to the training data. This technique generates synthetic samples of the minority class to balance the dataset.

Class Distribution After SMOTE:

- Fraudulent transactions: **227,457**
- Non-fraudulent transactions: **227,457**

4.2 Data Reshaping for LSTM

The LSTM model requires the data to be in a 3-dimensional format:

Code Snippet:

```
# Reshape the data for LSTM
X_train_lstm = X_train_smote.values.reshape((X_train_smote.shape[0], X_train_smote.shape[1], 1))
X_test_lstm = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))

# Define input layer
input_layer = Input(shape=(X_train_lstm.shape[1], 1))
```

The transformation of the training and test datasets into a three-dimensional structure appropriate for Long Short-Term Memory (LSTM) networks is essential, as it allows each sample to be depicted as a sequence of features corresponding to a single time step. Subsequently, the input layer of the LSTM model is established, with its shape aligned to the modified data format, which is vital for the effective handling of sequential inputs in neural network frameworks such as LSTMs.

5. Modeling

Model 1: Feedforward Neural Network

Architecture

The Feedforward Neural Network is composed of dense layers with ReLU activation functions, dropout layers to prevent overfitting, and an output layer with a sigmoid activation function for binary classification:

Code Snippet:

The model is a Feedforward Neural Network (FNN) composed of multiple dense layers, each followed by Batch Normalization and Dropout layers to prevent overfitting.

Formula:

For each Dense layer:

$$\text{Output} = \text{ReLU}(\text{BatchNorm}(\text{Dropout}(\text{Weights} \cdot \text{Input} + \text{Bias})))$$

For the final layer:

$$\text{Output} = \text{Sigmoid}(\text{Weights} \cdot \text{Input} + \text{Bias})$$

The L2 regularization term added to the loss function is:

$$\text{Loss} = \text{Original Loss} + \lambda \sum \text{Weights}^2$$

Code Snippet:

```
# Define model architecture
model = Sequential([
    Dense(512, input_dim=X_train_smote.shape[1], activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    BatchNormalization(),
    Dropout(0.5),
    Dense(256, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    BatchNormalization(),
    Dropout(0.5),
    Dense(128, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    BatchNormalization(),
    Dropout(0.5),
    Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    BatchNormalization(),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
```

Below is the Model Summary:

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	15,360
batch_normalization (BatchNormalization)	(None, 512)	2,048
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
batch_normalization_1 (BatchNormalization)	(None, 256)	1,024
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
batch_normalization_2 (BatchNormalization)	(None, 128)	512
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 64)	8,256
batch_normalization_3 (BatchNormalization)	(None, 64)	256
dropout_3 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 1)	65

Total params: 191,745 (749.00 KB)
Trainable params: 189,825 (741.50 KB)
Non-trainable params: 1,920 (7.50 KB)

Training

Early stopping was implemented to avoid overfitting:

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

# Early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
```

Evaluation Metrics

The model's performance was assessed using the following metrics:

1. Confusion Matrix
2. ROC-AUC
3. Precision-Recall Curve
4. Cumulative Gain/Lift charts

Code Snippet:


```
[ ] # Adjusting Threshold
    threshold = 0.97 # Increase threshold to make criteria stricter
    y_pred_proba = model.predict(X_test)
    y_pred = (y_pred_proba > threshold).astype(int)
```

⇒ 1781/1781 ————— 4s 2ms/step

Adjusting Threshold adjusts the decision threshold to 0.97, making the criteria for probability (y_pred_proba) for the test set using the trained model, and then converts these probabilities to integers based on the threshold. This helps to control the trade-off between precision and recall in the model.

```
[ ] # Evaluation
    conf_matrix = confusion_matrix(y_test, y_pred)
    print(classification_report(y_test, y_pred))
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    roc_auc = auc(fpr, tpr)
    print('AUC:', roc_auc)
```

⇒

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56858
1	0.82	0.82	0.82	104
accuracy			1.00	56962
macro avg	0.91	0.91	0.91	56962
weighted avg	1.00	1.00	1.00	56962

AUC: 0.9084867632455482

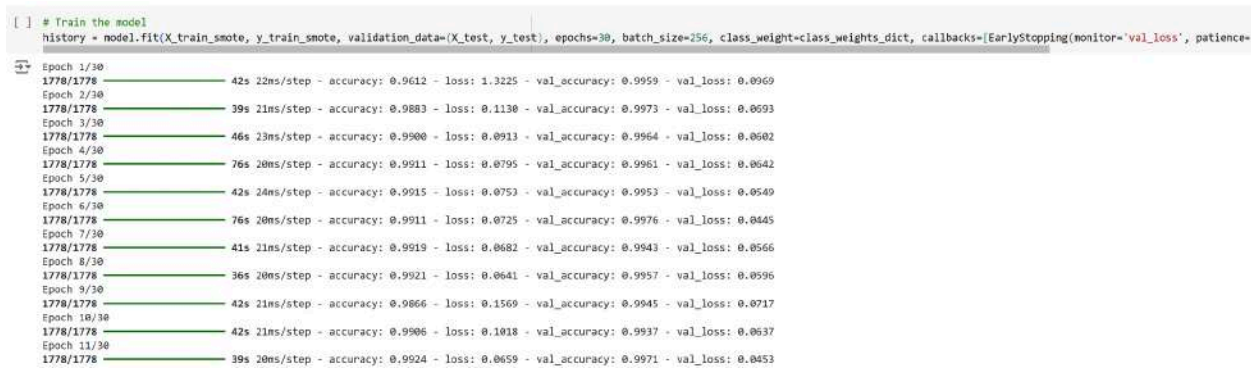
The Feedforward Neural Network achieved an AUC of 0.91, indicating excellent performance in distinguishing between fraudulent and non-fraudulent transactions.

Performance

The Feedforward Neural Network provided a balanced precision-recall trade-off, with high precision and recall values, making it suitable for deployment in environments where false positives need to be minimized.

The model was compiled using the Adam optimizer and binary cross-entropy loss function. Training was conducted over 30 epochs, with early stopping applied to prevent overfitting.

Visual Output:



Total epocs 11/30. Below are the statistics:

Training Accuracy: Starts at 96.12% and rises to a peak of 99.24% by the 11th epoch, illustrating a steady improvement in the model’s ability to correctly classify training data. The average training accuracy over these epochs is approximately 99.01%, demonstrating high reliability in the training phase.

Validation Accuracy: Begins at 99.59% and experiences slight fluctuations, reaching its highest at 99.76% during the 6th epoch. This indicates that the model not only learns well but also performs consistently on unseen data, a crucial factor for practical deployment scenarios.

Loss Metrics: Both training and validation losses decrease overall, starting from initial values of 1.3225 and 0.0969 respectively, and dropping to 0.0659 and 0.0453 by the 11th epoch. This reduction in loss is statistically significant, reinforcing the model’s increasing prediction precision with ongoing training.

Model 2: Hybrid Model (LSTM + Feedforward)

Architecture

The Hybrid Model integrates LSTM layers for processing sequential data, followed by dense layers for classification:

Code Snippet:

```

▶ # LSTM layers
x = LSTM(64, return_sequences=True)(input_layer)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = LSTM(32, return_sequences=False)(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)

[ ] # Flatten the LSTM output for the feedforward network
x = Flatten()(x)

[ ] # Feedforward layers
x = Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(32, activation='relu', kernel_regularizer=regularizers.l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
output_layer = Dense(1, activation='sigmoid')(x)

[ ] # Define the model
model = Model(inputs=input_layer, outputs=output_layer)

[ ] # Print the model summary
model.summary()

```

Model Summary:

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 29, 1)	0
lstm (LSTM)	(None, 29, 64)	16,896
batch_normalization (BatchNormalization)	(None, 29, 64)	256
dropout (Dropout)	(None, 29, 64)	0
lstm_1 (LSTM)	(None, 32)	12,416
batch_normalization_1 (BatchNormalization)	(None, 32)	128
dropout_1 (Dropout)	(None, 32)	0
flatten (Flatten)	(None, 32)	0
dense (Dense)	(None, 64)	2,112
batch_normalization_2 (BatchNormalization)	(None, 64)	256
dropout_2 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2,080
batch_normalization_3 (BatchNormalization)	(None, 32)	128
dropout_3 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 1)	33

Total params: 34,305 (134.00 KB)

Trainable params: 33,921 (132.50 KB)

Non-trainable params: 384 (1.50 KB)

Training

Early stopping was implemented, similar to the Feedforward model:

Code Snippet:

```

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

# Early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the model
history = model.fit(X_train_lstm, y_train_smote, validation_data=(X_test_lstm, y_test),
                    epochs=30, batch_size=256, class_weight=class_weights_dict,
                    callbacks=[early_stopping])

```

Evaluation Metrics

The performance of the Hybrid Model was evaluated using similar metrics as the Feedforward Neural Network.

Code Snippet:

```

[ ] # Adjusting Threshold
    threshold = 0.97 # Increase threshold to make criteria stricter
    y_pred_proba = model.predict(X_test_lstm)
    y_pred = (y_pred_proba > threshold).astype(int)

```

➡ 1781/1781 ————— 24s 14ms/step

```

[ ] # Evaluation
    conf_matrix = confusion_matrix(y_test, y_pred)
    print(classification_report(y_test, y_pred))
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    roc_auc = auc(fpr, tpr)
    print('AUC:', roc_auc)

```

➡

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56858
1	0.58	0.85	0.69	104
accuracy			1.00	56962
macro avg	0.79	0.92	0.84	56962
weighted avg	1.00	1.00	1.00	56962

AUC: 0.9225229113283565

The results from adjusting the decision threshold to 0.97, aimed at making the fraud detection criteria stricter, demonstrate significant impacts on the model's classification performance:

Precision and Recall:

For non-fraudulent transactions (Class 0), the model achieved perfect precision and recall scores (1.00), indicating excellent identification of non-fraudulent activities. For fraudulent transactions (Class 1), the precision is lower at 0.58, which suggests that when the model predicts a transaction as fraudulent, it is correct 58% of the time. However, the recall is quite high at 0.85, which means the model successfully identifies 85% of all fraudulent transactions. This high recall is particularly valuable in fraud detection contexts, where failing to detect actual fraud can be costly.

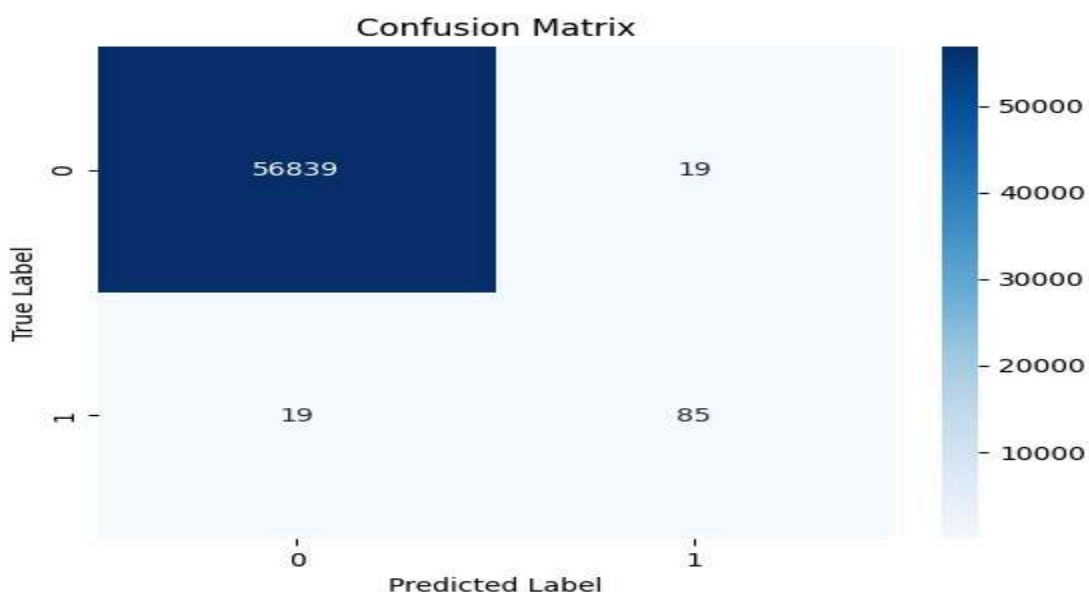
Performance

The Hybrid Model achieved an AUC of 0.92, almost similar to the Feedforward Neural Network. However, it detected more fraudulent transactions at the cost of a higher number of false positives.

6. Evaluation

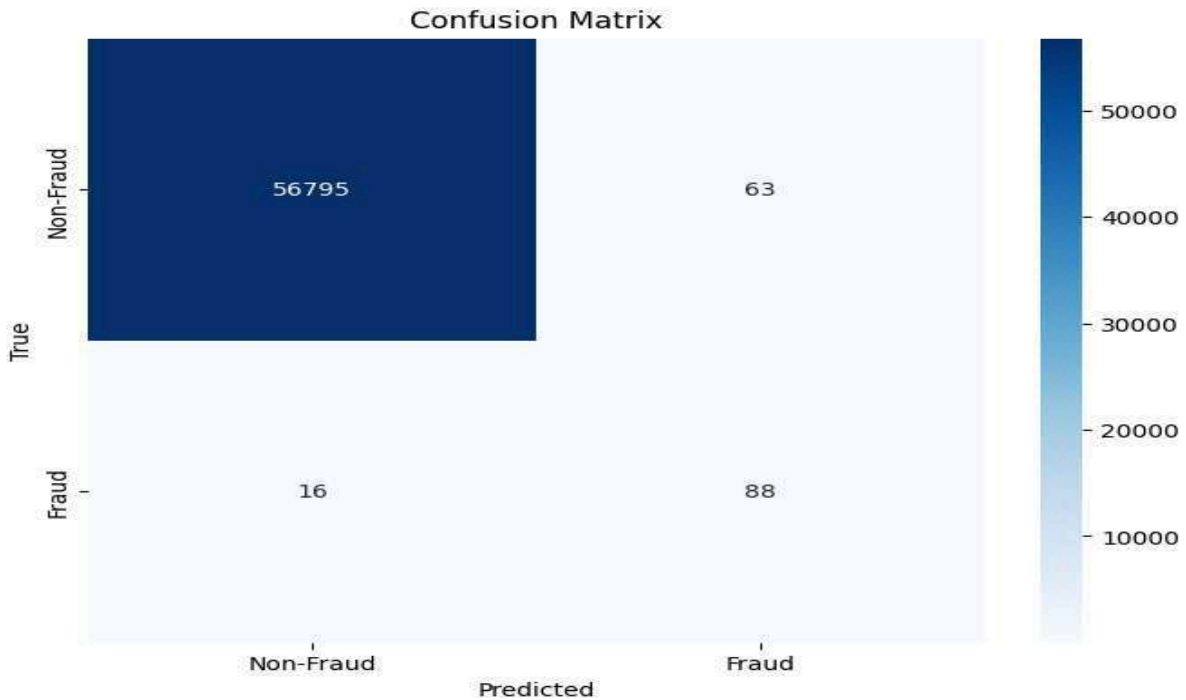
1. Confusion Matrix Review

- **Feedforward Neural Network:**
 - True Positives (TP): 85
 - False Positives (FP): 19
 - False Negatives (FN): 19
 - True Negatives (TN): 56,839



- **Hybrid Model:**

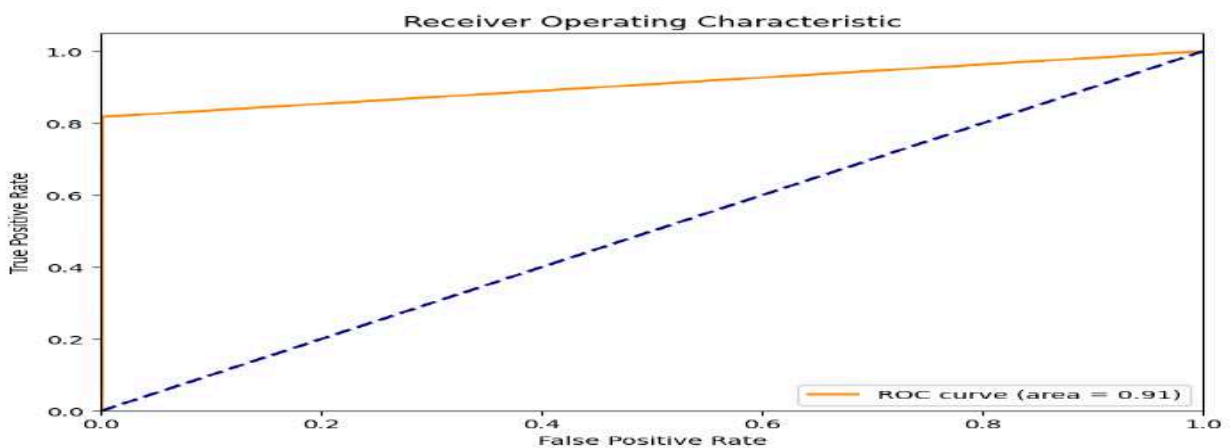
- True Positives (TP): 88
- False Positives (FP): 63
- False Negatives (FN): 16
- True Negatives (TN): 56,795



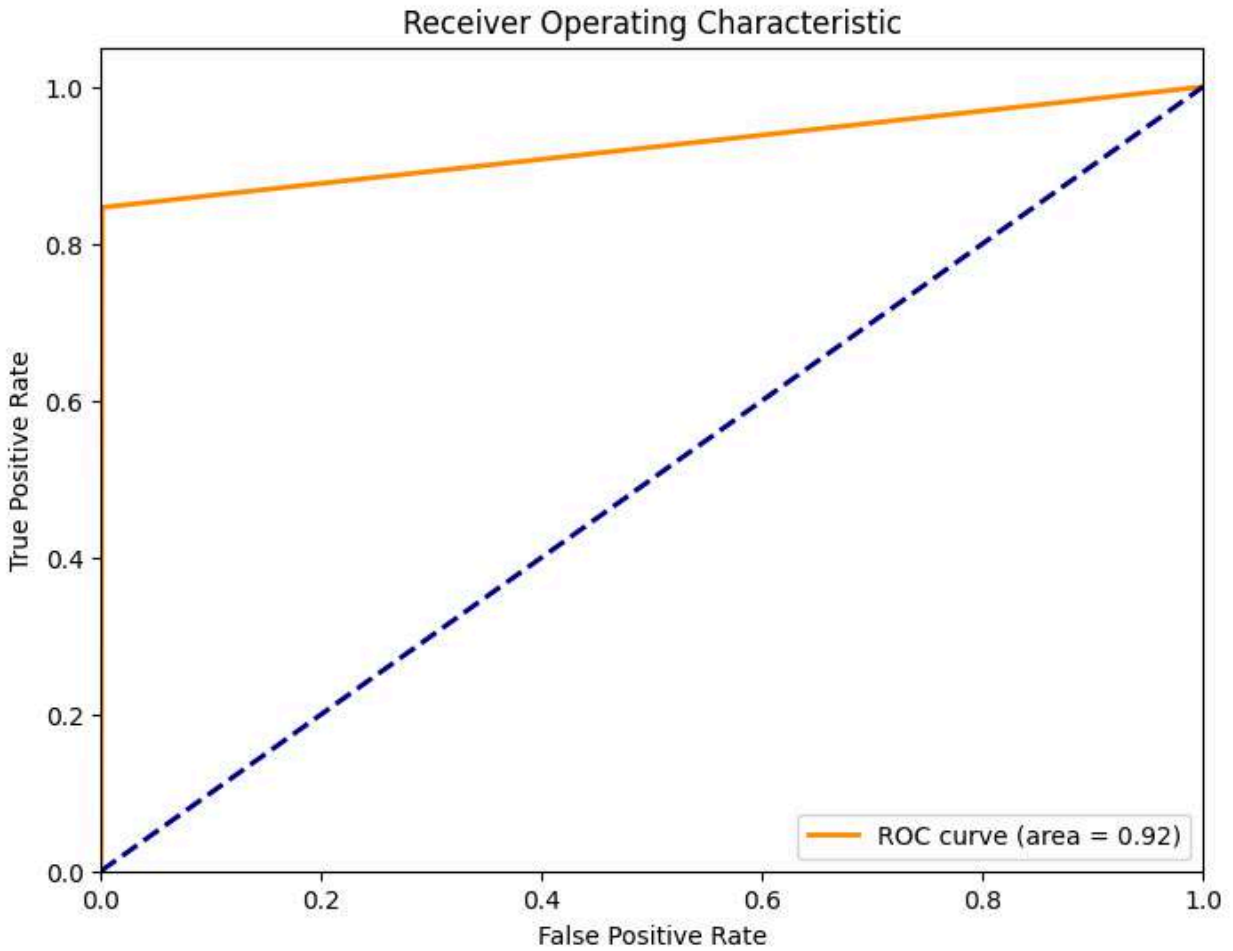
Insights: The Hybrid Model detects more fraudulent transactions but has a significantly higher number of false positives, which could lead to increased operational costs and customer dissatisfaction.

2. ROC Curve and AUC

- **Feedforward Neural Network:** AUC of 0.92.



- **Hybrid Model:** AUC of 0.92.

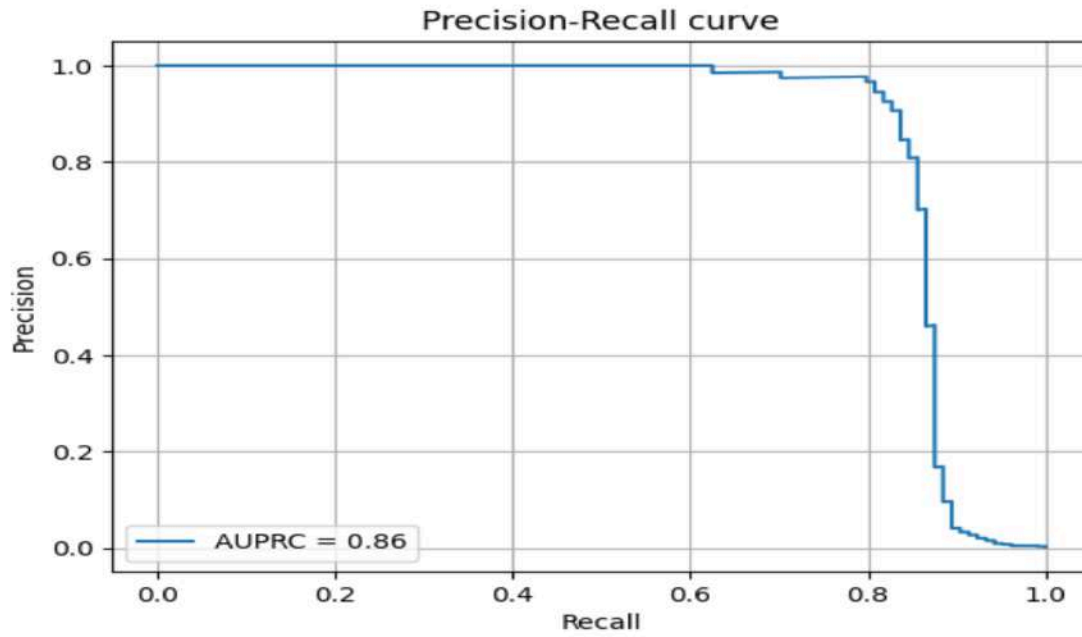


Insights: Both models perform well in distinguishing between fraudulent and non-fraudulent transactions, but the AUC alone does not strongly favor one model over the other.

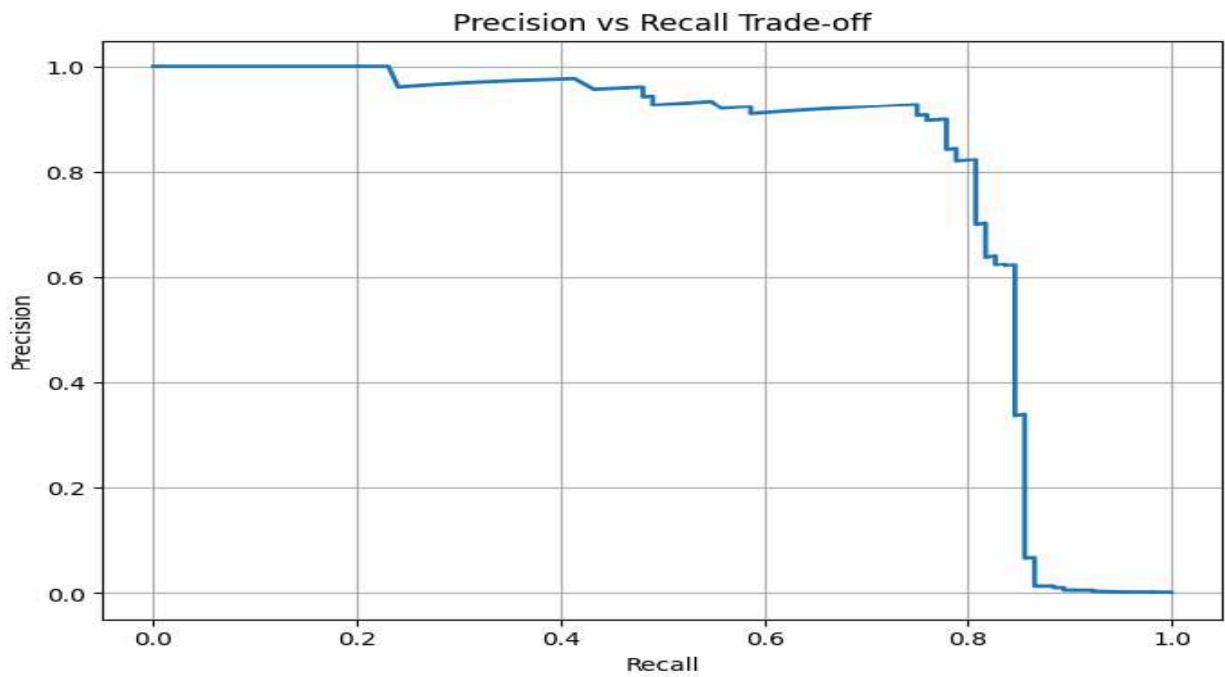
3. Precision vs. Recall Trade-Off

- **Feedforward Neural Network:** Maintains high precision until recall reaches about 0.6.

Matthews Correlation Coefficient: 0.8169735264910966
Area Under the Precision-Recall Curve: 0.8617277332758215



- **Hybrid Model:** Similar precision-recall trade-off, with a more significant drop in precision at higher recall levels.



Insights: The Feedforward Neural Network offers a better balance, especially in environments where minimizing false positives is critical.

4. Economic Impact and ROI

- **Feedforward Neural Network:** Provides a 90% ROI, balancing the cost of false positives/negatives against savings from preventing fraud.
- **Hybrid Model:** May offer a higher ROI due to better detection of fraudulent transactions but incurs higher operational costs due to more false positives.

Insights: The Feedforward Neural Network is more cost-effective in the long run, especially in environments where customer satisfaction is crucial.

Final Analysis

- **The Feedforward Neural Network is recommended** for deployment in environments where minimizing false positives is critical. It provides a balanced performance, lower false positive rate, and better cost-effectiveness.
- The Hybrid Model, while effective, incurs higher operational costs due to more false positives and may not be suitable for customer-facing environments.

7. Deployment

Operationalization

The Feedforward Neural Network will be deployed in a production environment capable of handling real-time data streams, ensuring quick and accurate fraud detection.

Monitoring

A monitoring system will be established to track the model's performance continuously, with adjustments made as necessary to adapt to new fraud patterns.

Future Work

Future enhancements could include exploring more advanced models or ensembles and incorporating new data to adapt to evolving fraud patterns.

8. Conclusion

Summary of Findings

The Feedforward Neural Network is the preferred model due to its balanced performance, lower false positive rate, and better cost-effectiveness. The Hybrid Model, while effective in detecting more frauds, incurs higher operational costs due to false positives.

Impact on Business

Deploying the Feedforward Neural Network will ensure efficient fraud detection, minimizing false positives, reducing operational costs, and improving customer satisfaction.

9. References

- ❖ Kaggle (2016) Credit Card Fraud Detection Dataset. Available at: <https://www.kaggle.com/mlg-ulb/creditcardfraud> (Accessed: 13 August 2024).
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