

CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING

*An Application Development –2 (Project) Report Submitted
In partial fulfillment of the requirement for the award of the degree of*

***Bachelor of Technology
in
Computer Science and Engineering (Data Science)***

by

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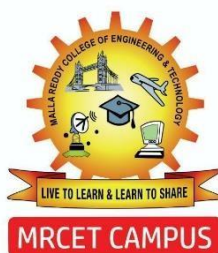
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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(EMERGING TECHNOLOGIES)**

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TECHNOLOGY**

(Autonomous Institution - UGC, Govt. of India)

**(Affiliated to JNTU, Hyderabad, Approved by AICTE, Accredited by NBA & NAAC – 'A' Grade, ISO 9001:2015
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2022-2023

DECLARATION

We hereby declare that the project entitled “**Credit Card Fraud Detection Using Machine Learning**” submitted to **Malla Reddy College of Engineering and Technology**, affiliated to Jawaharlal Nehru Technological University Hyderabad (JNTUH) aspart of III Year B.Tech – II Semester and for the partial fulfillment of the requirement for the award of **Bachelor of Technology in Computer Science and Engineering (DataScience)** is a result of original research work done by us.

It is further declared that the project report or any part thereof has not been previously submitted to any University or Institute for the award of degree or diploma.

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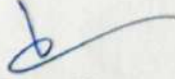


CERTIFICATE

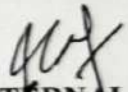
This is to certify that this is the bonafide record of the project titled “**Credit Card Fraud Detection Using Machine Learning** ” submitted by **D.Saikiran (20N31A6714), M.Luckydhar (20N31A6741) and MD.Rehan Pasha (20N31A6742)** of **B.Tech III Year –II Semester** in the partial fulfillment of the requirements for the degree of **Bachelor of Technology** in **Computer Science and Engineering (Data Science)**, Dept. of CSE (Emerging Technologies) during the year 2022-2023. The results embodied in this project report have not been submitted to any other university or institute for the award of any degree or diploma.


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ABSTRACT

The purpose of Credit Card Fraud Detection Using Machine Learning is to automate the existing manual system by the help of computerized equipment's and full-fledged computer software, fulfilling their requirements, so that their valuable data/information can be stored for a longer period with easy accessing and manipulation of the same. The required software and hardware are easily available and easy to work with.

Student Result Management System, as described above, can lead to error free, secure, reliable, and fast management system. It can assist the user to concentrate on their other activities rather to concentrate on the record keeping. Thus, it will help organization in better utilization of resources. The organization can maintain computerized records without redundant entries. That means that one need not be distracted by information that is not relevant, while being able to reach the information.

The aim is to automate its existing manual system by the help of computerized equipments and full-fledged computer software, fulfilling their requirements, so that their requirements, so that their valuable data/information can be stored for a longer period with easy accessing and manipulation of the same. Basically, the project describes how to manage for good performance and better services for the clients.

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CHAPTER 1

INTRODUCTION

Credit card fraud is a growing problem that costs billions of dollars annually, and detecting fraudulent transactions is a crucial task for financial institutions. Traditional rule-based approaches are often inadequate for detecting complex and evolving fraud patterns. Neural networks, particularly deep learning models, have shown promising results in detecting fraudulent transactions due to their ability to learn complex patterns from large amounts of data. However, the effectiveness of neural networks can be compromised by adversarial attacks, where malicious actors intentionally manipulate the input data to evade detection.

Adversarial training is a technique that trains neural networks to be robust against such attacks by generating adversarial examples during the training process. This approach has been shown to improve the robustness of neural networks against adversarial attacks and improve their overall performance.

In this thesis, we propose a credit card fraud detection system that utilizes neural networks and adversarial training to improve the accuracy and robustness of fraud detection. We will evaluate the performance of the proposed system on a real-world credit card fraud dataset and compare it with traditional machine learning models. We will also conduct experiments to evaluate the effectiveness of adversarial training in improving the robustness of the proposed system against adversarial attacks.

The results of this thesis will contribute to the development of more effective and robust credit card fraud detection systems that can protect financial institutions and consumers from fraudulent activities. The proposed approach can also be extended to other applications in which deep learning models are used for detection tasks. racticing manual system. This software is supported to eliminate and, in some cases, reduce the hardships faced by this existing system. Moreover, this system is designed for the particular need of the company to carry out operations in a smooth and effective manner.

The application is reduced as much as possible to avoid errors while entering the data. It also provides error message while entering invalid data. No formal knowledge is needed for the user to use this system. Thus, by this all it proves it is user-friendly. Student Result Management System, as described above, can lead to error free, secure, reliable, and fast

management system. It can assist the user to concentrate on their other activities rather to concentrate on the record keeping. Thus, it will help organization in better utilization of resources.

Every organization, whether big or small, has challenges to overcome and managing the information of Result, Student, Class, Subject, Semester. Every Student Result Management System has different Student needs, therefore we design exclusive employee management systems that are adapted to your managerial requirements. This is designed to assist in strategic planning, and will help you ensure that your organization is equipped with the right level of information and details for your future goals. Also, for those busy executive who are always on the go, our systems come with remote access features, which will allow you to manage your workforce anytime, at all times. These systems will ultimately allow you to better manage resources.

1.1 Problem Definition

Credit card fraud is a significant problem for financial institutions and customers, with millions of dollars lost each year due to fraudulent transactions. Traditional methods of detecting fraud, such as rule-based systems and statistical models, have limitations in detecting sophisticated fraud attempts. The problem is further compounded by the increasing volume and complexity of credit card transactions, which makes it challenging to identify fraudulent activities accurately. Therefore, there is a need for more sophisticated and effective fraud detection techniques that can keep pace with the evolving nature of fraud.

1.2 Motivation

A credit card fraud detection algorithm consists in identifying those transactions with a high probability of being fraud, based on historical fraud patterns. Machine learning, having three types, from that also the supervised and hybrid approach is more suitable for fraud detection.

1.3 Scope

The scope of this thesis is to design and implement a credit card fraud detection system using neural networks and adversarial training techniques. The research will involve collecting real-world credit card transaction data, preprocessing and cleaning the data, and building a neural network-based fraud detection model using popular deep learning frameworks such as TensorFlow or PyTorch.

The study will also explore the effectiveness of adversarial training in improving the robustness of the model to detect fraudulent transactions that mimic legitimate transactions. The research will involve generating adversarial examples and testing the model's performance on both clean and adversarial data.

Additionally, the thesis will compare the performance of the neural network-based fraud detection model with traditional rule-based and statistical models commonly used in the industry. The evaluation will involve assessing the model's accuracy, precision, recall, and F1 score, as well as its ability to detect both known and unknown types of fraud.

Overall, the thesis aims to contribute to the development of more sophisticated and effective credit

card fraud detection systems and provide insights into the potential of neural networks and adversarial training for fraud detection applications.

1.1 Existing System:

- Supervised learning techniques like logistic regression, decision trees, random forests, and are often used to detect fraud in credit card transactions. These techniques use a labelled dataset, where the fraud and non-fraud transactions are labelled, to train the model. The trained model is then used to predict whether a new transaction is fraudulent or not based on its features.
- Unsupervised learning techniques like clustering and anomaly detection are also used for fraud detection. In clustering, the transactions are grouped into different clusters based on their features, and any unusual or outlier transactions are identified as potentially fraudulent. Anomaly detection techniques are used to identify any transactions that deviate significantly from the norm and are potentially fraudulent.

1.2 Proposed System:

- The proposed system for credit card fraud detection will utilize a combination of neural networks and adversarial training to improve the accuracy and robustness of fraud detection.
- The system will also incorporate various data science techniques such as data pre-processing, feature selection, and visualization to ensure accurate predictions and insights.

CHAPTER-2

System Requirements

2.1 Software Requirements:

NAME OF THE COMPONENT	SPECIFICATION
Operating system	windows 10,Linux
Language Used	python
IDE	Jupyter

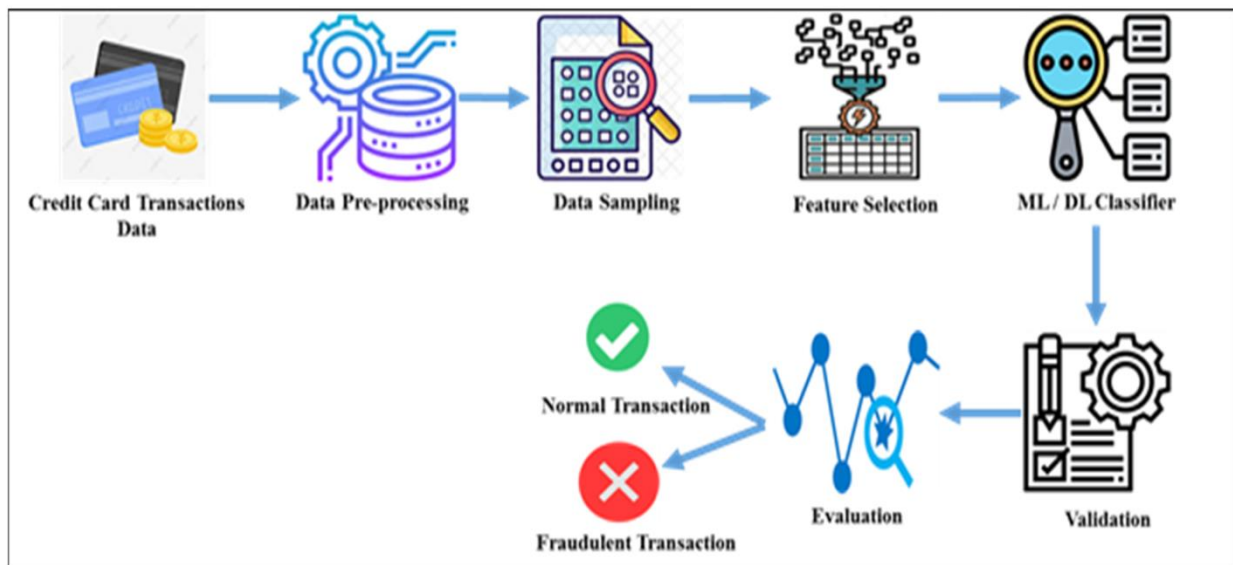
2.2 Hardware Requirements:

NAME OF THE COMPONENT	SPECIFICATION
Processor	Standard processor with 2.0GHZ
RAM	8GB RAM or more
Hard Disk	256 GB or more

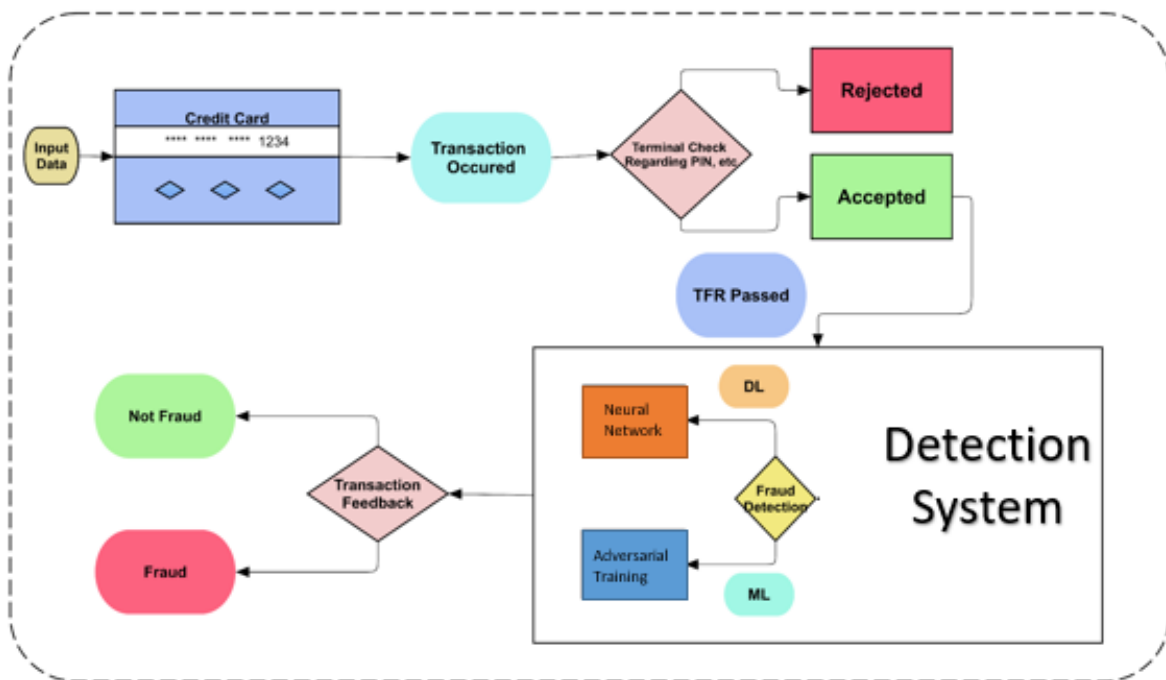
CHAPTER-3

System Design

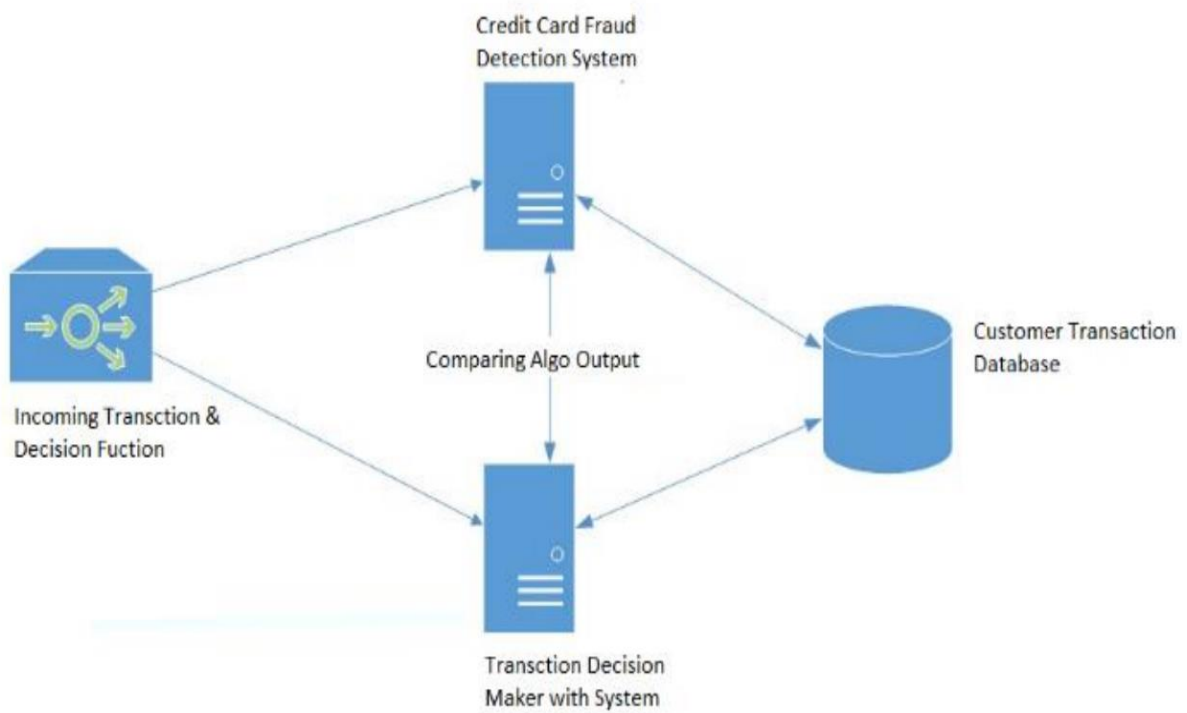
3.1 Dataflow Diagrams / UML Diagrams



3.2 USER USE CASE DIAGRAM:



3.3 System Architecture



CHAPTER 4

IMPLEMENTATION

Implementing credit card fraud detection using neural networks and adversarial training involves several steps. Here is a brief outline of the steps involved:

1. Data Preparation:

First, you will need to collect a dataset of credit card transactions, which includes both fraudulent and non-fraudulent transactions. Next, you will need to clean and preprocess the data by performing tasks such as data normalization, feature selection, and feature engineering.

2. Model Training:

Next, you will need to train a neural network model to classify the transactions as fraudulent or non-fraudulent. You may consider using deep learning frameworks such as TensorFlow or PyTorch for this purpose. You can experiment with different neural network architectures and hyperparameters to achieve better results.

3. Adversarial Training:

To improve the robustness of your neural network model against adversarial attacks, you may consider using adversarial training techniques. Adversarial training involves generating adversarial examples and adding them to the training data to make the model more resistant to attacks.

4. Model Evaluation:

After training the model, you will need to evaluate its performance on a separate test dataset. You can use metrics such as accuracy, precision, recall, and F1 score to measure the performance of the model.

5. Deployment:

Finally, you will need to deploy the model in a production environment to detect fraud in real-time. You can use frameworks such as Flask or Django to create a REST API that can receive credit card transactions and return the fraud prediction

4.1 TECHNOLOGIES USED:

There are several technologies that can be used for credit card fraud detection using neural networks and adversarial training. Here are some examples:

1. Deep Learning Frameworks:

Deep learning frameworks such as TensorFlow, PyTorch, and Keras can be used to train and deploy neural network models for fraud detection.

2. Python Libraries:

Python libraries such as NumPy, Pandas, and Scikit-Learn can be used for data preprocessing, feature engineering, and model evaluation.

3. Adversarial Attacks Libraries:

There are several adversarial attack libraries available for generating adversarial examples, including CleverHans, Foolbox, and ART.

6. Cloud Services:

Cloud services such as Google Cloud Platform or Amazon Web Services can be used to host the REST API and SQL database, making it easier to scale the system as needed.

These are just a few examples of the technologies that can be used for credit card fraud detection using neural networks and adversarial training. The choice of technology will depend on various factors such as the project requirements, budget, and development expertise.

Machine Learning

- Machine learning is a type of artificial intelligence that involves teaching computers to learn from data, without being explicitly programmed. It's like teaching a child how to recognize different types of fruit. You might show them pictures of different fruits, and explain what each one is called. Over time, the child learns to recognize each fruit based

on its features, such as its shape, color, and texture.

- Similarly, a machine learning algorithm is trained on a large set of data, such as images or text, and learns to recognize patterns in that data. The algorithm is given a specific task to accomplish, such as recognizing faces in an image or predicting stock prices. It then learns from the data, adjusting its parameters over time to make more accurate predictions.
- There are different types of machine learning algorithms, such as supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training the algorithm on labeled data, where each example is tagged with the correct answer. Unsupervised learning involves training the algorithm on unlabeled data where the algorithm must identify patterns on its own. Reinforcement learning involves training the algorithm to learn from feedback, such as rewards or punishments.
- The goal of machine learning is to create intelligent machines that can learn and adapt on their own, without being explicitly programmed. It's an exciting field that has the potential to transform many industries, from healthcare to finance to transportation.

Neural networks

- Imagine you are trying to teach a child how to recognize different animals. You might show them pictures of different animals and tell them what each one is called. Over time, the child learns to recognize each animal based on its features, such as the shape of its ears, the pattern on its fur, or the way it moves.
- A neural network works in a similar way. It's a computer program that is designed to learn from examples, just like a child learning to recognize animals. Instead of looking at pictures of animals, though, a neural network is trained on a large set of data, such as images or text.
- The network is made up of layers of artificial neurons, which work together to process the data and identify patterns in it. Each neuron takes in some input data, performs a calculation, and produces an output, which is then passed on to the next layer of neurons. By adjusting the strength of the connections between neurons, the network learns to make more accurate

predictions about the data it is analyzing.

- Just like the child learning to recognize animals, a neural network needs lots of examples in order to learn. But once it has been trained on enough data, it can be very good at recognizing patterns and making predictions based on new data it hasn't seen before. This is why neural networks are used in so many applications today, from image recognition to speech recognition to self-driving cars. Tests should be planned long before testing begins

Adversarial Training

- Adversarial training is a technique used in machine learning to make a model more robust against adversarial attacks. An adversarial attack is when an attacker intentionally inputs misleading data to trick the model into making a wrong prediction. It's like a magician using misdirection to fool an audience.
 - To defend against these attacks, adversarial training involves training a machine learning model on both clean and adversarial examples. The adversarial examples are generated by intentionally adding small perturbations to the input data, which are not noticeable to human eyes, but can fool the model.
 - By training on these adversarial examples, the model learns to be more resilient against these types of attacks. It's like practicing magic tricks with a partner who tries to misdirect you with fake moves, so you become more skilled at detecting the real ones.
 - Adversarial training has been shown to be effective in improving the robustness of machine learning models, especially in applications where security is critical, such as autonomous vehicles, fraud detection, and medical diagnosis.
- Overall, adversarial training is an important technique for making machine learning models more secure and trustworthy.

SOURCE CODE

```
import numpy as np

import pandas as pd

import tensorflow as tf

from tensorflow import keras

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix, classification_report

df = pd.read_csv(r"C:\Users\Saikiran\Desktop\AD2\creditcard.csv")

Df

list(df.columns)

df.describe()

df.info()

df.shape

correlations=df.corr()

sns.heatmap(data=correlations,square=True,cmap="bwr")

plt.yticks(rotation=0)

plt.xticks(rotation=90)

train_size=int(len(df)*0.7)

train_df=df[:train_size]

test_df=df[train_size:]

X_train=train_df.drop("Class",axis=1)

y_train=train_df["Class"]

X_test=test_df.drop("Class",axis=1)
```

```

y_test=test_df["Class"]

model=keras.Sequential([keras.layers.Dense(16,input_dim=X_train.shape[1],
activation="relu"),

keras.layers.Dense(24activation="relu"),keras.layers.Dropout(0.25),

keras.layers.Dense(20,activation="relu"),

keras.layers.Dense(24,activation="relu"),

keras.layers.Dense(1,activation="sigmoid")])

model.compile(optimizer="adam", loss="binary_crossentropy", metrics=["accuracy"])

model.fit(X_train, y_train, epochs=5, batch_size=15)

test_loss, test_acc = model.evaluate(X_test, y_test)

print("Test accuracy:", test_acc)

def adversarial_train(model, x, y, eps):

    with tf.GradientTape() as tape:

        tape.watch(x)

        y_pred = model(x)

        y_onehot = tf.one_hot(y, depth=y_pred.shape[-1])

        loss = tf.keras.losses.binary_crossentropy(y_onehot, y_pred)

        loss = tf.reduce_mean(loss)

    grad = tape.gradient(loss, x)

    x_adv = x + eps * tf.sign(grad)

    x_adv = tf.clip_by_value(x_adv, 0, 1)

    y_adv = tf.ones_like(y)

    X_combined = tf.concat([x, x_adv], axis=0)

    y_combined = tf.concat([y, y_adv], axis=0)

    return X_combined, y_combined

adv_model = keras.Sequential([

```

```

keras.layers.Dense(16, input_dim=X_train.shape[1], activation="relu"),
keras.layers.Dense(24, activation="relu"),
keras.layers.Dropout(0.25),
keras.layers.Dense(20, activation="relu"),
keras.layers.Dense(24, activation="relu"),
keras.layers.Dense(1, activation="sigmoid"))])

adv_model.compile(optimizer="adam", loss="binary_crossentropy", metrics=["accuracy"])

X_train_tf = tf.convert_to_tensor(X_train)
y_train_tf = tf.convert_to_tensor(y_train)

for i in range(10):

    X_combined, y_combined = adversarial_train(adv_model, X_train_tf, y_train_tf, eps=0.1)

    adv_model.fit(X_combined, y_combined, epochs=1, batch_size=15)

test_loss, test_acc = adv_model.evaluate(X_test, y_test)

print("Adversarial test accuracy:", test_acc)

from sklearn.metrics import classification_report

y_pred = adv_model.predict(X_test)
y_pred = adv_model.predict(X_test)
y_pred = np.round(y_pred)
y_pred=np.round(y_pred)

print(classification_report(y_test,y_pred))

cm=confusion_matrix(y_test,y_pred)

plt.figure(figsize=(8,6))

sns.heatmap(cm,annot=True,cmap="Blues",fmt="d",cbar=False)

plt.xlabel("PredictedLabels")

plt.ylabel("TrueLabels")

plt.title("ConfusionMatrix")

```

plt.show()

RESULTS

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.06692
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.33984
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.68928
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.17557
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.14126
...
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111864	1.014480	-0.50934
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924384	0.012463	-1.01622
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578229	-0.037501	0.64013
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800049	-0.163298	0.12320
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643078	0.376777	0.00879

284807 rows × 31 columns

Figure 1- Data Frame

```
list(df.columns)
```

```
['Time',  
'V1',  
'V2',  
'V3',  
'V4',  
'V5',  
'V6',  
'V7',  
'V8',  
'V9',  
'V10',  
'V11',  
'V12',  
'V13',  
'V14',  
'V15',  
'V16',  
'V17',  
'V18',  
'V19',  
'V20',  
'V21',  
'V22',  
'V23',  
'V24',  
'V25',  
'V26',  
'V27',  
'V28',  
'Amount',  
'Class']
```

Figure 2 –List of Columns

```
df.describe()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	3.918649e-15	5.682686e-16	-8.761736e-15	2.811118e-15	-1.552103e-15	2.040130e-15	-1.698953e-15	-1.893285e-16	-3.147640e-15
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+00	1.098632e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+01	-1.343407e+01
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-01	-6.430976e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-02	-5.142873e-02
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-01	5.971390e-01
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+01	1.559499e+01

8 rows x 31 columns

Figure 3 - Describing the data frame

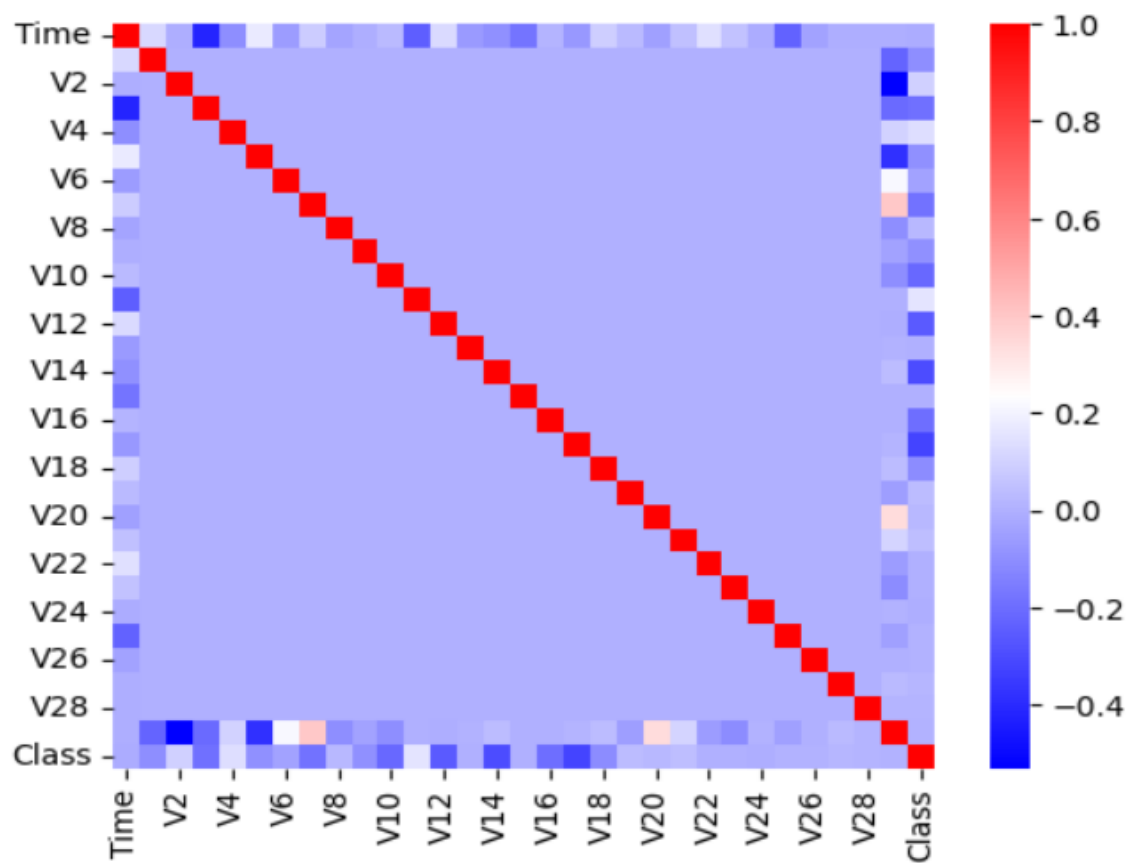


Figure 4 –Correlation Table

```
print("Adversarial test accuracy:", test_acc)
```

```
2671/2671 [=====] - 8s 3ms/step - loss: 0.0100 - accuracy: 0.9987  
Adversarial test accuracy: 0.9987360239028931
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	85335
1	0.00	0.00	0.00	108
accuracy			1.00	85443
macro avg	0.50	0.50	0.50	85443
weighted avg	1.00	1.00	1.00	85443

**Figure 5 –Performance
Evaluation**

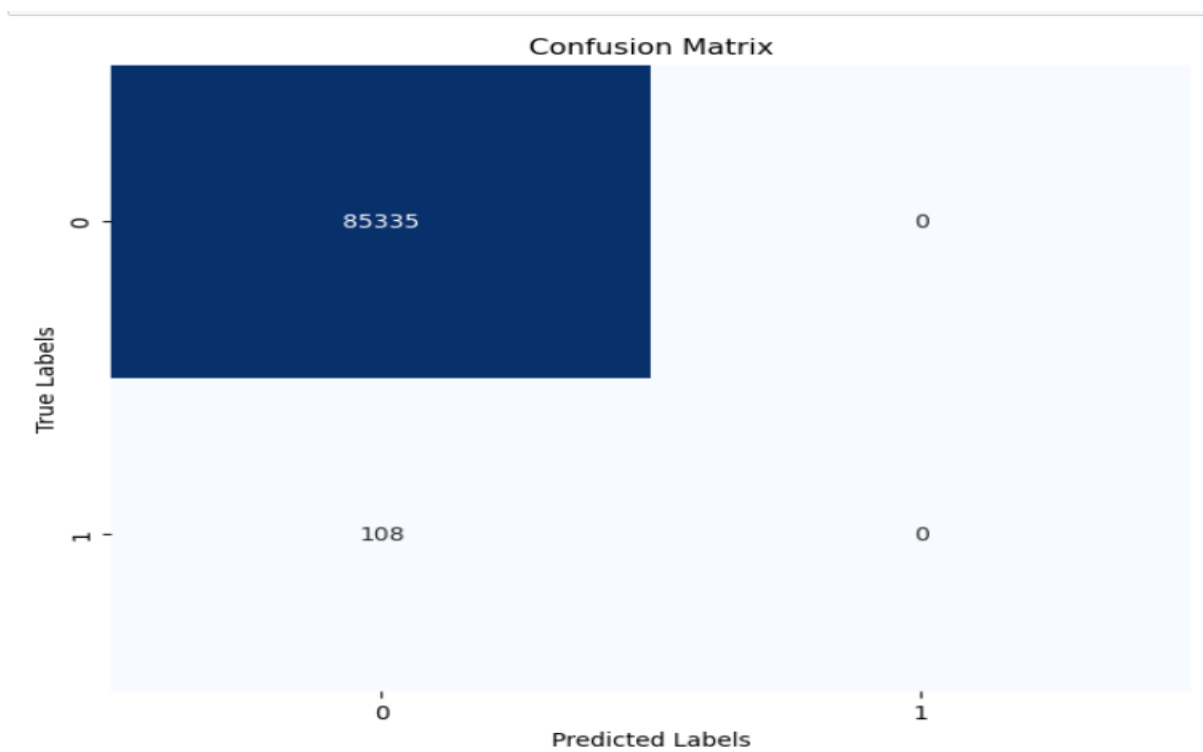


Figure 6 –Confusion Matrix

CONCLUSION

- In conclusion, credit card fraud detection is a critical problem that has significant financial implications for both consumers and financial institutions. Traditional rule-based fraud detection methods are often ineffective in detecting fraud in real-time, leading to a high rate of false positives and false negatives. As a result, there is a growing interest in developing machine learning-based solutions that can detect fraud more accurately and efficiently.
- One promising approach is to use neural networks trained using deep learning techniques. Neural networks can be trained to learn patterns in the transaction data that are indicative of fraud, and can be used to make predictions in real-time. However, these models are vulnerable to adversarial attacks, where an attacker can manipulate the input data to fool the model into making incorrect predictions.
- To address this vulnerability, adversarial training techniques can be used to train models that are more robust to such attacks. Adversarial training involves generating adversarial examples and adding them to the training data, which helps the model to learn to detect and resist adversarial attacks.
- The implementation of credit card fraud detection using neural networks and adversarial training involves several steps, including data preparation, model training, adversarial training, model evaluation, and deployment. Various technologies such as deep learning frameworks, Python libraries, adversarial attack libraries, Flask or Django, SQL databases, and cloud services can be used to implement the solution.
- Overall, the use of neural networks and adversarial training techniques shows promising results for improving the accuracy and efficiency of credit card fraud detection systems. However, there is still a need for further research and development to improve the robustness and scalability of these systems in real-world scenarios.

FUTURE SCOPE:

There is a significant future scope for credit card fraud detection using neural networks and adversarial training. Here are some potential areas of research and development:

1. Improved Neural Network Architectures:

Research can focus on developing more sophisticated neural network architectures that can better detect fraud while being more robust to adversarial attacks.

2. Improved Adversarial Training Techniques:

Adversarial training can be further refined to improve the robustness of the models. One area of research can focus on developing new techniques for generating adversarial examples that are more challenging for the model to detect.

3. Real-Time Detection:

Real-time detection of fraud is critical for minimizing the financial impact on both consumers and financial institutions. Research can focus on developing more efficient and scalable models that can make predictions in real-time.

4. Explainable AI:

Explainable AI is becoming increasingly important for applications where the decision-making process needs to be transparent. Research can focus on developing methods to make the decision-making process of neural networks more transparent, allowing users to understand why a particular prediction was made.

5. Incorporating Non-Financial Data:

Currently, most fraud detection models are trained only on transaction data. However, incorporating non-financial data such as user behavior, location, and device information can improve the accuracy of the models.

6. Online Learning:

Online learning can be used to continuously update the model based on new transaction data. This can help the model adapt to changing fraud patterns and improve its overall accuracy over time.

Overall, there is significant potential for research and development in credit card fraud detection using neural networks and adversarial training. Further advancements in this field can have a significant impact on reducing the financial impact of credit card fraud and improving the security of financial transactions

REFERENCES:

1. Géron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. O'Reilly Media, Inc.
2. Bhattacharyya, A., Bhowmik, T. K., & Chatterjee, A. (2021). A hybrid neural network for credit card fraud detection using Adaboost algorithm. *SN Computer Science*, 2(4), 1-17.
3. Wang, Z., Zhao, Y., & Li, Z. (2021). Credit Card Fraud Detection Method Based on Adversarial Neural Networks. In 2021 IEEE 4th International Conference on Information Systems and Computer Aided Education (ICISCAE) (pp. 587-591). IEEE.
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
5. Biggio, B., Corona, I., Maiorca, D., Nelson, B., Šrndić, N., Laskov, P., ... & Roli, F. (2013). Evasion attacks against machine learning at test time. In Joint European conference on machine learning and knowledge discovery in databases (pp. 387-402). Springer, Berlin, Heidelberg.
6. Ruff, L., Vandermeulen, R., Gørnitz, N., Deecke, L., Siddiqui, S. A., Binder, A., ... & Müller, K. R. (2020). Towards deep learning models resistant to adversarial attacks. *Nature Machine Intelligence*, 2(6), 299-313.
7. Li, Y., Li, X., & Gao, S. (2018). Credit Card Fraud Detection Based on Convolutional Neural Networks. In 2018 3rd International Conference on Computer and Communication Systems (ICCCS) (pp. 52-56). IEEE.
8. Dhage, S. R., & Badhe, Y. (2020). Credit card fraud detection using deep learning with various neural network models. In 2020 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT) (pp. 1509-1513). IEEE.
9. Kotsiantis, S. B., Tampakas, V., & Pintelas, P. (2006). Credit card fraud detection using clustering and neural networks. *Expert systems with applications*, 31(1), 79-91.