Investigating The Effectiveness of Neural Networks in Cryptanalysis

Research Question: To What Extent Can Neural Networks Be Used in the Cryptanalysis of Symmetric Encryptions?

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I. INTRODUCTION

Encryption or cryptography is a method to protect specific information by "transforming the information into a code that is unrecognizable by anyone who intercepts or steals it." [10] Long before modern encryption, the ancient Egyptians already utilized substitution ciphers to preserve the secrecy of ritual life from outside intruders [18]. The evolution of cryptography has developed since then, so much that users do not even understand what goes on in their computers to ensure their data are encrypted and secured from cyberattacks.

Even though cryptography can encrypt a message into a cipher text that makes it illegible, it is also essential to consider how ciphered texts are produced using an encryption algorithm, meaning "a step-by-step procedure for solving a problem or accomplishing some end" [1]. Therefore, by reverse engineering the encryption algorithm, it is possible to find a pattern in the encryption process, thus a way to decrypt the ciphered text without knowing the key for encryption. Decoding messages from non-readable text without knowing the key is known as cryptanalysis [15]. It's plausible to think that our cryptography technology has developed to the extent that humans can't reverse engineer these complicated encryption algorithms. Yet, there is one technology that could be used to reenact human logic in a much more efficient way, machine learning [7]. The rise in popularity of machine learning has improved its usage in facial recognition, autonomous driving, virtual assistance, regression modeling, classification, clustering, and, most importantly, predictions of all sorts [7]. Accordingly, machine learning can be linked with cryptography to see whether it is possible to decrypt encrypted messages by knowing numerous plaintexts and their corresponding cipher text to brute force the encryption algorithm.

In this investigation, I will attempt to discover whether the artificial neural network is efficient in decrypting messages encrypted by the Data Encryption Standard (DES) without knowing the 56-bit key used to encrypt the messages. The dataset will be every 8-byte word in the English dictionary turned into binary bits. The application of DES is no longer the NIST federal standard [9], but a derivation, Triple-DES, is now used broadly in finance and credit card payment [11]. Being able to decrypt DES with machine learning signifies that a breach of data security could emerge in the future, as it proves machine learning models can execute cryptanalysis. This could easily cause social unrest due to the leakage of personal and corporate data, which is both unethical and a breach of human rights. Hence why this investigation is so crucial to take preemptive measures in encryption systems to prevent machine learning from decrypting messages.

II. THEORETICAL BACKGROUND

A. Artificial Neural Networks

This investigation will mainly focus on artificial neural networks, also known as just neural networks, a subset of machine learning, that uses data and algorithms to replicate how human beings learn. The name neural network is inspired by the biological structure of the human brain, where neurons connect to other neurons to transfer information. This neural network is known as supervised learning, which makes use of labeled training data to predict or classify values [7].

1. Neurons

Just like the nodes in a human brain, ANNs also have nodes or artificial neurons, which have a weight and threshold value (bias) [15]. When the output of a node is larger than the threshold, the node is activated through an activation function to send data to the next layer of nodes. An example formula for a node to fire the activation function is,

$$\sum_{i=1}^{m} w_i x_i + b = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$$

$$output = f(x) = \left\{ \begin{array}{ll} 1, & \text{if } \sum w_1 x_1 + b \geq 0 \\ 0, & \text{if } \sum w_1 x_1 + b < 0 \end{array} \right\}$$

Where m is the weight generated once the input layer is determined, x is the input or the training data, and b is the bias (threshold value). The output is then sent using the activation function, acting as an input for the next node. In this investigation, we will use the ReLU activation function since our output will only be either 0 or 1 [20]. Hence any exponential or logarithmic activation would be unnecessary since the output will be rounded up to binary. Below is the graphical demonstration of ReLU.

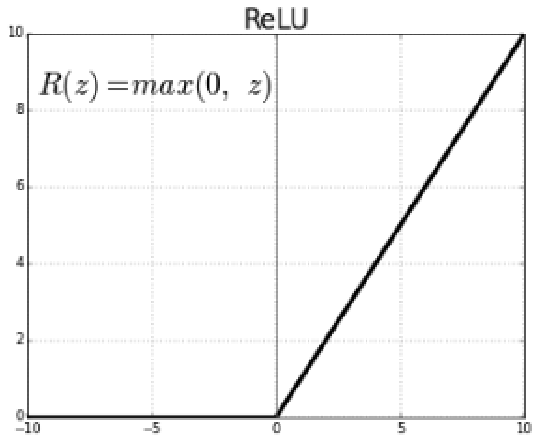


Figure 1: ReLu Function [20]

2. Layers

Neural networks are made of layers consisting of 3 major types of layers: input layer, hidden layer, and output layer. The input layer is the first layer that the training data is fed into. Through each epoch - the number of cycles in training - the input layer will take in data from the output layer from the previous node. Unlike the input and output layers which are all singular, the number of hidden layers depends on the investigation. The hidden layer consists of a designated amount of nodes, which act as a parameter for training and where essentially, the learning of the algorithm happens. When we have multiple layers of the hidden layers, the neural network is considered a multilayer perceptron [15].

3. Multilayer Perceptrons

Multilayer Perceptrons or feedforward neural networks are typical systems used for classification [15]. A perceptron is one unit of the node, which is the simplest form of a neural network. Figure 2 is a typical example of an MLP consisting of an input layer, a hidden layer(s), and an output layer. This type of neural network is advantageous in real life since the causation of an event usually takes in other correlations, thus imitating when a human considers multiple factors when considering a problem, hence the multiple inputs of the MLP.

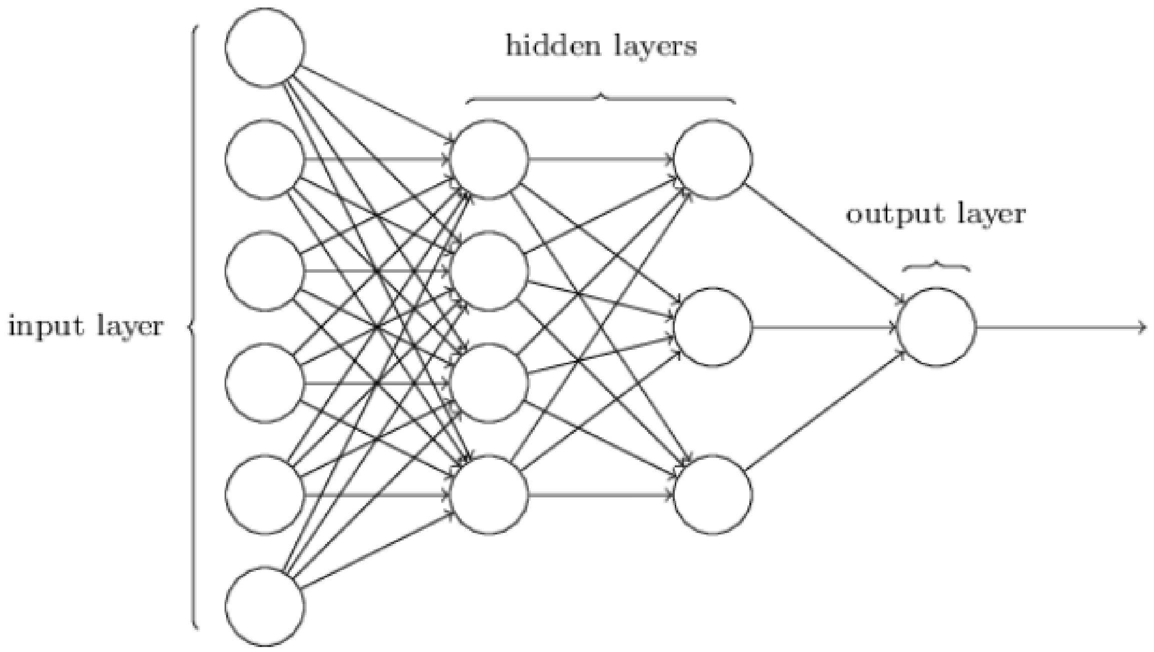


Figure 2: Visual Representation of Multilayer Perceptron [13]

The reason why this investigation will be using an MLP with multiple layers of hidden layers instead of a singular layer is that the DES encryption has 16 rounds of encryption rather than a single round. Utilizing an MLP, we can simulate the scenario where the multiple layers and nodes correspond to the different steps in DES encryption methods.

4. Cost Functions

To measure the performance of the machine learning model, a cost function or loss function is often used. It is a function that interprets the value between the predicted value and the absolute value. It is one of the most important indexes to look at while training a machine learning model, and the goal is to minimize the value of the cost function [17]. The cost function is calculated by the chaing weight and bias; with each different function, the metrics for determining the weight are also different.

In our investigation, we will use the binary cross entropy loss function [17]. This cost function was inspired by the information theory, where bits are lost during the transfer between layers to layers, suitable for our investigation where our data will be in the form of binary bits. Below is a formula to calculate the binary cross entropy function,

$$\text{Loss} = -\frac{1}{m}\sum_{i=1}^{m} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot (1 - \hat{y}_i)$$

Where i is the sample index, $\hat{y}$ is the predicted value, y is the expected value, and m is the number of samples in the dataset. In other related works, researchers have found that the mean square error loss function [2] was also appropriate for the scenario, with a 97% accuracy and 0.00586 margins of outside error. Below is the formula for the MSE,

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2$$

5. Optimizer (Gradient Descent)

To improve or minimize our loss function, we can use optimizers, which are tools to minimize the loss function by updating weights and biases of the internal parameters of the model. A standard optimization algorithm is called gradient descent. In the diagram below, on the y-axis, there is the value given by the cost function, and on the x-axis, there is the weight. The optimizer calculates the gradient and determines the minimum cost, where the model is the most accurate with the least cost function value. Moreover, the optimizer we will be using is Adam (Adaptive Moment Estimation), which also utilizes momentum: adding fractions to the previous gradient to the current one [14].

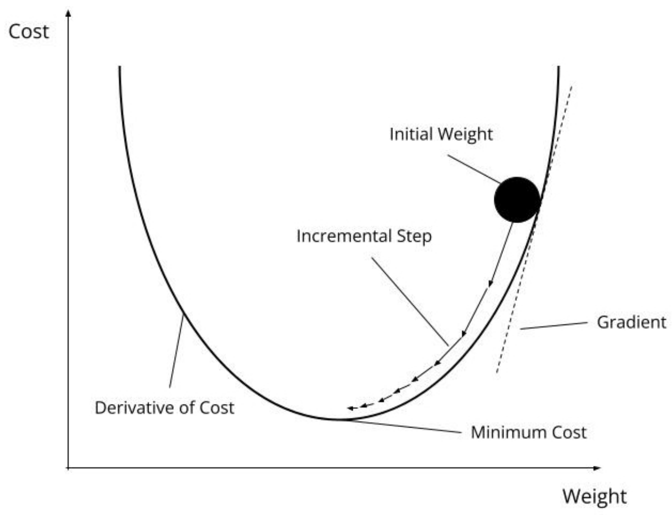


Figure 3: Cost vs Weight in an Optimizer[6]

B. Data Encryption Standards & Cryptanalysis

1. Encryption

The process of encryption is described as “transforming the digital information into a code that is unrecognizable by anyone who intercepts or steals it” [10]. The encryption method differs from algorithm to algorithm, and each method is considered a cipher. Currently, the four most famous ciphers widely used are Triple DES, RSA (Rivest-Shamir-Adleman), Twofish, and AES (Advanced Encryption Standard).

These cipher algorithms fall into two genres of encryption: symmetric and asymmetric. To understand how to decrypt encryption, it is essential to know how both encryption work for the investigation to have a practical outcome. The main difference is that symmetric encryption utilizes only one private key for encryption and decryption. In contrast, asymmetric encryption uses the user’s public key to encrypt and the user’s private key to decrypt the message sent. This means that asymmetric key encryption is irreversible since, after encrypting, the sender will not be able to retrieve the message back; hence for the sake of investigation, symmetric key encryption would be more appropriate to consider, as the investigation seeks only to find if machine learning is an appropriate tool for data decryption.

2. Cryptanalysis

Cryptography is the study of creating secret messages using encryption methods [15]. On the other hand, Cryptanalysis studies how these encryption techniques can be bypassed without knowing any key used in the encryption, helping develop more secure encryption and find flaws in the system. The method to decrypt is called cryptanalytic attacks, and the two common attacks are linear and differential cryptanalysis[8]. These two attacks require a large quantity of either plain texts and (or) cipher texts. Due to the requirement of a large dataset, the job is suitable for machine learning classification, hence the reason to combine cryptanalysis and machine learning.

3. Data Encryption Standards(DES)

One of the first symmetric encryption, called Data Encryption Standard (DES) [9] was soon abandoned after it was created. It was not strong enough to prevent linear or differential brute force cryptanalysis. Still, this encryption method is valuable for the investigation, as we won't use the typical mathematical approach in brute-forcing the encryption but rather utilize machine learning. DES takes 64-bit data in a block as input and produces 64-bit data after the encryption. Depending on the length of the text or the size of the encrypted data, DES will generate corresponding blocks. When the length of text exceeds 64, will blank bits will be padded, meaning "different ways to add extra bytes" to the block [9].

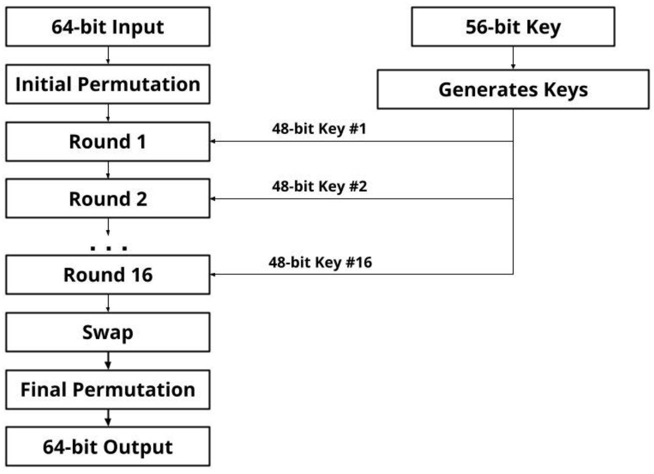


Figure 4: DES Algorithm Overview [16]

i. Key Generation

Since DES is a type of symmetric encryption, it only requires one private key, initially 64-bit, but every 8th bit in the data block is discarded, constructing a main key of 56-bit. Each round of DES generates a new key through a key transformation where the 56-bit key is halved, and depending on the round, DES performs a circular left shift of one or two indexes. After the shift, the 56-bit is combined back together, while again, the 8th bits are discarded, forming a unique 48-bit key per round. This process in cryptography is known as compression permutation. [9]

ii. Permutation (Transposition)

After the padding of input and generation of the key, the encryption process begins. Firstly the 64-bit input will go under the initial permutation function, a phase in the transposition procedure typically known as the diffusion process of the encryption. This means that the bits have their position switched with other bits to create a random yet reversible new sequence of bits that contains all the original bits in different orders. After the plain text is permuted, it is separated into the two blocks of 32-bit left and right original plain text. The final permutation essentially repeats the initial permutation at the end of the entire algorithm. [16]

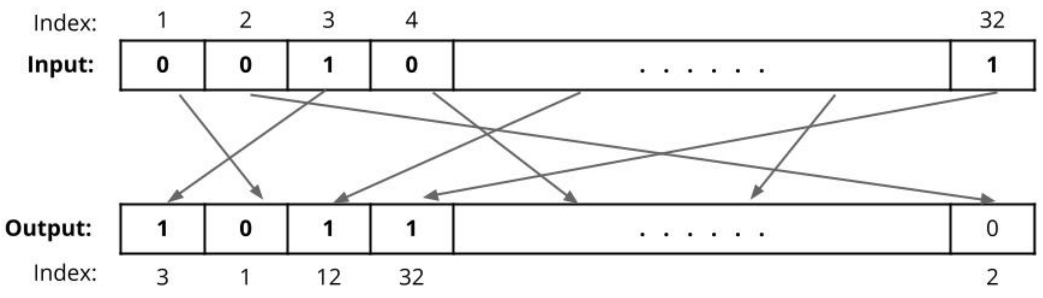


Figure 5: Permutation Algorithm[16]

iii. DES Round

Every round of DES has the same operation with different inputs per round key. The input is taken from the previous round of DES or the initial permutation as left and right input blocks with 32 bits. From the diagram, we can see that in the output of a DES round, the left half output is simply the input of the original right block, and the right half of the output is the outcome of XORing [3] the left half input and the mangler function of the original right half. The mangler function [3] contains:

1. Expansion Permutation, dividing 32-bit into eight blocks of 4-bit, then adding 2-bit in each block, and lastly performing bit permutation on all eight blocks to result in a 48-bit block.

2. XOR Swapping [3] performs three rounds of XOR (Exclusive or) on the text with the 48-bit per round key, concluding with a 48-bit block.

3. S-Box Substitution uses subblock and s-box to convert the 48-bit block into a 32-bit block.

4. P-box Permutation permutes the 32 bits into a 16 by two permutation table.

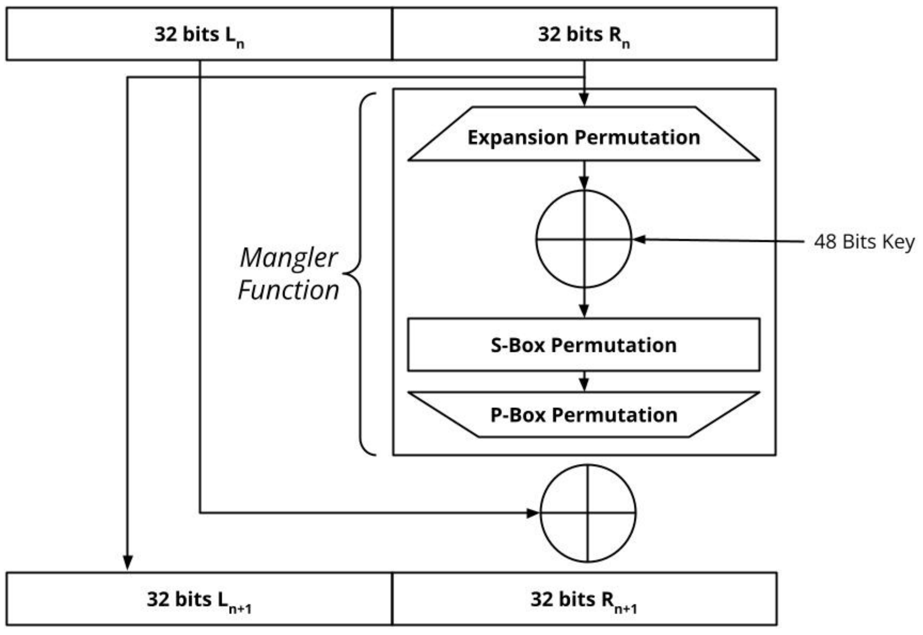


Figure 6: Specific DES Round Algorithm[16]

III. METHODOLOGY

A. Investigation

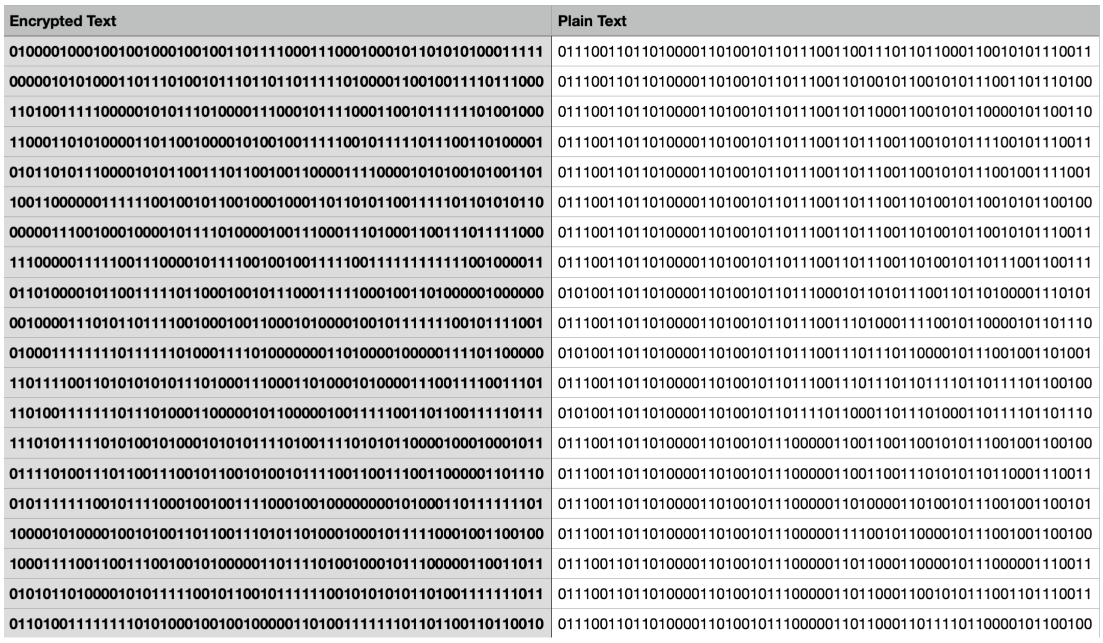
In this investigation, a huge problem was the way to represent the input and output to feed into the network, as well as the structure choice of the algorithm. The investigation utilized Google Colab to train the machine model online; while using the programming language of Python, I was able to create and modify the dataset and implement the DES algorithm (see appendix).

B. Experimental Procedure

1. Download all the words in the English dictionary
2. Dataset 1: Collect all the words that have a character length of 8 through filtering
3. Dataset 2: Generate random binary bits as plain text with a length of 64 bits in total
4. With the DES algorithm, encrypt all the words
5. Converted the plain text and cipher text into binary of 64 bits
6. Split the 64-bit block into an array of '1's and '0's and export it to a CSV file.
7. Split the test sample into training and testing
8. Upload the files into Google Colab
9. Train the model using scikit-learn using *Binary Cross Entropy* as loss function and *ADAM* as optimizer.
10. Generate predictions on the test data
11. Hypertune the learning rate, epochs for maximum accuracy, and minimum loss
12. Repeat steps 9-11 until an appropriate loss and accuracy.

C. Data Generation & Processing

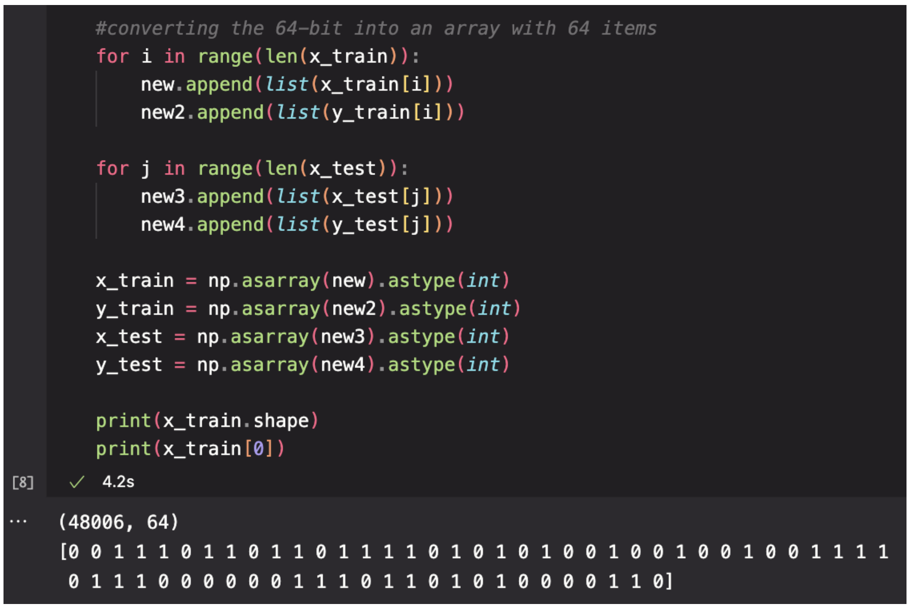
In terms of generating the dataset, my approach was first to collect words [21] with a character length of 8, equal to 64 bits or 8 bytes. Thus without padding [9], the DES can encrypt every message with the same length to minimize outside error. Then with the DES algorithm [5], the plain text gets encrypted into bits, which cannot be directly converted into binary. Hence it is necessary to decode the bits into Latin and convert the string into binary. To compare the real-life scenario where not all messages are English, we've also generated 64 random bits as separate datasets. Here is an example of the dataset, where the cipher text is the input, and the plain text is the output.



Encrypted Text	Plain Text
0100001000100100100010010011011110001110001000101101010100011111	0111001101101000011010010110111001100111011011000110010101110011
0000010101000110111010010111011011011110100001100100111110111000	0111001101101000011010010110111001101001011001010111001101110100
1101001111100000101011101000011100010111100011001011111101001000	0111001101101000011010010110111001101100011001010110000101100110
1100011010100001101100100001010010011111001011111011100110100001	0111001101101000011010010110111001101110011001010111100101110011
0101101011100001010110011101100100110000111100001010100101001101	0111001101101000011010010110111001101110011001010111001001111001
1001100000011111100100101100100010001101101011001111101101010110	0111001101101000011010010110111001101110011010010110010101100100
0000011100100010000101111010000100111000111010001100111011111000	0111001101101000011010010110111001101110011010010110010101110011
1110000011111001110000101111001001001111100111111111111001000011	0111001101101000011010010110111001101110011010010110111001100111
0110100001011001111101100010010111000111110001001101000001000000	0101001101101000011010010110111000101101011100110110100001110101
0010000111010110111100100010011000101000010010111111100101111001	0111001101101000011010010110111001110100011110010110000101101110
0100011111110111111010001111010000000110100001000001111101100000	0101001101101000011010010110111001110111011000010111001001101001
1101111001101010101011101000111000110100010100001110011110011101	0111001101101000011010010110111001110111011011110110111101100100
1101001111111011101000110000010110000010011111001101100111110111	0101001101101000011010010111101100011011101000110111101101110
1110101111101010010100010101011110100111101010110000100010001011	0111001101101000011010010111000001100110011001010111001001100100
0111101001110110011100101100101001011110011001110011000001101110	0111001101101000011010010111000001100110011101010110110001110011
0101111111001011110001001001111000100100000000101000110111111101	0111001101101000011010010111000001101000011010010111001001100101
1000010100001001010011011001110101101000100010111110001001100100	0111001101101000011010010111000001110010110000101110010011001000
1000111100110011100100101000001101111010010001011100000110011011	0111001101101000011010010111000001101100010000101110000001110011
0101011010000101011111001011001011111100101010101101001111111011	0111001101101000011010010111000001101100011001010111001101110011
0110100111111110101000100100100000110100111111101101100110110010	0111001101101000011010010111000001101100011011110110000101100100

Figure 7: Training & Testing Dataset

After inputting the dataset into the CSV file for both training and testing, when training the model, these 64-bit blocks will be split into individual bits and combined in an array, as demonstrated below. According to Linus Lagerhjelm [15], this simulates the situation where the nodes of the neural network are acting directly on each corresponding bit vector given by the cryptographic algorithm.



```
#converting the 64-bit into an array with 64 items
for i in range(len(x_train)):
    new.append(list(x_train[i]))
    new2.append(list(y_train[i]))

for j in range(len(x_test)):
    new3.append(list(x_test[j]))
    new4.append(list(y_test[j]))

x_train = np.asarray(new).astype(int)
y_train = np.asarray(new2).astype(int)
x_test = np.asarray(new3).astype(int)
y_test = np.asarray(new4).astype(int)

print(x_train.shape)
print(x_train[0])
```

```
[8]  ✓  4.2s
```

```
(48006, 64)
[0 0 1 1 1 0 1 1 0 1 1 0 1 1 1 1 0 1 0 1 0 1 0 0 1 0 0 1 0 0 1 0 0 1 1 1 1
 0 1 1 1 0 0 0 0 0 0 1 1 1 0 1 1 0 1 0 1 0 0 0 0 1 1 0]
```

Figure 8: Splitting Text into Bit-Arrays for Dataset

D. Model Architecture

The machine model, training, data importing, prediction, and plotting are written in Python using Sckit-Learn, NumPy, Pandas, and Matplotlib. I will use multilayer perceptrons to build my algorithm. The hidden layer will have the configuration of nodes such that the four layers will be 256, 512, 512, and 256.

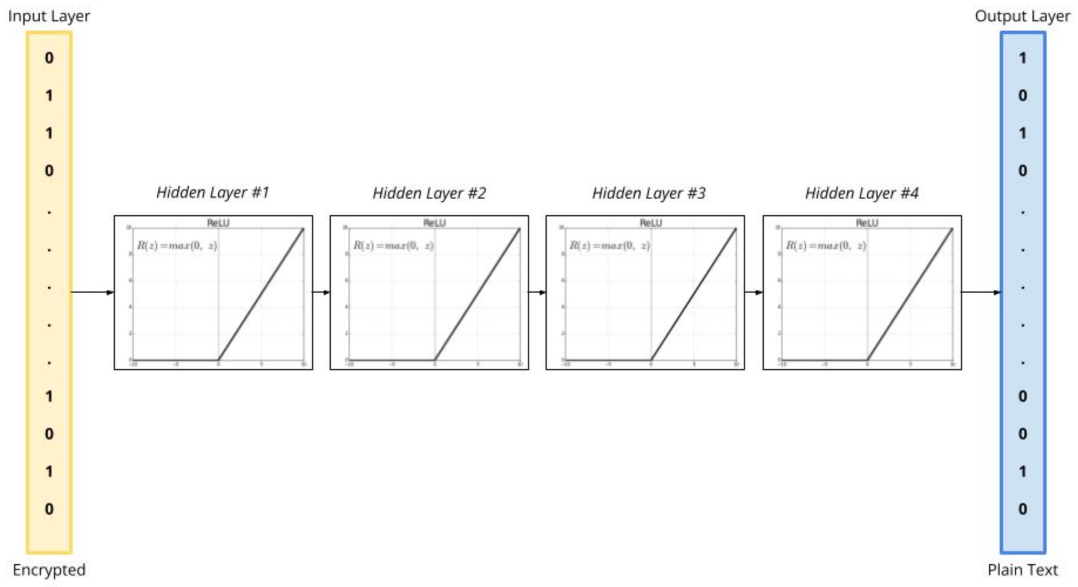


Figure 9: Model of Neural Network Used[2]

The activation function will be ReLU [20]. The loss function would be the default binary cross entropy. The optimizer used will be Adam. Adam is an algorithm based on the stochastic gradient descent algorithm while combining the RMSProp, and AdaGrad. Compared to a recently proposed quasi-Newton method (SFO) [14] that performed fabulously on the optimization of MLP, Adam is faster in both epochs and wall-clock time while also using the dropout function to prevent overfitting. [14]

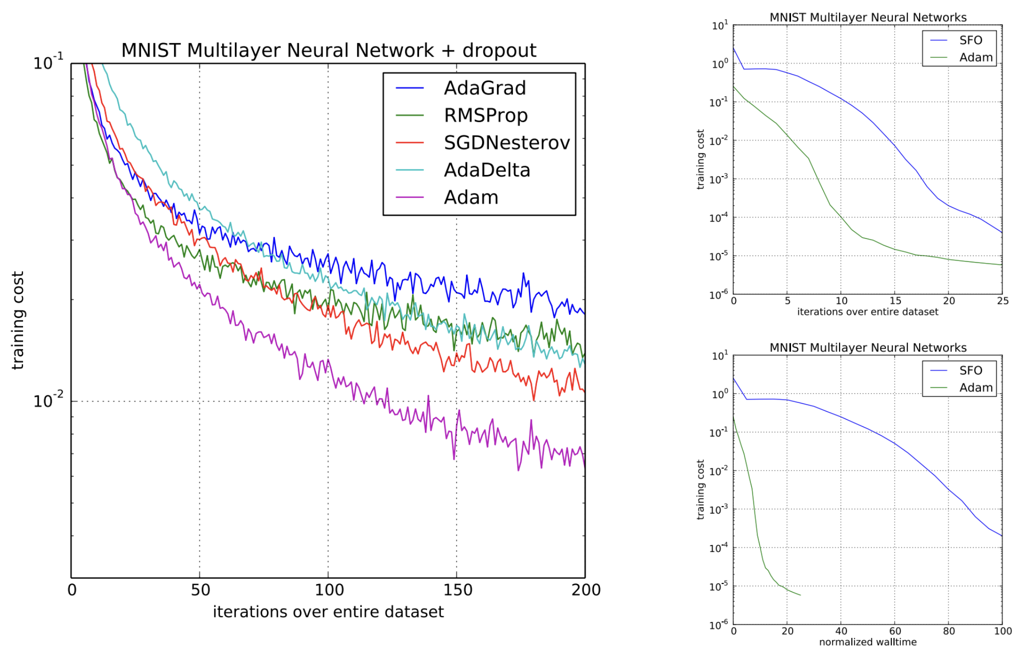


Figure 10: Comparison of Adam and Other Optimizers [14]

In addition, the learning rate, an additional parameter, regulates how much our neural network's weights are based on the loss gradient. In this case, I choose adaptive learning, which means that for every two epochs, if the loss value has not decreased by the target value, then it will slow down the learning process. This can help reduce the loss value as well as increase the precision and accuracy of the model, at the same time maximizing the time consumed to train this model [12]. The set 100 epochs will end once the loss value has not decreased in the interval of 0.001 for the past five epochs to ensure we've reached the minimum loss value.

IV. ANALYSIS & CONCLUSION

A. Data Presentation

Dictionary Dataset - Performance Metrics

Table created by taking every 10th epoch for cross-validation with the test set of the dictionary.

Log Loss:	Accuracy:	Precision:	Recall:	F1 Score:	Hamming Loss:
21.92	0.705	0.72	0.719	0.719	0.295
19.172	0.704	0.717	0.722	0.72	0.296
17.599	0.705	0.718	0.722	0.72	0.295
16.178	0.707	0.722	0.718	0.72	0.293
14.962	0.707	0.721	0.722	0.722	0.293
14.404	0.708	0.723	0.72	0.721	0.292
13.507	0.709	0.724	0.722	0.723	0.291
12.56	0.712	0.729	0.72	0.725	0.288
12.424	0.717	0.735	0.723	0.729	0.283
11.95	0.751	0.782	0.73	0.755	0.249

Dictionary Dataset - Confusion Matrix

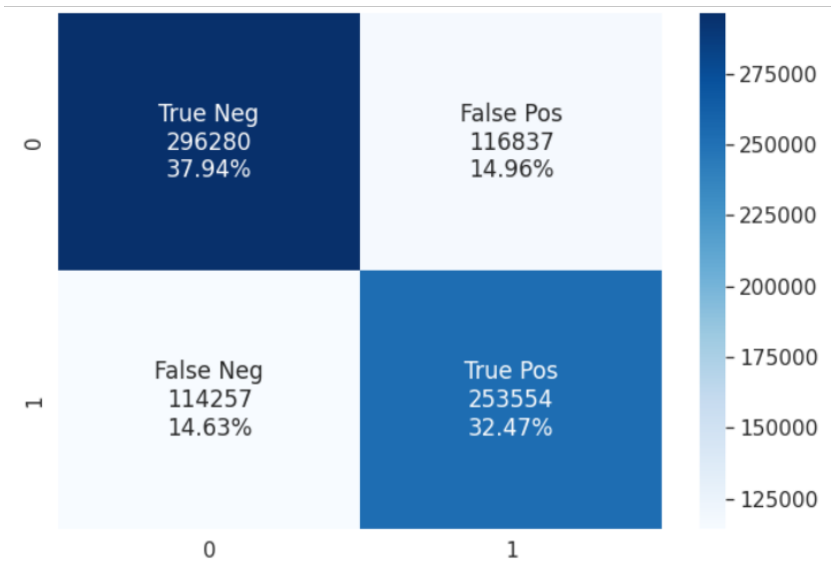


Figure 11: Dictionary Dataset - Confusion Matrix

Random Bits - Performance Metrics

Table created by taking every 10th epoch for cross-validation with the test set of random bits.

Loss:	Accuracy:	Precision:	Recall:	F1 Score:	Hamming Loss:
44.361	0.500	0.500	0.537	0.518	0.500
44.352	0.500	0.499	0.551	0.524	0.500
44.335	0.500	0.500	0.527	0.513	0.500
44.301	0.501	0.500	0.514	0.507	0.499
44.242	0.501	0.500	0.513	0.506	0.499
44.144	0.501	0.500	0.513	0.507	0.499
44.012	0.500	0.500	0.516	0.508	0.500
43.859	0.500	0.499	0.513	0.506	0.500
43.695	0.500	0.500	0.515	0.507	0.500
43.532	0.500	0.500	0.514	0.506	0.500

Random Bits - Confusion Matrix

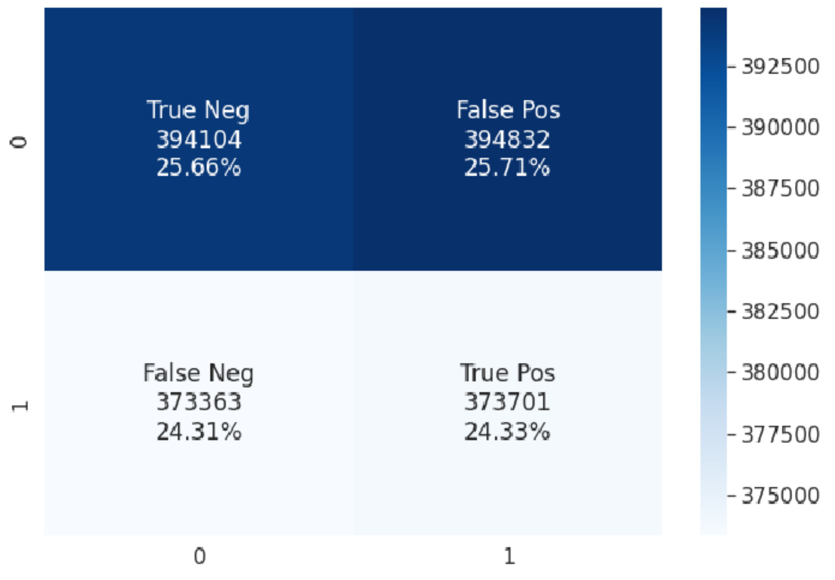


Figure 12: Random Bits - Confusion Matrix

B. Evaluation Metrics & Explanation

After training the neural network for decryption, we need to use the test set to verify specific metrics typically used in classification problems. We have 64 binary bits representing one plain text, meaning 64 classifications the algorithm makes for each plain text. This type of machine learning algorithm is commonly known as multi-class, multi-output classification, which currently doesn't have any unique evaluation metrics. Therefore, the metrics used to evaluate the model are the typical loss, binary accuracy, recall, precision, and the F1 score.

To begin, a way to demonstrate the algorithm's performance on the binary bits could be a visual representation known as a confusion matrix [12]. In figure 11, we see a confusion matrix that gives the amount of true and false predictions on positive and negative items. In this investigation, the positive would be predicting 1, and the negative would be predicting 0. This was done manually by calculating true positive, true negative, false positive, and false negative. Even though confusion matrices are generally not used to verify multi-output binary classification problems, they offer a sufficient summary of the performance in terms of balances in the dataset and training.

On the other hand, the loss can be measured in two different ways, one as the binary cross-entropy function, another as the hamming loss [4]. Binary cross entropy or log loss was the function used in the algorithm's training, which is the negative average of the log of correctly predicted probabilities [19]. Hamming loss evaluates how often a label or index is misclassified, meaning that false positives and negatives will raise hamming loss. In contrast, true positives and true positives will minimize the hamming loss.

Accuracy is one of the most overlooked metrics in an algorithm, though it is a critical metric to assess the value of this algorithm [15]. The closer to having perfect accuracy means that the more accurate the decrypted message will be. This may sound obvious, but in other machine learning scenarios, accuracy can be misleading. For example, binary classification of snow forecasts can achieve 99% accuracy by predicting that there will be no snow every single time, but this means that in the condition where there is supposed to be snow, the predictor still predicts no snow, creating a useless algorithm with high accuracy but no potential use. In this case, the accuracy calculated is by looking at each index of the 64 bits rather than the encrypted message as a whole. The formula to calculate the accuracy is shown below [12],

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

By using the values in the confusion matrix, we can obtain values of precision, recall, and the f1-score. The precision represents the percentage of positive instances out of the total optimistic predictions. This allows us to understand how often the model predicts true and whether it is right. The recall, on the other hand, is defined as the percentage of true positive predictions out of all positive values. Lastly, the F1 score is the harmonic mean between precision and recall. [12]

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FP}$$

$$\text{F1 score} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Though the metrics of precision and recall are used in this investigation, it does not seem very suitable for the scenario since these metrics treat the problem as a typical classification problem. In our case, 1 and 0 are both important, but these metrics only give us information about the positive predictions. The reason for including these metrics is for future improvement, as these metrics provide an insightful contribution to some issues with the dataset and model itself, such as overfitting or underfitting [12].

C. Result Analysis

The first abnormal metric we see in the data is the high log loss rate of 11.95% for the dictionary dataset. This is because the loss value shows the total loss for all 64 bits since they are under a single array. If we divide 11.95% by 64, we get a low log loss of 0.19%. This means that the model, in general, predicted closely what the true value is; the hamming loss values also demonstrated that only 24.9 % of the 1,536,000 bits were mispredicted. The accuracy of the first model with a dictionary as input has a high accuracy of 75% in the final epoch. In addition, the precision and F1 score rapidly increased in the end. Recall, on the other hand, was always hovering around the 7.2 to 7.3 section without a significant increase or decrease, showing relevancy between the plain and ciphered text. The result seems reasonable as the key for encryption was not given; it was able to create a new algorithm to represent the relationship between the plain and ciphered message.

If we look at the evaluation metrics for the random bits dataset, we can see that most values hovered at 0.5, which is not a good sign; this signifies the values for evaluation were 50%. Perhaps because there were only two options for the algorithm to predict, meaning that the algorithm did not find a pattern between the plaintext and ciphertext. The loss value was extremely high, and after reviewing the dataset, the conclusion for this dataset was that the randomly generated bytes did not have any pattern, unlike the dictionary, where a letter corresponds to a specific binary representation. The metrics value then makes sense as the model has a 50% chance of guessing whether or not the value is 0 or 1, hence producing 0.5 for accuracy, precision, F1 score, and hamming loss. Therefore, the dictionary result will be the primary focus of this investigation.

D. Limitations of Investigation

The main limitation I realized throughout the investigation was how this algorithm wouldn't apply to an actual cryptanalytic attack. Firstly, even though the evaluated accuracy of 75% represents a high probability of predicting the correct binary bits, it still would not apply to real-life cryptanalysis. When you transfer the predicted binary bits back to ASCII for a legible text, if there is 1 bit of error, the character would be completely different than the original text, as each character corresponds to a combination of binary bits; hence the model would not be functioning if we don't have close to 99% accuracy to obtain the perfectly decrypted message. Secondly, the key was set to be the same for all encryption, but keys can change in actual encryption; hence it is hard to know if the encrypted message is encrypted by the same key or different keys, creating uncertainty even if there was a large amount of plain text and encrypted text provided for cryptanalysis. Lastly, it would be unethical to decrypt without permission, there isn't an ethical way to obtain such a large amount of plain and cipher text in real-life situations. Though the algorithm should not be applied, the investigation still demonstrates how neural networks are viable tools for cryptanalysis.

In addition, the model chosen imposed another limitation to the investigation due to its lack of modularity. The sklearn MLP model selected for the inquiry has limited the loss function to cross-entropy(log loss), so I could not experiment with other loss functions to hyper-tune the model. It also did not have an option for dropout layers which ensures the model does not overfit or underfit [12], meaning when training using the training dataset, it will generalize an algorithm applicable only to the training dataset instead of focusing on finding a generalized relation that is applicable in every single scenario, causing the accuracy and different metrics not to be optimal when predicting the testing dataset. In addition, I utilized over four layers of the hidden layer and a total of 1536 nodes. The connection between each node creates a heavily chaotic web of neuron firing and weight calculating taking a huge amount of computation power, which causes unnecessary redundancy and inefficiency. [22]

E. Conclusion

In conclusion, this investigation aimed to assess the ability of neural networks to perform cryptanalysis of DES encryption. After the experiment on both datasets, I was led to the conclusion that neural networks are indeed viable for this application, specifically when the original text is a word in the English dictionary.

V. APPENDIX

Machine Learning Training & Analysis

```python
#Useful libraries
import sys
import numpy as np
import os
import pandas as pd

#Common Model Helpers
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, confusion_matrix,
                                precision_score, hamming_loss,
                                roc_curve,average_precision_score
from sklearn.metrics import plot_confusion_matrix, auc,roc_curve,
                                log_loss, f1_score,
                                matthews_corrcoef
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

#Visualization
import seaborn as sn
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.pylab as pylab
from pandas.plotting import scatter_matrix

#Pickle to save model
import pickle
from joblib import dump, load

#Plot Style
mpl.style.use('ggplot')
sn.set_style('white')
sn.set(font_scale=1.4)
```

```
pylab.rcParams['figure.figsize'] = 12,8

#Import data
dataset = pd.read_csv('dataset.csv')
data = dataset[['1','2']]
x = list(data['1'])
y = list(data['2'])

x = np.asarray(x).astype(str)
y = np.asarray(y).astype(str)

#Splitting dataset
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,
                                     random_state=43)

new  = []
new2 = []
new3  = []
new4 = []

#Converting the 64-bit into an array with 64 items
for i in range(len(x_train)):
    new.append(list(map(int,x_train[i])))
    new2.append(list(map(int,y_train[i])))

for j in range(len(x_test)):
    new3.append(list(map(int,x_test[j])))
    new4.append(list(map(int,y_test[j])))

#Convert the array from string array to interger
x_train = np.asarray(new).astype(int)
y_train = np.asarray(new2).astype(int)
x_test = np.asarray(new3).astype(int)
y_test = np.asarray(new4).astype(int)
```

```
#Fitting train & test input
scaler = StandardScaler()
scaler.fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
x_test = scaler.transform(y_test)

#Classificiation for True Negative, True Positive, False Negative &
                                        False Positive
def classfication(predictions):
    TN = 0
    TP = 0
    FN = 0
    FP = 0

    for i in range(len(predictions)):
        for j in range (len(predictions[i])):
            if predictions[i][j] == 0 and y_test[i][j] == 0:
                TN = TN + 1
            elif predictions[i][j] == 1 and y_test[i][j] == 1:
                TP = TP + 1
            elif predictions[i][j] == 0 and y_test[i][j] == 1:
                FN = FN + 1
            elif predictions[i][j] == 1 and y_test[i][j] == 0:
                FP = FP + 1

    return TN,TP,FN,FP

#Metrics for evaluation
def metrics (TN,TP,FN,FP):
    accuracy = (TP+TN)/(TP+TN+FP+FN)
    recall = (TP)/(TP+FN)
    precision = (TP)/(TP+FP)
    f1 =  (2*(precision*recall))/(precision + recall)
    return accuracy,recall,precision,f1

#Neural Network Architectural Structure
mlp = MLPClassifier(hidden_layer_sizes=(256,512,512,256),
                    max_iter=1,
                    activation = "relu",
                    verbose = True,
                    solver = "adam",
                    random_state= 60,
                    tol=0.00005,
                    learning_rate = 'adaptive',)

#Define our own metrics
accuracy = []
precision = []
recall = []
hloss = []
loss = []
f1_score = []
mcc= []

#Repeat training to collect metrics data
mlp.fit(x_train, y_train)
dump(mlp, 'predictor.joblib')
for i in range (3):
    mlp = load('predictor.joblib')
    mlp.partial_fit(x_train, y_train)
    predictions = mlp.predict(x_test)
    TN,TP,FN,FP = classfication(predictions)
    acc,rec,prec,f1 =  metrics(TN,TP,FN,FP)
    accuracy.append(round(acc,3))
    precision.append(round(prec,3))
    recall.append(round(rec,3))
    hloss.append(round(hamming_loss(y_test,predictions),3))
    loss.append(round(mlp.loss_,3))
    f1_score.append(round(f1,3))
    dump(mlp, 'predictor.joblib')
    #print(classification_report(y_test,predictions,zero_division=1))

#Confusion matrix graphing
cf_matrix = [TP,FP,FN,TN]

group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix]
group_percentages = ["{0:.2\%}".format(value) for value in cf_matrix/np
                                    .sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,
                                    group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)

cf_matrix = [[TP,FP],[FN,TN]]
plt.figure(figsize = (10,7))
sn.heatmap(cf_matrix, annot=labels, fmt='', cmap='Blues')
plt.savefig(os.path.join(sys.path[0],'confusion matrix.png'))
```

Dictionary Filtering

```
import csv

d = open("dict.txt","r")
data = d.readlines()

for lines in (data):
    if len(lines.rstrip()) == 8:
        d.write(f"{lines}")
```

DES Encryption for Dictionary

```
import pyDes
import random
import csv
import pandas as pd
```

```
def string_to_bits(s):
    new = s.decode("latin-1")
    return ''.join(format(ord(i), '08b') for i in new)

def bytes_to_bits(bytes):
    return ''.join(format(byte,'08b') for byte in bytes )

def generate_data():
    d = pyDes.des("DESCRYPT")
    result = []

    f = open("61008.txt","r")

    for lines in f.readlines():
        indata = lines.strip()
        indatabits = ''.join(format(ord(x), '08b') for x in indata)
        outdata = d.encrypt(indata)
        outdatabits = string_to_bits(outdata)
        result.append((outdatabits,indatabits))
    return result

data = generate_data()

sheet = pd.read_csv("real.csv")

for i in range(len(data)):
    sheet.loc[i,"1"] = data[i][0]
    sheet.loc[i,"2"] = data[i][1]

sheet.to_csv("real.csv",index=False)
```

DES Encryption Algorithm

```
import pyDes
import random
import csv
import pandas as pd

def string_to_bits(s):
    new = s.decode("latin-1")
    return ''.join(format(ord(i), '08b') for i in new)

def bytes_to_bits(bytes):
    return ''.join(format(byte,'08b') for byte in bytes )

def generate_data(N):
    d = pyDes.des("DESCRYPT")
    result = []
    #Lines of code to show encrypted data being generated
    for i in range (N) :
        indata = random.getrandbits(64).to_bytes(8, "big")
        #
        indatabits = bytes_to_bits(indata)
        outdata = d.encrypt(indata)
        outdatabits = string_to_bits(outdata)
        result.append((outdatabits,indatabits))
    return result
```

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