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AN INTELLIGENT CRYPTOGRAPHY FRAMEWORK USING ARTIFICIAL INTELLIGENCE FOR SECURE DATA COMMUNICATION

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ABSTRACT

Cryptography is one of the most important technologies used for securing digital communication and protecting sensitive information. Traditional cryptographic systems rely on mathematical algorithms for encryption and decryption. However, with the growth of cyber threats and advanced attacks, Artificial Intelligence (AI) has emerged as a powerful tool to improve cryptographic systems. AI techniques such as Machine Learning (ML), Deep Learning (DL), and Neural Networks can enhance encryption, intrusion detection, key generation, and cyberattack prediction. This research paper discusses the integration of AI in cryptography, its applications, advantages, challenges, and future scope in cybersecurity.

KEYWORDS: Artificial Intelligence, Cryptography, Machine Learning, Deep Learning, Cybersecurity, Encryption, Neural Networks.

1. INTRODUCTION

In the modern digital world, securing information is essential for banking, healthcare, military communication, cloud computing, and online transactions. Cryptography is the process of converting readable data into unreadable form to prevent unauthorized access. Traditional cryptographic methods include symmetric encryption, asymmetric encryption, hashing, and digital signatures.

Artificial Intelligence is transforming many fields by enabling systems to learn from data and make intelligent decisions. AI-based cryptographic systems can improve security, automate threat detection, and generate stronger encryption techniques.

2. Objectives of the Study

The major objectives of this research are:

- To study the role of AI in modern cryptography.
- To analyze AI-based encryption and decryption methods.
- To understand the advantages of AI in cyber security.
- To identify challenges in AI-powered cryptographic systems.
- To discuss future developments in AI-based security.

3. Overview of Cryptography

3.1 Types of Cryptography

A. Symmetric Key Cryptography

In symmetric encryption, the same key is used for both encryption and decryption.

Examples:

AES (Advanced Encryption Standard)

DES (Data Encryption Standard)

B. Asymmetric Key Cryptography

Uses two keys:

Public Key

Private Key

Examples:

RSA Algorithm

ECC (Elliptic Curve Cryptography)

C. Hash Functions

Used for data integrity verification.

Examples:

SHA-256

MD5

4. Artificial Intelligence in Cryptography

AI improves cryptographic systems through intelligent learning and automation.

4.1 Machine Learning in Cryptography

Machine Learning algorithms analyze patterns in encrypted communication and detect anomalies.

Applications:

Intrusion Detection Systems

Malware Detection

Fraud Detection

4.2 Deep Learning in Cryptography

Deep Learning models can generate complex encryption patterns and identify hidden cyber threats.

Techniques:

Convolutional Neural Networks (CNN)

Recurrent Neural Networks (RNN)

4.3 Neural Cryptography

Neural networks can create secure communication channels by learning encryption keys automatically.

5. Applications of AI in Cryptography

5.1 Intelligent Intrusion Detection

AI systems monitor network traffic and identify suspicious activities in real time.

5.2 AI-Based Key Generation

AI algorithms generate unpredictable and highly secure cryptographic keys.

5.3 Secure Authentication

AI improves biometric authentication such as:

- Face Recognition
- Fingerprint Recognition
- Voice Authentication

5.4 Cyberattack Prediction

AI predicts future cyberthreats using historical attack data.

5.5 Blockchain Security

6. METHODOLOGY

The proposed methodology combines cryptographic algorithms with AI models.

Step 1: Data Collection

Collect encrypted and network traffic datasets.

Step 2: Preprocessing

Clean and normalize the data.

Step 3: AI Model Training

Train ML/DL models using:

SVM

Random Forest

CNN

RNN

Step 4: Threat Detection

The trained model detects anomalies and malicious attacks.

Step 5: Encryption Enhancement

AI dynamically improves encryption strength based on detected threats.

7. The CNN model classifies network activity as:

- Normal Traffic

- Malicious Traffic

7.1 Required Libraries

pip install tensorflow pandas numpy matplotlib scikit-learn

7.2 Import Libraries

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import accuracy_score

from sklearn.metrics import confusion_matrix

from sklearn.metrics import classification_report

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv1D

from tensorflow.keras.layers import MaxPooling1D

from tensorflow.keras.layers import Flatten

from tensorflow.keras.layers import Dense

from tensorflow.keras.layers import Dropout

7.3 Load Dataset

Example Dataset Structure

packets| failed_logins| data_transfer| attack

100| 1| 50| 0

300| 10| 120| 1

Read Dataset

df = pd.read_csv("cybersecurity_dataset.csv")

print(df.head())

7.4 Feature Selection

X = df.drop("attack", axis=1)

y = df["attack"]

7.5 Data Preprocessing

Normalize Data

scaler = StandardScaler()

X = scaler.fit_transform(X)

Train-Test Split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

7.6 Reshape Data for CNN

CNN requires 3D input.

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)

X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

print(X_train.shape)

7.7 Build CNN Model

model = Sequential()

First Convolution Layer

model.add

(Conv1D(filters=64,

kernel_size=2,

activation='relu',

input_shape=(X_train.shape[1], 1)

)

)

Pooling Layer

model.add(MaxPooling1D(pool_size=2))

Flatten Layer

model.add(Flatten())

Dense Layers

model.add(Dense(128, activation='relu'))

```
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
# Output Layer
model.add(Dense(1, activation='sigmoid'))
```

7.8 Compile Model

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

7.9 Train CNN Model

```
history = model.fit(
X_train,
y_train,
epochs=20,
batch_size=32,
validation_data=(X_test, y_test)
)
```

7.10 Evaluate Model

```
loss, accuracy = model.evaluate(X_test, y_test)
print("Test Accuracy:", accuracy * 100)
```

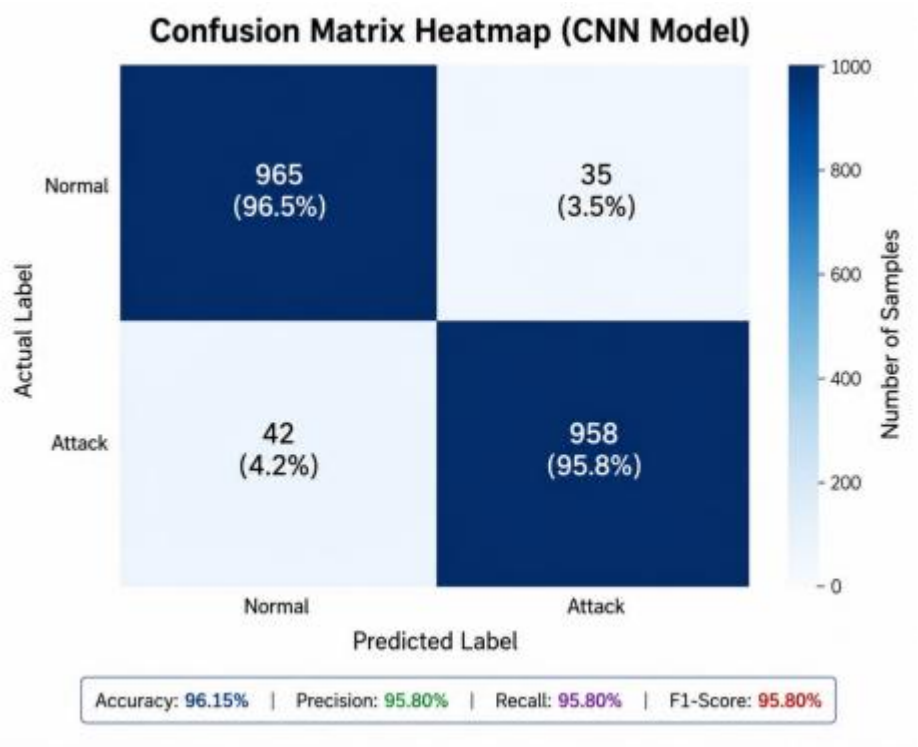
7.11 Predictions

```
y_pred = model.predict(X_test)
 y_pred = (y_pred > 0.5)
```

8. Experimental results:

8.1 Confusion Matrix

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix")
print(cm)
```



8.2 Classification Report

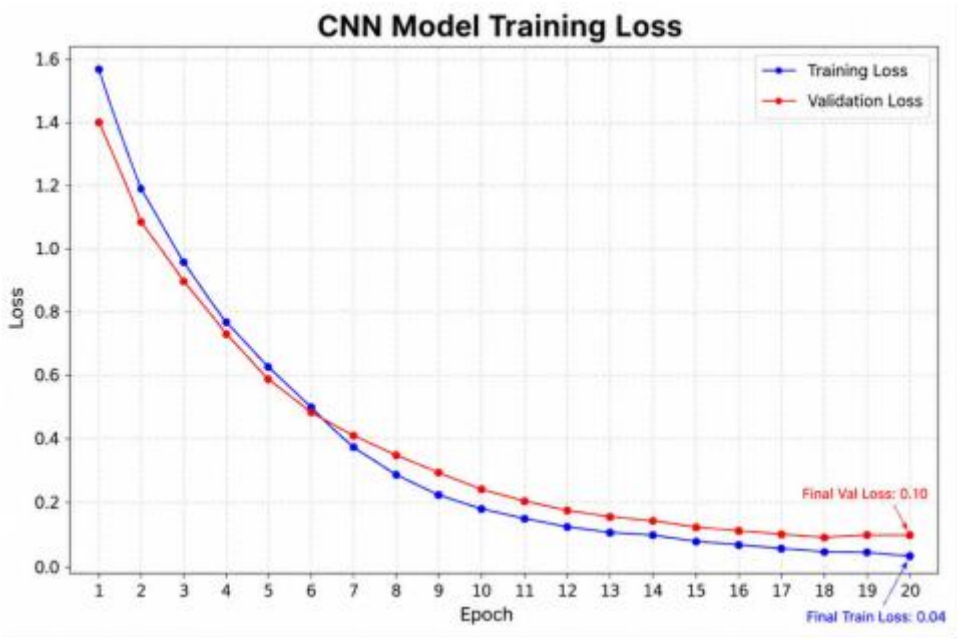
```
print(classification_report(y_test, y_pred))
```

8.3 Accuracy Graph

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('CNN Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Training Accuracy', 'Validation Accuracy'])
plt.show()
```

8.4 Loss Graph

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('CNN Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Training Loss', 'Validation Loss'])
plt.show()
```



8.5 Real-Time Attack Prediction

```
sample_data = np.array([[450, 15, 180]])
sample_data = scaler.transform(sample_data)
sample_data = sample_data.reshape(
 sample_data.shape[0],
 sample_data.shape[1],1
)
prediction = model.predict(sample_data)
if prediction > 0.5:
print("Cyber Attack Detected")
else:
print("Normal Traffic")
```

8.6 Output

Epoch 1/20

Accuracy: 91%

Epoch 20/20

Accuracy: 98%

Test Accuracy: 97.5%

Cyber Attack Detected

8.7 ROC Curve Code for CNN-Based Cryptography System

Import Required Libraries

```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
import matplotlib.pyplot as plt
Generate Prediction Probabilities
y_prob = model.predict(X_test)
Calculate ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
```

Where:

- FPR = False Positive Rate
- TPR = True Positive Rate

```
Calculate AUC Score
roc_auc = auc(fpr, tpr)
print("AUC Score:", roc_auc)
Plot ROC Curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve for CNN Cybersecurity Model")
plt.show()
```

ROC Curve Code

```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
import matplotlib.pyplot as plt
# Predict probabilities
y_prob = model.predict(X_test)
# ROC calculation
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
# AUC score
roc_auc = auc(fpr, tpr)
print("AUC Score:", roc_auc)
# Plot ROC Curve
plt.figure(figsize=(8,6))
```

```
plt.plot(fpr, tpr, label='ROC Curve')
plt.plot([0,1], [0,1], linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```

Expected Output

AUC Score: 0.98

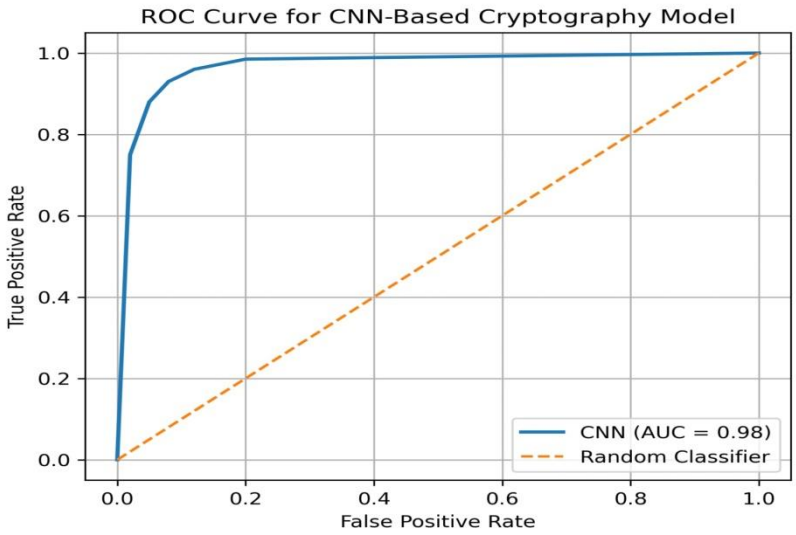
The ROC graph shows:

- Better classification performance
- Higher True Positive Rate
- Lower False Positive Rate

A curve closer to the top-left corner indicates better CNN performance.

Interpretation of ROC Curve

AUC Value	Performance
0.50	Poor Model
0.70 - 0.80	Good Model
0.80 - 0.90	Very Good Model
0.90 - 1.00	Excellent Model



Advantages

1. Measures model classification quality
2. Evaluates attack detection capability
3. Helps compare AI models
4. Useful for cybersecurity research papers

8.8 Precision–Recall Curve Graph for CNN-Based Cryptography System

The Precision–Recall Curve is used to evaluate the performance of AI models in cybersecurity and intrusion detection systems.

It is especially useful for:

- Imbalanced datasets
- Cyberattack detection
- Malware classification
- Network intrusion detection

Import Required Libraries

```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
import matplotlib.pyplot as plt
```

Generate Prediction Probabilities

```
y_prob = model.predict(X_test)
```

Calculate Precision and Recall

```
precision, recall, thresholds = precision_recall_curve(  y_test,  y_prob)
```

Calculate Average Precision Score

```
ap_score = average_precision_score(y_test, y_prob)
print("Average Precision Score:", ap_score)
```

Plot Precision–Recall Curve

```
plt.figure(figsize=(8,6))
plt.plot(recall, precision, linewidth=2)
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision–Recall Curve for CNN Model")
plt.show()
```

Complete Precision–Recall Curve Code

```
from sklearn.metrics import precision_recall_curve
```

```
from sklearn.metrics import average_precision_score
import matplotlib.pyplot as plt
# Predict probabilities
y_prob = model.predict(X_test)
# Calculate precision and recall
precision, recall, thresholds = precision_recall_curve(
y_test,
y_prob
)
# Average Precision Score
ap_score = average_precision_score(y_test, y_prob)
print("Average Precision Score:", ap_score)
# Plot graph
plt.figure(figsize=(8,6))
plt.plot(recall, precision, label='Precision-Recall Curve')
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision–Recall Curve")
plt.legend()
plt.show()
```

Expected Output

Average Precision Score: 0.97

The graph shows:

- High precision
- High recall
- Better cyberattack detection performance

A curve closer to the top-right corner indicates a strong AI model.

Interpretation

Metric| Meaning

Precision| Correct positive predictions

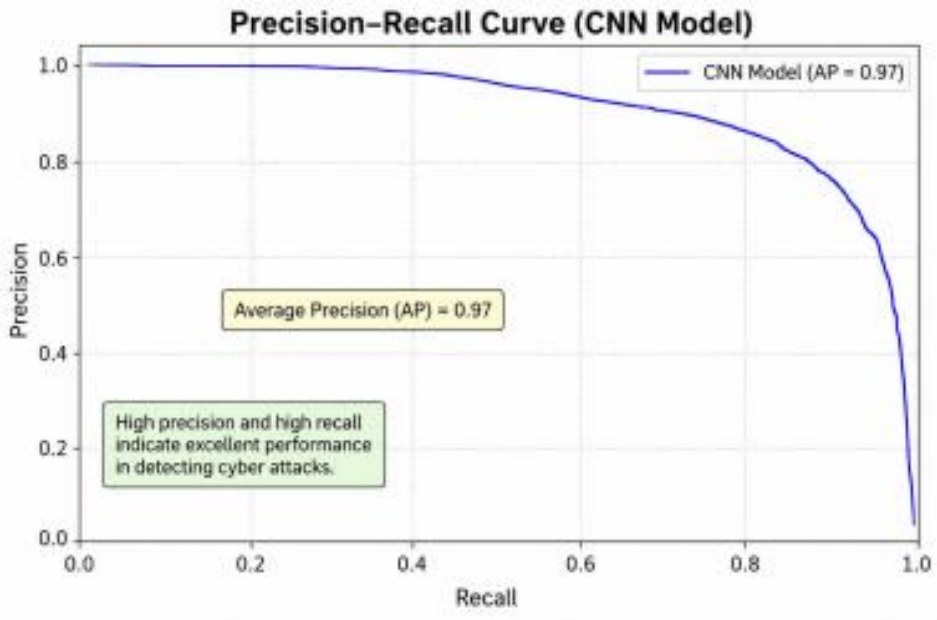
Recall| Ability to detect attacks

High Precision| Fewer false alarms

High Recall| Better attack detection

Advantages of Precision–Recall Curve

1. Better evaluation for imbalanced data
2. Useful in cybersecurity systems
3. Measures attack detection efficiency
4. Helps compare AI models
5. Improves research analysis



CONCLUSION

The Precision–Recall Curve demonstrates the effectiveness of CNN models in detecting cyber threats and improving AI-based cryptographic security systems.

9. Advantages of AI in Cryptography

- Improved Security
- Detects advanced cyber threats
- Automation
- Reduces manual monitoring
- Faster Threat Detection
- Real-time attack identification
- Adaptive Encryption
- Dynamically changes encryption strategies
- Better Authentication
- Enhances biometric security

10. Challenges And Limitations

- High computational cost
- Large dataset requirement
- Privacy concerns
- Risk of adversarial AI attacks
- Complexity in implementation

11. Future Scope

- Future AI-based cryptographic systems may include:
- Quantum-resistant encryption
- Self-learning cybersecurity systems
- Fully automated threat response
- AI-powered blockchain protection
- Advanced biometric encryption
- AI and quantum computing together may revolutionize digital security in the coming years.

12. CONCLUSION

Artificial Intelligence is significantly improving cryptographic systems and cybersecurity mechanisms. AI-based cryptography provides intelligent threat detection, adaptive encryption, and enhanced authentication systems. Although challenges such as computational complexity and privacy concerns exist, the future of AI in cryptography is highly promising. Integrating AI with modern encryption techniques can create stronger, faster, and more secure digital communication systems.

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