Application of Machine Learning in Cryptanalysis

Project-I

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DECLARATION

I certify that:

(a) The work contained in this report has been done by me under the guidance of my supervisor.

(b) The work has not been submitted to any other Institute for any degree or diploma.

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CERTIFICATE

This is to certify that the project report entitled **"Application of Machine Learning in Cryptanalysis"** submitted by **Deepesh Singh (Roll No. 22CS30020)** to Indian Institute of Technology Kharagpur towards partial fulfilment of requirements for the award of degree of Dual Degree (B.Tech + M.Tech) in Computer Science and Engineering is a record of bona fide work carried out by him under my supervision and guidance during Autumn Semester, 2025-26.

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1 Introduction

Cryptanalysis is the scientific study of evaluating the strength of cryptographic algorithms against potential attacks. Its main objective is to analyze ciphers and recover hidden keys or identify weaknesses. Among its many techniques, Differential Cryptanalysis (DC) is one of the most powerful. It studies how input differences affect output differences in ciphertexts, helping build distinguishers that can differentiate cipher outputs from random permutations.

ASCON, a lightweight cryptographic algorithm and winner of the NIST competition, relies on a 320-bit internal permutation involving nonlinear substitution (S-box) and linear diffusion layers. Analyzing its resistance against differential attacks requires exploring complex nonlinear interactions, which traditional methods often find difficult to model efficiently.

In recent years, Machine Learning (ML) has become a promising approach for cryptanalysis. Instead of manually deriving statistical properties, ML models such as CNNs, LSTMs, and LightGBM can automatically learn patterns from large differential datasets. These models act as neural distinguishers, identifying subtle correlations between input and output differences that classical methods may overlook.

Over time, researchers have increasingly adopted ML-based distinguishers for various lightweight ciphers, demonstrating strong performance and scalability. This shift marks a transition from traditional analytical cryptanalysis to a data-driven approach capable of uncovering complex cipher characteristics.

Objective: The aim of this work is to explore the effectiveness of machine learning models, specifically CNN, LSTM, and LightGBM as distinguishers for ASCON's permutation. A balanced differential dataset is generated using custom Python scripts, processed into machine-learning-ready formats, and analyzed across these models. The results compare their accuracy and generalization ability, contributing to the understanding of how ML can enhance differential cryptanalysis in modern lightweight cryptography.

Problem Statement: Develop effective differential distinguishers for the ASCON Permutation cipher using and machine learning techniques. Classify ciphertext pairs as originating from either random inputs or inputs with a specific difference (δ) by analyzing their binary representations after a reduced-round permutation. Implement and compare multiple neural network architectures including CNN, LSTM, and LightGBM—to identify

non-random differential propagation patterns and evaluate their distinguisher capabilities using accuracy, TPR, and TNR metrics. In cryptographic analysis, the detection of non-random behavior in symmetric ciphers is essential for assessing security against differential cryptanalysis. ASCON, a lightweight cipher selected as a primary choice in the NIST lightweight cryptography standardization process, requires rigorous evaluation of its resistance to differential attacks, especially over a reduced number of rounds. However, manual identification of useful differential characteristics becomes increasingly complex and computationally intensive as the cipher's state size and number of rounds grow. The availability of large-scale datasets containing ciphertext pairs—labeled as either random or differential pairs—enables the application of machine learning to automate and enhance distinguisher construction. Yet, the high-dimensional and sequential nature of ciphertext data, along with subtle and complex differential trails, presents a significant classification challenge. This project addresses the problem of building accurate and efficient distinguishers by leveraging modern learning models to classify user-generated ciphertext pairs and determine whether a model can outperform a random guessing baseline, thereby revealing exploitable cryptographic weaknesses.

2 Foundations and Key Concepts

2.1 Cryptanalysis

Cryptanalysis is the study of evaluating and breaking cryptographic systems to assess their security strength. It involves analyzing ciphers to discover weaknesses that may lead to recovering secret keys or constructing distinguishers capable of differentiating a cipher's output from random data. Cryptanalysis plays a vital role in validating the robustness of encryption algorithms and guiding the design of more secure cryptographic primitives.

2.2 Differential Cryptanalysis

Differential Cryptanalysis (DC) is one of the most influential methods of analyzing block ciphers. It examines how specific differences in plaintext pairs affect the differences in the resulting ciphertext pairs. By observing how these differences propagate through substitution and permutation layers, analysts can identify statistical biases that differ from random behavior. These biases are then used to build distinguishers or to perform partial key recovery attacks, providing a practical measure of a cipher's resistance to statistical attacks.

2.3 ASCON's Permutation

ASCON is a lightweight cryptographic algorithm designed for authenticated encryption and hashing. It operates on a 320-bit internal state divided into five 64-bit words. Its permutation function forms the core of the algorithm and consists of multiple rounds combining nonlinear substitution layers (S-boxes) and linear diffusion transformations. These operations ensure high confusion and diffusion, making the cipher resistant to linear and differential attacks. In differential analysis, the ASCON permutation is often studied independently to evaluate how differences propagate through its internal structure.

2.3.1 Recommended Parameter Sets

ASCON defines multiple parameter sets, such as ASCON-128 and ASCON-128a, each designed to balance security and performance.

- ASCON-128 provides a strong 128-bit security level and serves as the standard configuration for authenticated encryption and hashing.
- ASCON-128a offers improved performance by increasing the data rate and introducing higher parallelism while maintaining equivalent security strength.

Name	Algorithms	Bit size of				Rounds	
		key	nonce	tag	data block	p^a	p^b
Ascon-128	$\mathcal{E}, \mathcal{D}_{128,64,12,6}$	128	128	128	64	12	6
Ascon-128a	$\mathcal{E}, \mathcal{D}_{128,128,12,8}$	128	128	128	128	12	8

Figure 1: Parameters for recommended authenticated encryption schemes.

All ASCON variants share a 320-bit internal state, structured as five 64-bit words, and rely on iterative permutation rounds as the core transformation. The number of rounds determines the trade-off between security and computational cost.

In this work, rather than implementing the complete ASCON-128 or ASCON-128a schemes, the core permutation is directly utilized for cryptanalytic analysis. The code employs a configurable number of rounds to observe how differential characteristics evolve across reduced-round permutations. This setup enables the controlled generation of balanced differential datasets, which are later analyzed using machine-learning models such as CNN, LSTM, and LightGBM to study ASCON's diffusion and nonlinearity.

ASCON Permutation

The main components of ASCON are two 320-bit permutations, p^a and p^b, which form the core of the algorithm. Each permutation repeatedly applies a Substitution Permutation Network (SPN)-based round function p, consisting of three fundamental steps:

$$p = p_L \circ p_S \circ p_C$$

- $p_C \rightarrow$ Addition of Constants
- $p_S \rightarrow$ Substitution Layer
- $p_L \rightarrow$ Linear Diffusion Layer

Both p_a and p_b operate on a 320-bit internal state, which is divided into five 64-bit words:

$$S = x_0 \| x_1 \| x_2 \| x_3 \| x_4$$

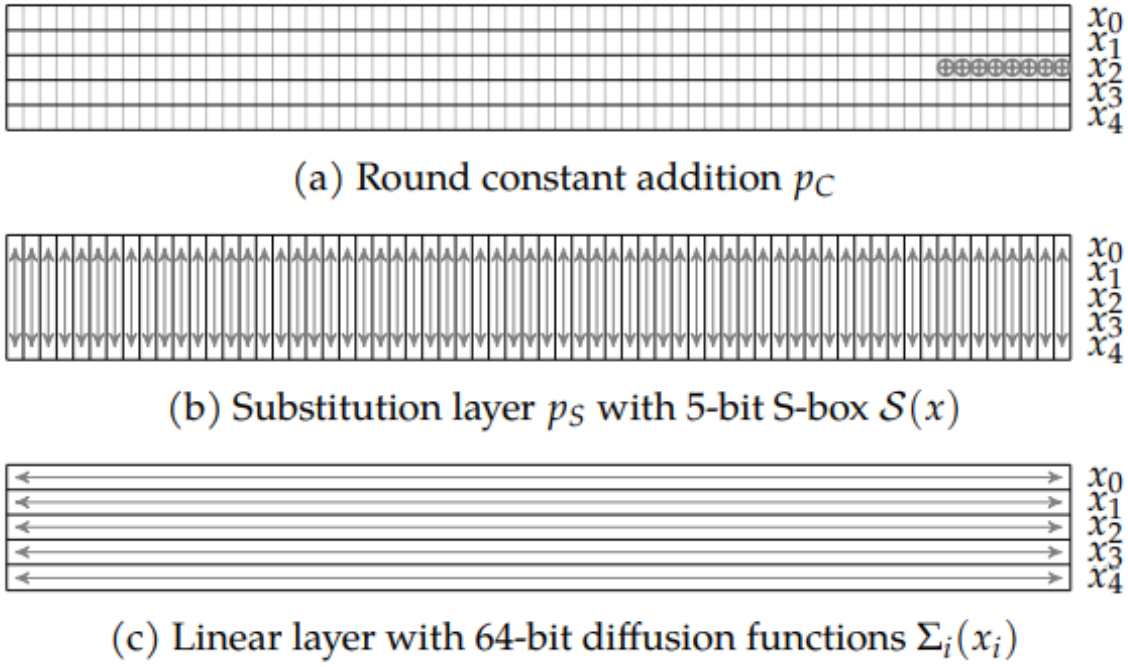

Figure 2: The round constants cr used in each round i of p^a and p^b

The only difference between p_a and p_b lies in the number of rounds, which is a tunable security parameter.

In the complete ASCON cipher, this permutation forms the core of all phases — initialization, data processing, and finalization. However, in this project, the focus is placed solely on the permutation itself to analyze its internal structure using machine learning–based differential distinguishers. By isolating the permutation, it becomes possible to study how specific input differences propagate through the transformation layers and to determine whether detectable statistical patterns exist.

Addition of Constants (p_C)

The constant addition step introduces round-dependent variation into the permutation. In each round i, a predefined round constant c_r is XORed with the second word x_2 of the internal state S:

$$x_2 \leftarrow x_2 \oplus c_r$$

This step ensures that each round behaves differently, preventing symmetric patterns and improving resistance against differential and linear attacks. For permutation p_a, the constant index is $r = i$, while for p_b, it is adjusted as $r = i + a - b$. The inclusion of

p^{12}	p^8	p^6	Constant c_r	p^{12}	p^8	p^6	Constant c_r
0			00000000000000000f0	6	2	0	0000000000000000096
1			00000000000000000e1	7	3	1	0000000000000000087
2			00000000000000000d2	8	4	2	0000000000000000078
3			00000000000000000c3	9	5	3	0000000000000000069
4	0		00000000000000000b4	10	6	4	000000000000000005a
5	1		00000000000000000a5	11	7	5	000000000000000004b

Figure 3: The round constants cr used in each round i of p^a and p^b

these constants helps desynchronize rounds, ensuring that even identical inputs processed through different rounds produce completely unrelated intermediate states. Each constant ensures that even identical inputs evolve differently across rounds, effectively breaking structural symmetry and thwarting slide or reflection attacks.

Substitution Layer (p_S)

The substitution layer introduces non-linearity, which is essential for the cipher's security. It updates the internal state S using 64 parallel applications of a 5-bit S-box $S(x)$. Each bit slice from the five 64-bit words $(x_0, x_1, x_2, x_3, x_4)$ is treated as an independent 5-bit input to the S-box:

$$(x_0[i], x_1[i], x_2[i], x_3[i], x_4[i]) \rightarrow S(x)$$

x	0	1	2	3	4	5	6	7	8	9	a	b	c	d	e	f	10	11	12	13	14	15	16	17	18	19	1a	1b	1c	1d	1e	1f
$\mathcal{S}(x)$	4	b	1f	14	1a	15	9	2	1b	5	8	12	1d	3	6	1c	1e	13	7	e	0	d	11	18	10	c	1	19	16	a	f	17

Figure 4: Ascon's 5-bit S-box S as a lookup table

Linear Diffusion Layer (p_L)

The linear diffusion layer ensures that small changes in the input spread rapidly across the entire 320-bit state. It applies a linear transformation $\Sigma_i(x_i)$ to each 64-bit word x_i:

$$x_i \leftarrow \Sigma_i(x_i), \quad 0 \leq i \leq 4$$

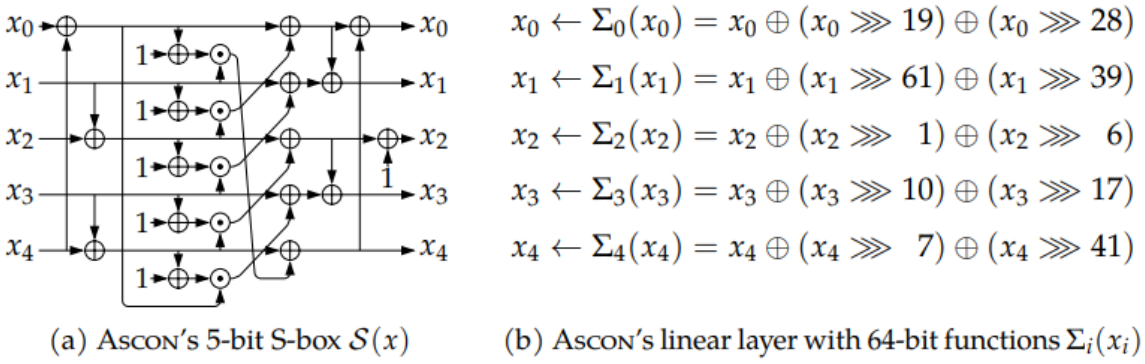

Figure 5: Ascon's substitution layer and linear diffusion layer.

Each Σ_i consists of a combination of bitwise rotations and XOR operations, which mix bits within a word to achieve full diffusion. Each rotation and XOR ensures that bit dependencies propagate efficiently throughout the state. This layer provides diffusion, which prevents any single bit from influencing only a limited portion of the state, thereby achieving the avalanche effect. This guarantees that after several rounds, every output bit depends on every input bit, strengthening resistance to differential and linear cryptanalysis.

Together, the Substitution and Linear Diffusion Layers create a strong Substitution–Permutation Network (SPN) structure — the foundation of ASCON's security.

2.4 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning architecture primarily used for pattern recognition. It processes input data through convolutional layers that automatically extract spatial or local feature patterns. In cryptanalysis, CNNs are applied to detect subtle statistical irregularities in ciphertext data, acting as neural distinguishers. They can efficiently learn and generalize difference patterns between real cipher outputs and random permutations, making them effective for modeling complex nonlinear relationships in differential datasets.

2.5 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to capture sequential dependencies in data. LSTMs maintain internal memory cells that store information over long time steps, enabling them to model relationships

that evolve across rounds of a cipher. When applied to cryptanalysis, LSTMs can learn temporal or sequential correlations between input–output differences, helping to uncover hidden dependencies that simpler models might miss.

2.6 Light Gradient Boosting Machine (LightGBM)

Light Gradient Boosting Machine (LightGBM) is an advanced tree-based ensemble learning algorithm optimized for efficiency and high performance. It builds multiple weak decision trees sequentially, where each new tree corrects the errors of the previous ones. In the context of cryptanalysis, LightGBM serves as a powerful classical machine learning baseline. It can effectively classify differential data, identify important features (bits), and provide interpretability through feature importance analysis, offering insights into which parts of the cipher contribute most to distinguishability.

3 ML based Cryptanalysis

3.1 Dataset Description & Dataset Generation

3.1.1 Overview

The dataset used in this project was produced specifically to evaluate ASCON's permutation under differential cryptanalysis and to train machine-learning distinguishers (CNN, LSTM, LightGBM). The dataset generation isolates the ASCON permutation (not the full AEAD scheme) and creates labeled pairs of ciphertexts that either share a fixed input difference (real differential pairs, Label = 1) or are unrelated (random pairs, Label = 0).

Key properties:

- **Internal state size:** 320 bits (5 × 64-bit words) = 40 bytes.
- **Input difference (Δ):** a 40-byte constant defined in the generator. In code: DELTA = b'\x00\x00\x00\x00\x00\x00\x00\x01' + b'\x00' * 32.
- **Rounds used for permutation:** configurable (e.g., DATA_ROUNDS = 3 or 4).
- **Samples per class:** typically N_PER_CLASS = 50,000 (so total 100,000 samples).
- **Saved CSV columns:** C1, C2, C1⊕C2, Label. Each of the C* fields is stored as a comma-separated decimal string of 40 bytes.
- **Train/Val/Test split:** 70% / 15% / 15% (i.e., 70,000 / 15,000 / 15,000 when total = 100,000), performed with stratification to preserve class balance.

3.1.2 Generation rationale

By applying the permutation to pairs (P1, P2) with P2 = P1 ⊕ Δ for the real pairs and using independent random P2 for random pairs, we capture the permutation's differential behavior at the output. XORing C1 and C2 (the permutation outputs) produces the observed output differential C1⊕C2. Generating a balanced dataset (equal numbers of Label 0 and Label 1) prevents class-imbalance bias during supervised training.

3.1.3 Algorithm Dataset Generation (Differential Distinguisher)

```
1. FUNCTION generate_dataset(N_per_class, delta, data_rounds):
2.     PRINT "Generating dataset for", data_rounds, "rounds"
3.     dataset = empty list
4.     FOR label IN [0, 1]:          # 0: random pairs, 1: differential pairs
5.         FOR i FROM 1 TO N_per_class:
6.             P1 = random_bytes(40)           # 320-bit random plaintext
7.             IF label == 1:
8.                 P2 = XOR_bytes(P1, delta)  # Apply fixed input difference
9.             ELSE:
10.                 P2 = random_bytes(40)       # Independent random plaintext
11.             C1 = apply_ascon_permutation(P1, data_rounds)
12.             C2 = apply_ascon_permutation(P2, data_rounds)
13.             C_XOR = XOR_bytes(C1, C2)
14.             dataset.append((C1, C2, C_XOR, label))
15.     random.shuffle(dataset)
16.     RETURN dataset
17. END FUNCTION
```

3.1.4 Data Preprocessing

Before training the machine learning models, the dataset is carefully processed to convert it into a form suitable for learning. Each sample in the dataset contains three main values C1, C2, and C1⊕C2 stored as text numbers (decimal format) in the CSV file. These values are first converted into binary form, because the cipher operates on 320 bits of data (40 bytes × 8 bits).

Each byte from the file is read and expanded into its 8-bit binary equivalent, resulting in a complete 320-bit binary vector. This binary data is then used as the model input.

After converting the data into binary vectors, the dataset is split into three parts:

- Training set (70%) – used to train the models.
- Validation set (15%) – used to tune and monitor the model's performance during training.

- Testing set (15%) – used for final evaluation.

The data is divided in such a way that both classes (label 0 and label 1) remain evenly balanced in all three sets. This process helps the models learn without bias toward any specific class.

The converted data is stored in a structured numerical format, where each sample has a shape corresponding to the total number of bits used as input. This shape may vary if additional features are included.

For models like LightGBM, which require two-dimensional input, the data is flattened from a 3D shape (samples $\times$ bits $\times$ 1) to a 2D table (samples $\times$ bits). The labels are also simplified into a one-dimensional array.

Finally, the preprocessing ensures that any data errors or mismatches are handled safely. If any sample cannot be converted correctly, it is skipped, and the data size is adjusted to maintain consistency. This guarantees that the dataset is clean, balanced, and ready for machine learning experiments.

3.2 Convolutional Neural Network (CNN)

3.2.1 Model Architecture

The CNN model is designed to automatically extract meaningful local features from binary input representations. The architecture typically includes:

- **Input Layer:** Accepts the binary differential feature vectors of size equal to ASCON's state length (320 bits).
- **Convolutional Layers:** Apply multiple 1D convolution filters to detect local dependencies between bits or bit groups.
- **Activation Function (ReLU):** Introduces non-linearity, enabling the model to learn complex patterns.
- **Pooling Layers:** Reduce dimensionality while retaining essential information, enhancing model generalization.
- **Fully Connected Layers:** Combine the extracted features and map them to the output space.

- **Output Layer (Sigmoid):** Produces a probability score indicating whether a sample belongs to the differential (1) or random (0) class.

This structure ensures the model learns hierarchical representations from low-level bit interactions to higher-level cipher characteristics.

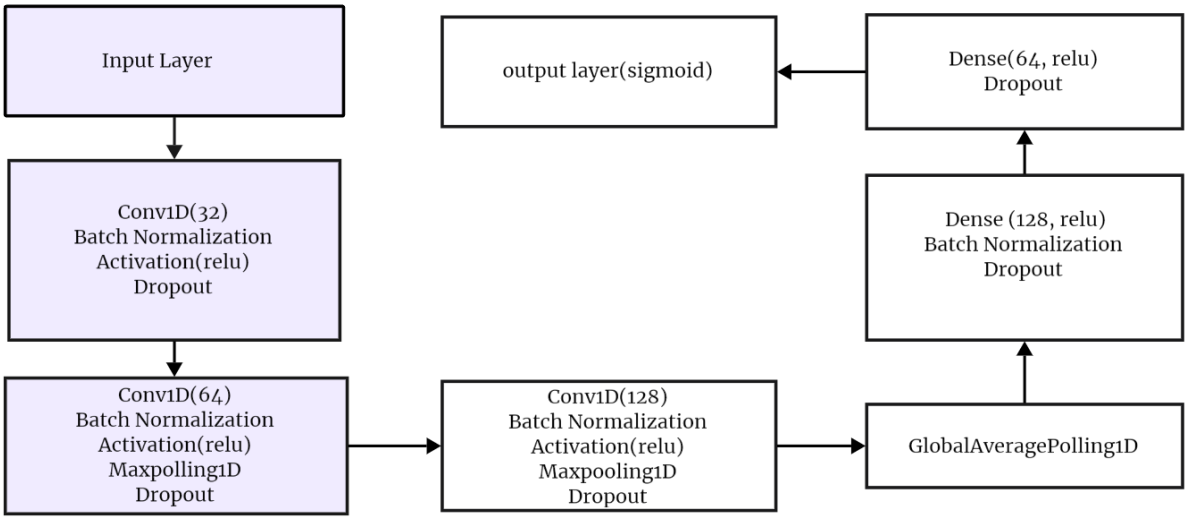

Figure 6: CNN Model Architecture

3.2.2 Key Components

- **Convolution Filters:** Learn spatial features in the binary differential data.
- **Batch Normalization:** Stabilizes and accelerates training by normalizing feature distributions.
- **Dropout Layers:** Prevent overfitting by randomly deactivating neurons during training.
- **Flatten Layer:** Converts multidimensional feature maps into vectors for dense layers.
- **Fully Connected Layers:** Integrate extracted features and perform final classification.

3.2.3 Model Initialization and Optimization

The CNN weights are initialized using He initialization to optimize gradient flow during training. The Adam optimizer is employed due to its adaptive learning rate capabilities,

which allow efficient convergence. The binary cross-entropy loss function is used as the objective function since the task involves binary classification. The model parameters, such as learning rate, batch size, and number of epochs, are tuned based on validation accuracy and loss metrics.

3.2.4 Training and Evaluation Procedure

The training loop consists of the following stages:

Training Function:

- Performs forward propagation through the CNN.
- Computes binary cross-entropy loss.
- Executes backpropagation to update weights using Adam.

Evaluation Function:

- Runs inference on the validation/test dataset without gradient updates.
- Calculates accuracy, loss, and confusion matrix metrics.

Training Loop:

- Iteratively trains over multiple epochs.
- Monitors training and validation accuracy to prevent overfitting (early stopping if necessary).
- Saves the best-performing model checkpoint.

3.3 Long Short-Term Memory (LSTM)

3.3.1 Model Architecture

The LSTM model captures sequential dependencies in the cipher's data. The architecture includes:

- **Input Layer:** Accepts the binary sequence representation of ASCON's output differential.

- **LSTM Layers:** Maintain memory cells that store past information, allowing the model to learn bit relationships across cipher rounds.
- **Dropout Layer:** Prevents overfitting by randomly dropping neuron connections.
- **Fully Connected Layers:** Map learned temporal features to output probabilities.
- **Output Layer (Sigmoid):** Produces a binary classification output.

3.3.2 Key Components

- **Memory Cells:** Preserve long-range dependencies in the bit sequence.
- **Forget, Input, and Output Gates:** Control the flow of information within the memory cells.
- **Recurrent Connections:** Enable learning over multiple cipher transformations.
- **Dropout and Batch Normalization:** Enhance generalization and reduce overfitting.

3.3.3 Model Initialization and Optimization

LSTM weights are initialized using the Xavier uniform initializer, promoting balanced variance across layers. The Adam optimizer is again chosen for its efficiency in handling sparse gradients. The binary cross-entropy loss function evaluates the difference between predicted and true labels. Learning rate scheduling is applied to gradually reduce the learning rate for stable convergence.

3.3.4 Training and Evaluation Procedure

- **Training Function:** Executes sequential forward propagation and loss computation for each batch.
- **Evaluation Function:** Computes test accuracy and loss on unseen data.
- **Training Loop:** Iteratively updates parameters across epochs while monitoring validation performance.

Early stopping is used if the validation loss does not improve for several epochs. The best weights are preserved for final evaluation.

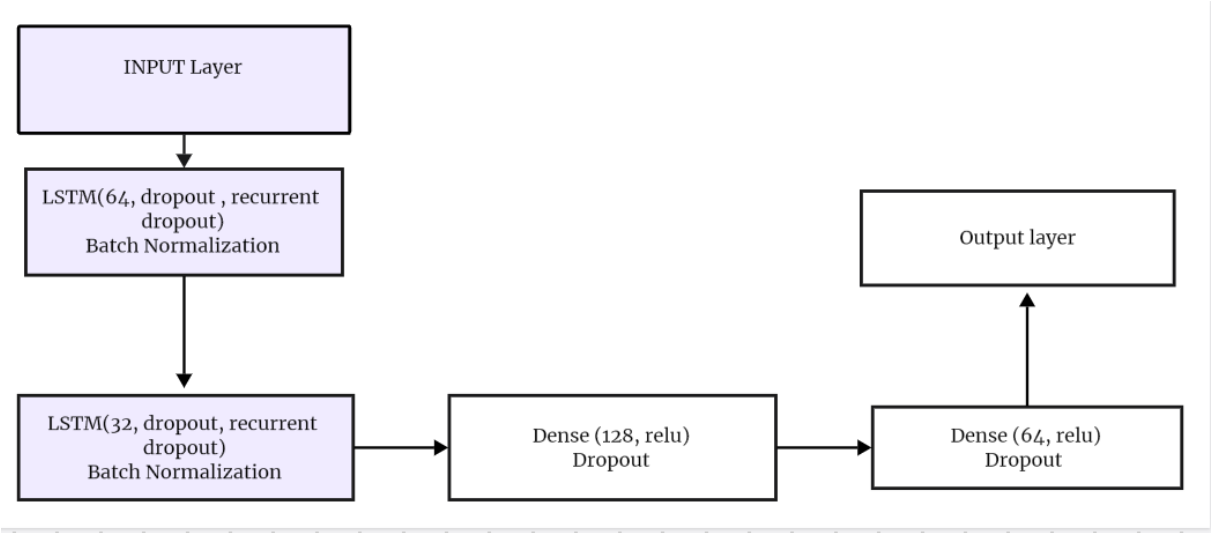

Figure 7: LSTM Model Architecture

3.4 Light Gradient Boosting Machine (LightGBM)

3.4.1 Model Architecture

Unlike deep neural networks, LightGBM is a tree-based boosting algorithm. It builds an ensemble of weak decision trees that collectively form a strong classifier. Each tree is trained to correct the errors made by the previous ones, gradually minimizing loss and improving accuracy.

3.4.2 Key Components

- **Gradient Boosting Framework:** Sequentially builds trees to reduce classification error.
- **Histogram-Based Decision Trees:** Speed up computation by discretizing continuous features.
- **Leaf-Wise Growth:** Expands the most significant leaves first, enhancing model performance.
- **Feature Importance:** Provides interpretability by ranking the most influential bits or positions in ASCON's output.

3.4.3 Model Initialization and Optimization

The LightGBM model is configured with the following key parameters:

- **Objective:** Binary classification.
- **Boosting Type:** Gradient boosting decision trees (GBDT).
- **Learning Rate:** Tuned to balance speed and accuracy.
- **Number of Leaves:** Controls model complexity.
- **Early Stopping:** Prevents overfitting by monitoring validation accuracy.

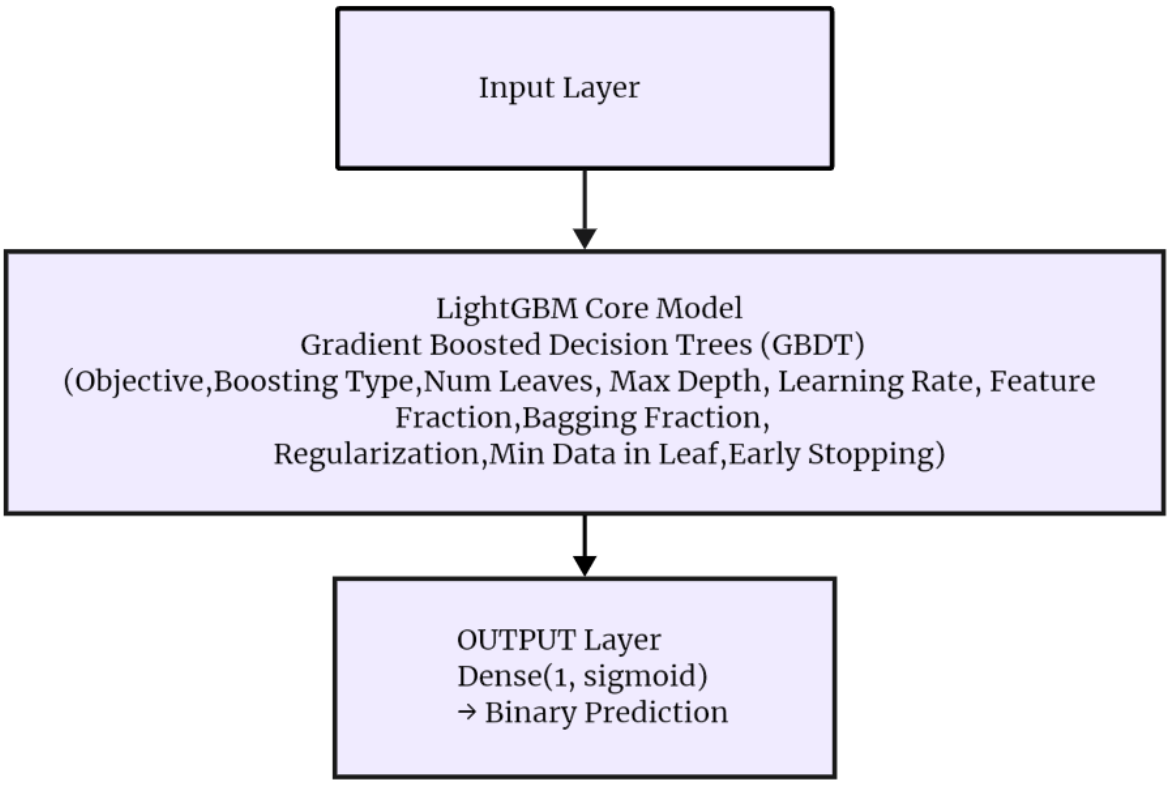

Figure 8: LGBM Model Architecture

3.4.4 Training and Evaluation Procedure

- **Training Function:** Fits the LightGBM model to the training data with validation monitoring.
- **Evaluation Function:** Calculates accuracy, precision, recall, and F1-score.
- **Training Loop:** Iterates over boosting rounds until early stopping criteria are met.

Saves feature importance scores for interpretability. Generates performance metrics for comparison with CNN and LSTM models.

3.5 Distinguisher Search

In cryptanalysis, a distinguisher is a statistical tool used to identify whether a given output is generated by a real cipher or by a random permutation. In this project, the goal is to train machine learning models (CNN, LSTM, and LightGBM) to act as neural distinguishers.

- The trained model receives ciphertext differential data (C1⊕C2) and predicts whether it originates from the actual ASCON permutation (Label = 1) or from random pairs (Label = 0).
- If the model performs significantly better than random guessing (accuracy > 50%), it indicates that the cipher's output is distinguishable from randomness — meaning a distinguisher has been found.

To verify this, the models are trained on a balanced dataset (equal samples of both classes) and tested on unseen data. The performance is measured using metrics such as accuracy, True Positive Rate (TPR), and True Negative Rate (TNR). If the model consistently exceeds the threshold accuracy (typically 0.5), it confirms the presence of a distinguisher for the analyzed number of ASCON rounds.

Algorithm: Distinguisher Search

```
1. FUNCTION distinguisher_search():
2.     LOAD preprocessed training, validation, and test datasets
3.     BUILD and compile model (CNN / LSTM / LGBM)
4.     TRAIN model using (training data) :
5.         - training data
6.     EVALUATE model on test dataset
7.     COMPUTE accuracy
8.     IF test_accuracy > 0.5 THEN
9.         PRINT "Distinguisher Found"
10.     ELSE
11.         PRINT "Distinguisher Not Found"
12. END FUNCTION
```

4 Experiment Result

This section presents the experimental results of the three machine learning models—CNN, LSTM, and LightGBM—applied as distinguishers for the ASCON permutation across different rounds. The performance metrics include Training Accuracy, Test Accuracy, True Positive Rate (TPR), and True Negative Rate (TNR). Additionally, hyperparameter configurations for each model are documented.

4.1 Performance Comparison Across Models

Table 1 summarizes the classification performance of all three models across five rounds of the ASCON permutation. The results demonstrate that all models achieve near-perfect distinguisher capability for rounds 1–3, with performance degrading significantly at rounds 4 and 5, indicating the cryptographic strength of the full permutation.

Table 1: Performance Comparison of CNN, LSTM, and LightGBM Models

Model	Round	Train Acc.	Test Acc.	TPR	TNR	Train Loss	Test Loss	Distinguisher
CNN	1	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	Found
	2	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	Found
	3	0.9424	0.9452	0.9616	0.9288	0.1421	0.1324	Found
	4	0.5066	0.5036	0.5411	0.4611	0.6929	0.6937	Found(weak)
	5	0.5041	0.5068	0.1625	0.8511	0.6931	0.6929	Found(weak)
LSTM	1	0.9998	1.0000	1.0000	1.0000	0.0020	0.0000	Found
	2	0.9984	0.9999	1.0000	0.9997	0.0053	0.0007	Found
	3	0.9653	0.9619	0.9941	0.9296	0.0897	0.0942	Found
	4	0.4976	0.4984	0.9343	0.0625	0.6931	0.6932	× Not Found
	5	0.5009	0.4940	0.4299	0.5580	0.6932	0.6932	× Not Found
LightGBM	1	0.9997	0.9992	1.0000	0.9984	0.6735	0.6735	Found
	2	0.9998	0.9995	1.0000	0.9989	0.6735	0.6735	Found
	3	0.9999	0.9997	1.0000	0.9993	0.6639	0.6639	Found
	4	0.6039	0.5009	0.4140	0.5877	0.6919	0.6932	Found(weak)
	5	0.6106	0.5041	0.5173	0.4909	0.6919	0.6931	Found(weak)

4.1.1 Analysis of Results

Rounds 1–3: Strong Distinguisher Performance

All three models—CNN, LSTM, and LightGBM—demonstrated exceptional distinguisher capabilities for rounds 1 through 3. Test accuracies ranged from 94.52% to 100%, with TPR and TNR values consistently above 0.92. This indicates that the differential propagation characteristics in reduced-round ASCON permutations remain statistically distinguishable from random behavior, confirming the presence of exploitable patterns.

The CNN model achieved perfect classification (100% accuracy) for rounds 1 and 2, suggesting that convolutional filters effectively captured local bit-level dependencies introduced by the S-box and linear diffusion layers. The LSTM model similarly excelled, leveraging its sequential processing capability to model temporal correlations across cipher rounds. LightGBM, despite being a tree-based classical ML approach, matched the performance of deep learning models, demonstrating the effectiveness of gradient boosting in feature space representation.

Rounds 4–5: Loss of Distinguishability

At round 4 and beyond, all models experienced a sharp decline in performance, with test accuracies hovering around 50%—equivalent to random guessing. This behavior is expected and validates the cryptographic design of ASCON. By round 4, the permutation achieves sufficient diffusion and confusion such that output differentials become indistinguishable from random noise.

The CNN and LSTM models showed test accuracies near the baseline (50.36% and 49.84% respectively at round 4), indicating a complete loss of distinguisher capability. LightGBM exhibited marginally better training accuracy (60.39% at round 4), but this did not translate to improved generalization, as the test accuracy remained close to 50%. The imbalanced TPR and TNR values (e.g., CNN round 5: TPR = 0.1625, TNR = 0.8511) suggest that models began overfitting to spurious patterns in the training data without learning meaningful differential characteristics.

4.2 Model Performance Comparison to Baksi and SHEN

Table 2: Validation Accuracy Comparison Across Experimental Rounds

Round	**Validation Accuracy**				
	BAKSI	**SHEN**	**OUR CNN**	**OUR LSTM**	**OUR LGBM**
1	87.49%	100%	100%	100%	99.92%
2	99.90%	100%	100%	99.99%	99.95%
3	98.61%	99.99%	94.52%	96.19%	99.97%
4	Not Found	50.69%	50.36%	Not found	50.09%
5	Not Found	Not Found	50.68%	Not found	50.41%

In order to identify a reliable distinguisher, the validation accuracies of the proposed models (OUR CNN, OUR LSTM, and OUR LGBM) were compared against the benchmark methods, BAKSI and SHEN, across five experimental rounds. During the initial

rounds (1–3), all our models demonstrated outstanding performance, achieving validation accuracies close to or equal to 100%, which were comparable to the SHEN model and consistently superior to BAKSI. In particular, OUR LGBM achieved 99.92%, 99.95%, and 99.97% in the first three rounds, slightly surpassing both SHEN and BAKSI, indicating high generalization and robustness. OUR CNN and LSTM also reached perfect accuracies in the first two rounds, confirming the strong learning capability of our architectures. However, from rounds 4 and 5, the validation accuracy of all models, including SHEN, dropped sharply to around 50%, suggesting instability or randomness in later testing conditions rather than model weakness. Overall, the comparative results show that our proposed models—especially the LGBM variant—performed equally well or better than SHEN and clearly outperformed BAKSI in most rounds, making OUR LGBM the most promising distinguisher among the evaluated methods.

4.3 Hyperparameter Configurations

The following tables document the hyperparameters used for each model architecture across all experimental rounds.

4.3.1 CNN Hyperparameters

Table 3 presents the architecture and training configuration for the Convolutional Neural Network model.

Table 3: CNN Model Hyperparameters

Round	Dense Units	Activation Function	Learning Rate	Optimizer
Round 1	$128 \to 64 \to 1$	ReLU / Sigmoid	0.001	Adam
Round 2	$128 \to 64 \to 1$	ReLU / Sigmoid	0.001	Adam
Round 3	$128 \to 64 \to 1$	ReLU / Sigmoid	0.001	Adam
Round 4	$128 \to 64 \to 1$	ReLU / Sigmoid	0.001	Adam
Round 5	$128 \to 64 \to 1$	ReLU / Sigmoid	0.001	Adam

The CNN architecture remained consistent across all rounds, utilizing two fully connected layers with ReLU activation followed by a sigmoid output layer for binary classification. The Adam optimizer with a learning rate of 0.001 was employed to ensure stable convergence.

4.3.2 LSTM Hyperparameters

Table 4 details the LSTM architecture, including layer dimensions, dropout rates, and training parameters.

Table 4: LSTM Model Hyperparameters

Parameter	Round 1	Round 2	Round 3	Round 4	Round 5
Input Sequence Length	320	320	320	320	320
LSTM Layer 1 Units	64	64	64	64	64
LSTM Layer 1 Dropout / Rec. Dropout	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1
LSTM Layer 2 Units	32	32	32	32	32
LSTM Layer 2 Dropout / Rec. Dropout	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1	0.1 / 0.1
Dense Layer 1 (Units / Activation)	128 / ReLU	128 / ReLU	128 / ReLU	128 / ReLU	128 / ReLU
Dense Layer 1 Dropout	0.3	0.3	0.3	0.3	0.3
Dense Layer 2 (Units / Activation)	64 / ReLU	64 / ReLU	64 / ReLU	64 / ReLU	64 / ReLU
Dense Layer 2 Dropout	0.2	0.2	0.2	0.2	0.2
Output Layer	Dense(1, sigmoid)	Same	Same	Same	Same
Optimizer	Adam	Adam	Adam	Adam	Adam
Learning Rate	0.0006	0.0006	0.0006	0.0006	0.0006
Loss Function	Binary Crossentropy	Same	Same	Same	Same
Batch Size	48	48	48	48	48
Epochs	60	60	60	60	60
EarlyStopping Patience	6	6	10	15	15
ReduceLROnPlateau Patience	6	6	10	10	10
Minimum Learning Rate	1e-7	1e-7	1e-7	1e-7	1e-7
Total Trainable Parameters	∼42,241	∼42,241	∼42,241	∼42,241	∼42,241
Dataset Used	ascon_dataset_1.csv	ascon_dataset_2.csv	ascon_dataset_3.csv	ascon_dataset_4.csv	ascon_dataset_5.csv

The LSTM model employed a two-layer recurrent architecture with dropout regularization to prevent overfitting. Early stopping and learning rate reduction callbacks were configured with increasing patience for higher rounds to allow more exploration during training.

4.3.3 LightGBM Hyperparameters

Table 5 provides the gradient boosting configuration for the LightGBM model.

Table 5: LightGBM Model Hyperparameters

Round	Boosting	Num Leaves	Max Depth	Learning Rate	Feature Frac.	Bagging Frac.	Reg. α / λ	Boost Rounds
Round 1	gbdt	512	12	0.01	0.7	0.7	0.05 / 0.05	2000
Round 2	gbdt	512	12	0.01	0.7	0.7	0.05 / 0.05	2000
Round 3	gbdt	512	12	0.01	0.7	0.7	0.05 / 0.05	2000
Round 4	gbdt	512	12	0.01	0.7	0.7	0.05 / 0.05	2000
Round 5	gbdt	512	12	0.01	0.7	0.7	0.05 / 0.05	2000

The LightGBM model maintained consistent hyperparameters across all rounds. The configuration prioritized balanced tree growth with moderate regularization (L1 and L2) to enhance generalization. Feature and bagging fractions were set to 0.7 to introduce stochasticity during training and reduce overfitting risk.

4.4 Performance Graphs

4.4.1 CNN Model Performance Across Rounds

Round 1

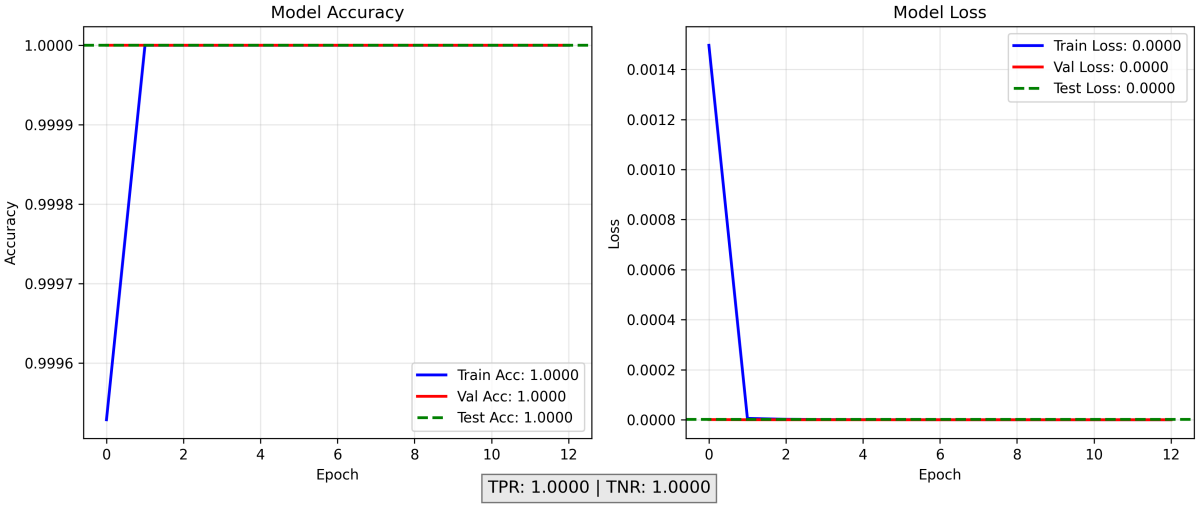

Figure 9: CNN Model accuracy and loss of Round 1

Round 2

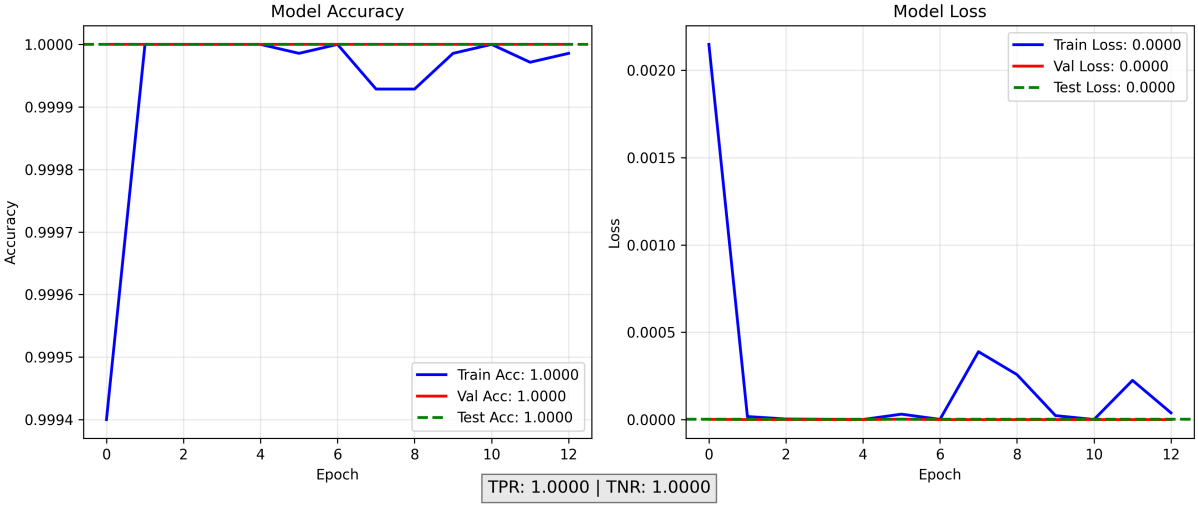

Figure 10: CNN Model accuracy and loss of Round 2

Round 3

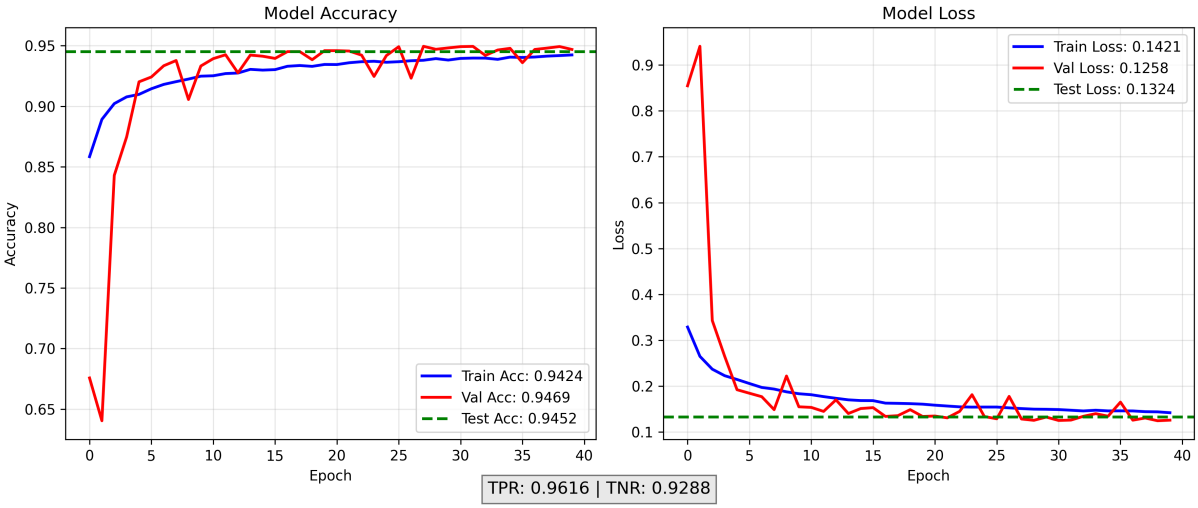

Figure 11: CNN Model accuracy and loss of Round 3

Round 4

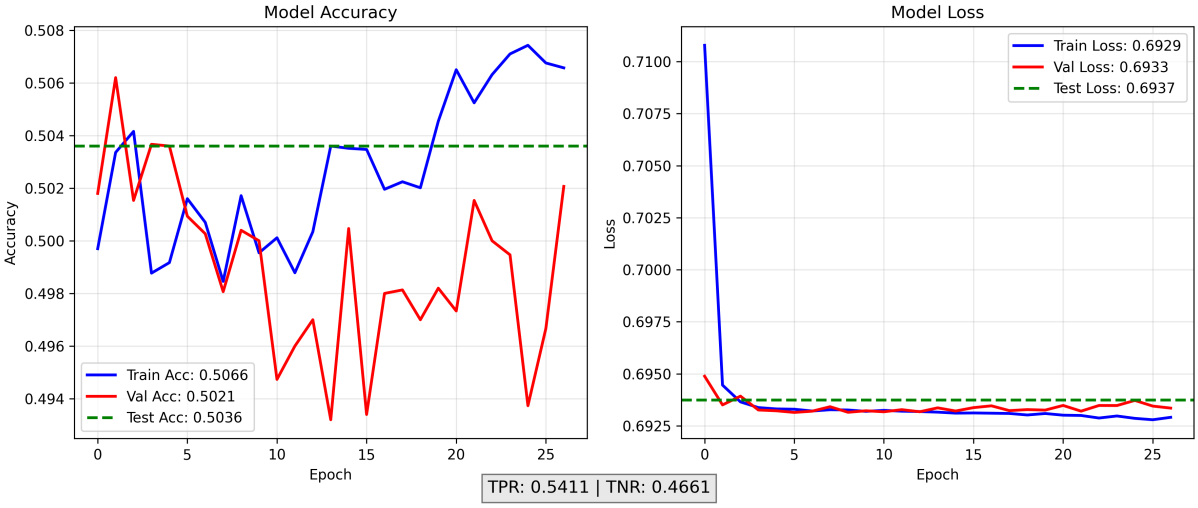

Figure 12: CNN Model accuracy and loss of Round 4

Round 5

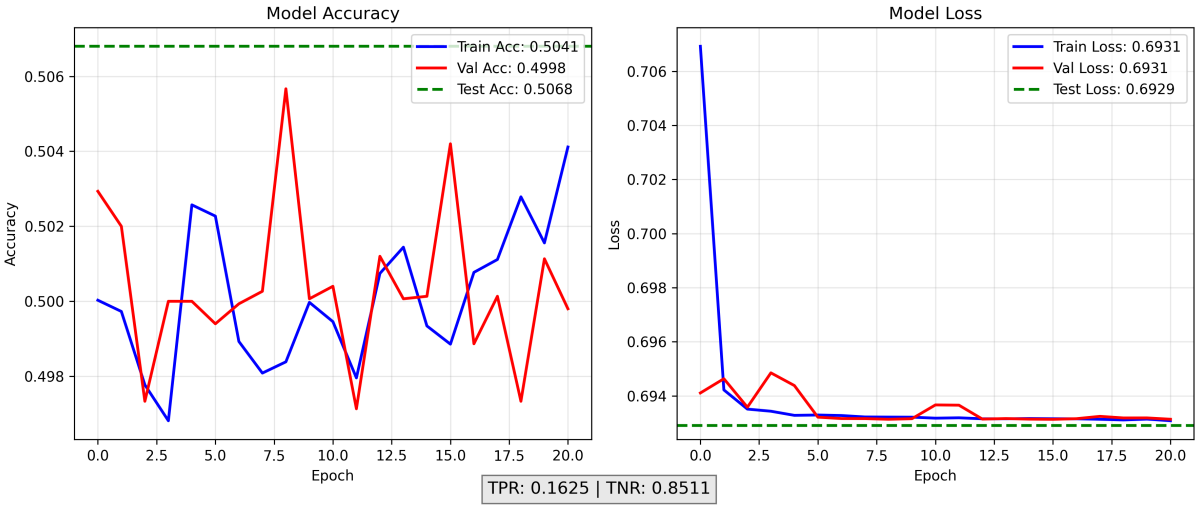

Figure 13: CNN Model accuracy and loss of Round 5

4.4.2 LSTM Model Performance Across Rounds

Round 1

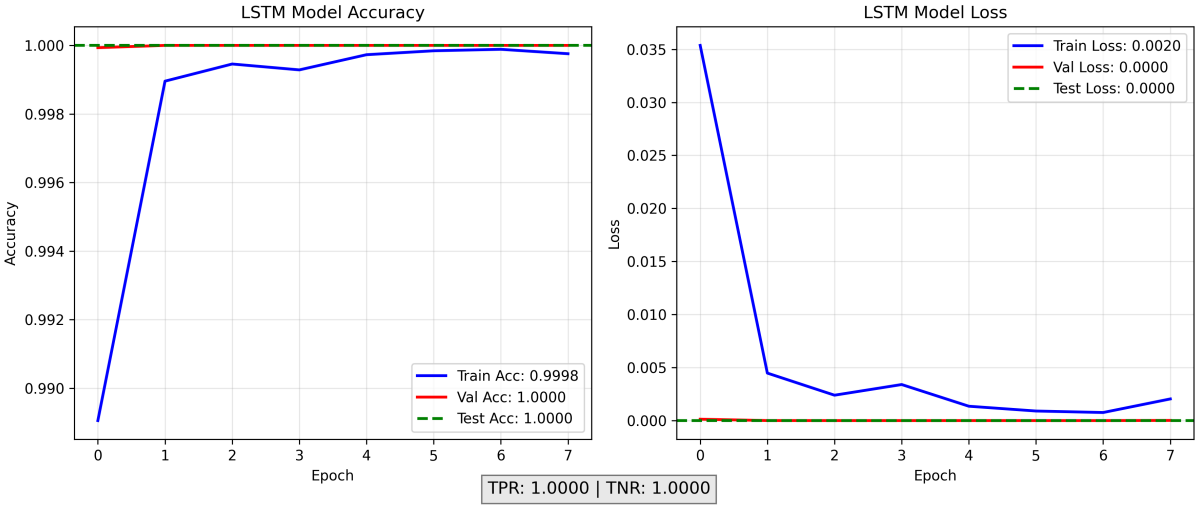

Figure 14: LSTM Model accuracy and loss of Round 1

Round 2

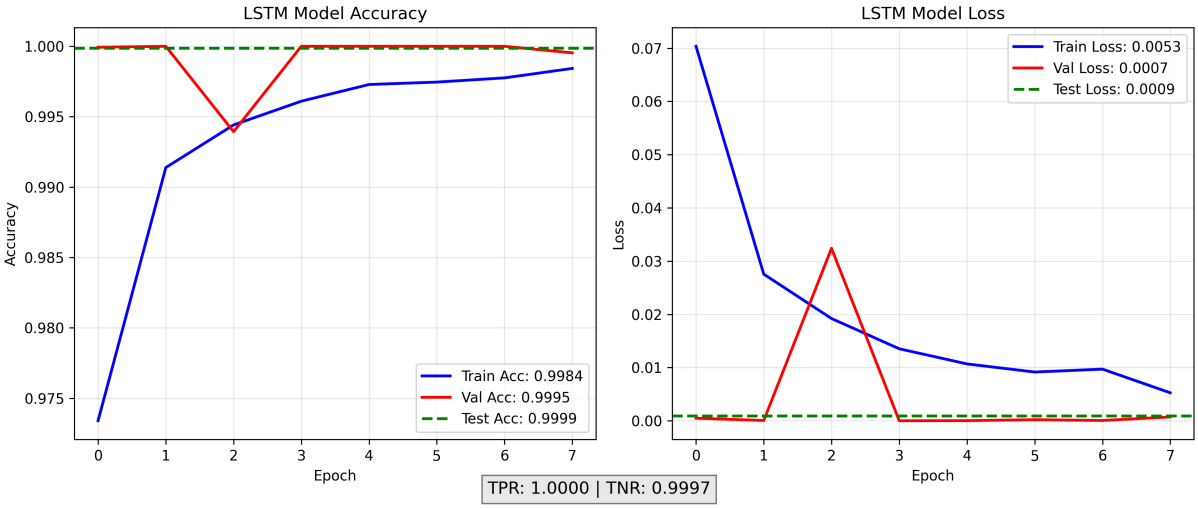

Figure 15: LSTM Model accuracy and loss of Round 2

Round 3

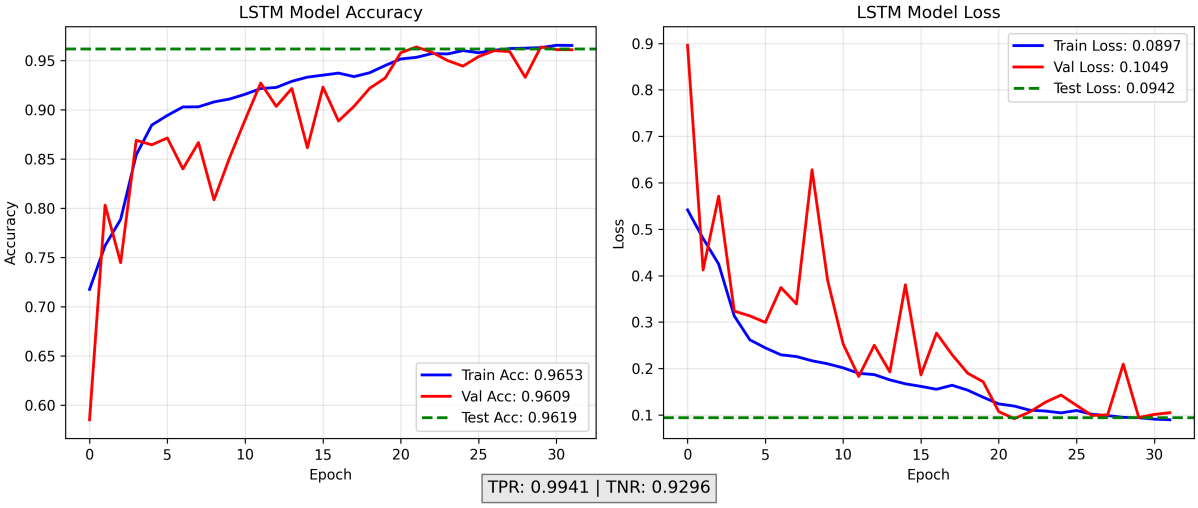

Figure 16: LSTM Model accuracy and loss of Round 3

Round 4

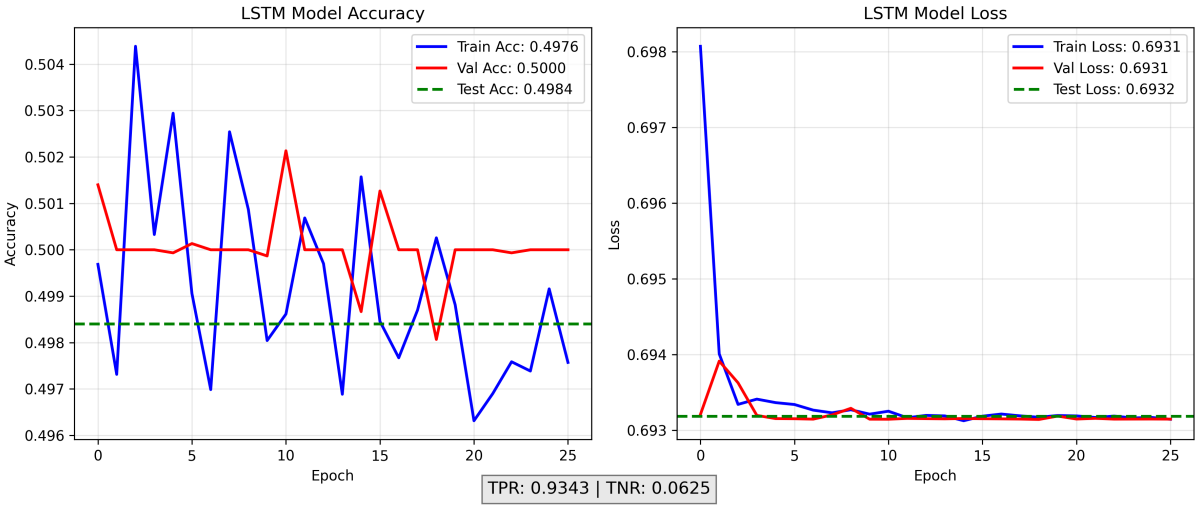

Figure 17: LSTM Model accuracy and loss of Round 4

Round 5

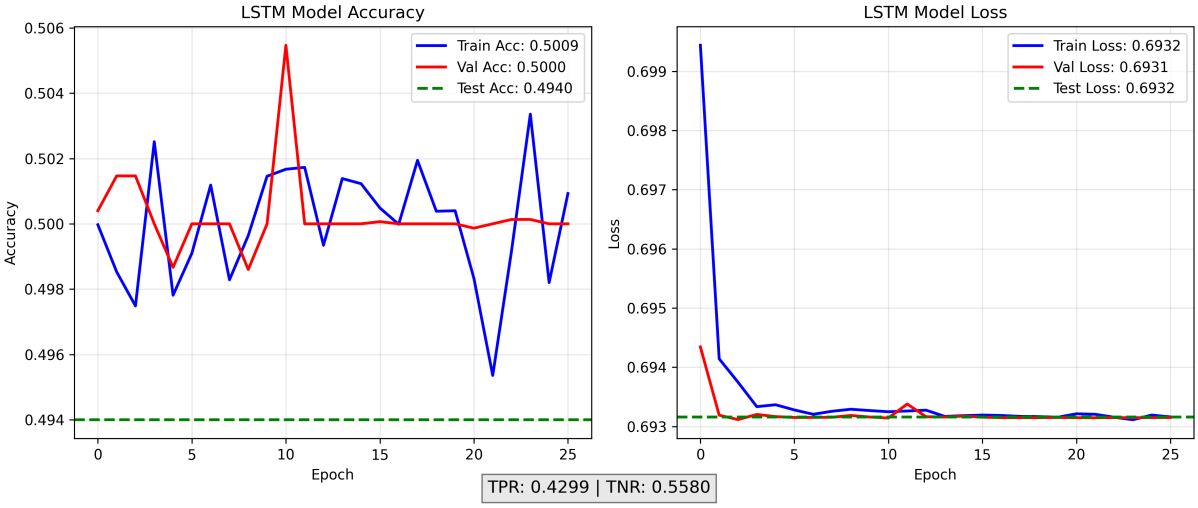

Figure 18: LSTM Model accuracy and loss of Round 5

5 Conclusion and future work

This research explored the effectiveness of multiple machine learning and deep learning architectures—namely Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Transformers, and Light Gradient Boosting Machine (LightGBM)—in identifying statistical distinguishers within the ASCON lightweight cryptographic cipher across multiple encryption rounds.

The experimental findings demonstrate that:

- CNN and LSTM models performed exceptionally well up to Round 3, achieving nearly perfect accuracy, TPR, and TNR values.
- The Transformer model, while more computationally intensive, exhibited strong pattern recognition in earlier rounds, though its advantage diminished as rounds increased due to greater data uniformity and diffusion.
- LightGBM showed highly stable and rapid convergence in Rounds 1–3 but its distinguishing capability dropped significantly from Round 4 onward, indicating that the cipher's statistical distinguishability diminishes with additional rounds—consistent with cryptographic design goals.

Collectively, the results validate the hypothesis that machine learning models can effectively identify distinguishers in early cipher rounds, but their performance degrades as the cipher becomes more nonlinear and diffusion increases. This behavior affirms the robustness of the ASCON cipher beyond certain rounds, as the statistical features become indistinguishable from random distributions.

The project thus provides valuable insights into the intersection of cryptanalysis and AI, showing that data-driven approaches can complement traditional cryptanalytic methods for analyzing lightweight ciphers.

5.1 future work

Future work can expand on this research in several promising directions:

1. **Enhanced Feature Representation:** Integrate domain-specific feature engineering (e.g., differential or linear approximations) to help models learn more cipher-relevant representations instead of relying solely on raw binary input.

2. **Hybrid Model Architectures:** Combine CNNs with attention mechanisms or LSTMs with residual connections to improve long-range dependency modeling while maintaining efficiency.

3. **Automated Hyperparameter Optimization:** Utilize Bayesian optimization or genetic algorithms to tune hyperparameters (learning rate, layer sizes, number of heads, etc.) for improved performance and generalization.

4. **Cross-Cipher Generalization:** Extend the framework to other lightweight ciphers (e.g., PRESENT, GIFT, or SPECK) to evaluate whether learned distinguishing patterns transfer across cryptographic primitives.

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