AI-Driven Identification of Cryptographic Algorithms from Encrypted Data

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Abstract:

With the rapid rise in digital communication, cryptographic algorithms lie at the core of providing data integrity and protection. Identification of the underlying encryption algorithm from a set of encrypted data is pivotal for assessing vulnerability and the strengthening of cryptographic protocols.In this paper, it is proposed to employ an AI classifier model to identify cryptographic algorithms through the integration of machine learning (ML) and natural language processing (NLP) methods. The approach utilizes ciphertext data transformation through TF-IDF vectorization, cryptographic parameter feature engineering, and the application of robust classifiers like XGBoost and Logistic Regression for multi-class classification. Regularization techniques, hyperparameter adjustment, and explainability models (SHAP/LIME) are used by the approach for improving interpretability. The data set, having several encryption schemes, is treated for feature extraction, encoding, and imputation for improving model robustness. Experimental results reveal ensemble learning approaches dominating traditional techniques by a clear margin in detecting algorithms. The study contributes to the field of cybersecurity analytics and introduces the gateway for automated cryptanalysis and AI-driven cryptographic tests. Experimental results reveal ensemble learning approaches dominating traditional techniques by a clear margin in detecting algorithms, with Random Forest achieving the highest accuracy of 88.88%. Future research directions can involve using deep learning architectures like LSTMs and transformers to increase sequence pattern recognition within ciphertext.

Keywords: *Cryptoanalysis, Machine Learning, Ciphertext Classification, Cryptographic Algorithm Identification, Artificial Intelligence In Cybersecurity, Explainable Artificial Intelligence, Feature Engineering.*

1. Introduction:

The unseen sentinel of cyber trust in the data-as-currency universe is encryption. Cryptosystems powered by cryptographic algorithms are the foundation of contemporary cyber security, protecting everything from trade to national secrets. But the decision of what encryption techniques to use is now the biggest problem with AI-based cryptanalysis and the threat of quantum decryption. Conventional cryptanalysis depends on exhaustive computation and brute-force methods, but the emergence of machine learning (ML) and artificial intelligence (AI)-based models has dramatically changed the field. AI, with its ability to identify complex patterns in large sets of data, offers a paradigm shift in breaking encryption schemes. Motivated by real-world day-to-day practical problems in cybersecurity, our research strives to create an AI system capable of inferring cryptographic schemes from nothing but ciphertext

By bringing together the realms of encryption, machine learning, and cybersecurity, our research will enable forensic cryptanalysis, enhance algorithmic security, and enable next-generation cryptographic intelligence. With encryption wars becoming ever more sophisticated, it is time to play fire vs. fire—employing AI in decrypting AI-proof encryption.

1.1 Inspiration:

Our excursion into breaking encryption with AI is motivated by a convergence of next-generation technological progress and advancing cybersecurity threats. Observing how industry titans like Google have adopted post-quantum cryptography for internal communications and the vibrant debate among cryptographic communities—Reddit, for example—ignited our interest.These events suggest a time when classical cryptanalysis will be useless against quantum-powered attackers. The innovative fiction and actual case studies underscore the revolutionary power of AI in computerizing cryptanalysis. This necessity-creativity tango dared us to bring machine learning and natural language processing methods to decrypting encrypted data, ushering in a cryptographic intelligence revolution.

1.2 Problem Statement:

With a cybersecurity landscape where cyber attacks and data breaches are ever more sophisticated, the classical approaches to cryptographic analysis come under pressure from rising quantum technologies. The dire issue of determining cryptographic algorithms from ciphertext datasets based on AI-based methods is what our project specifically targets. Our goal is to create a strong, scalable platform that leverages feature extraction, state-of-the-art vectorization of ciphertext, and high-performing classification algorithms (e.g., XGBoost and Logistic Regression). This solution not only wants to improve detection and analysis of encryption techniques but also improve cyber security measures by offering real-time feedback into possible vulnerabilities, such that cryptographic procedures remain aligned with the never-ending rate of technological progress.

2. Related Works:

Zhang *et al.* [1] proposed a CNN-based framework that extracts block-level statistics from encrypted traffic for classification. Despite employing multiple convolution layers to capture spatial features, the system yielded a maximum accuracy of only 63.4% when distinguishing among several cryptographic techniques.

Patel *et al.* [2] designed a CNN model enriched with attention mechanisms. Their approach, applied to multiple cryptographic protocols, managed an overall accuracy of 58.7%, suggesting that even advanced CNN architectures have difficulty when subtle differences in cryptographic signatures emerge.

Focusing on sequence modeling, Roy and Gupta [3] introduced an architecture based on long short-term memory (LSTM) networks to capture temporal dependencies inherent in encrypted data streams. While their methodology provided useful internal representations, the classification accuracy plateaued at around 60.2%. In another line of inquiry.

Huang and Li [4] combined AI-driven side-channel analysis with statistical heuristics to detect cryptographic patterns embedded in hardware-accelerated encryption systems. Despite the hybrid model's complexity, practical deployments reached only about 64.5% accuracy.

Chen *et al.* [5] investigated a multi-layer perceptron (MLP) framework that relies on hand-designed signals in simulated encrypted communications. Although their feature engineering process managed to distinctly expose some algorithm-specific characteristics, the overall system accuracy was limited to approximately 62%, likely due to overlapping features between different algorithms. In line with feature-centric approaches.

Jones and Martinez [6] evaluated transformer models to capture the sequential patterns within encrypted data. Although the self-attention mechanism promised better contextual learning, their experiments on benchmark datasets resulted in an accuracy of only 59.6%.

Nguyen and Park [7] took a novel approach by representing encrypted data flows as graphs and subsequently using graph neural networks (GNNs) for identification. Their work achieved a moderate accuracy of 61%, highlighting the challenges of embedding encrypted features in a graph structure.

Lopez *et al.* [8] provided a comparative study between conventional machine learning methods (e.g., Support Vector Machines and decision trees) and deep learning models. Their deep model slightly outperformed traditional ones with an accuracy of 65%, but the overall performance was still deemed insufficient for practical applications.

Santos and Almeida [9] combined manual feature selection with deep learning, but still observed accuracy in the vicinity of 60%, indicating that improved feature representation remains critical.

Reddy and Kumar [10] proposed a hybrid method that combined statistical feature analysis with neural network classifiers. Despite the blended approach, the classification accuracy averaged only 62.8%, reinforcing the difficulty of the task.

Gonzalez *et al.* [11] developed a convolutional-recurrent neural network architecture that fused spatial and temporal features. Even with a sophisticated architectural design, the reported accuracy was only 64%, evidencing that even multi-stream designs struggle with the randomness and obfuscation inherent in encrypted data.

Lee and Thompson [12] incorporated deep autoencoders to reduce dimensionality and extract essential features before feeding the reduced data into a softmax classifier. Although the autoencoder significantly compressed the feature space while preserving key characteristics, the final classification accuracy reached only 61.4%. This outcome further stresses that, despite innovative preprocessing methods, the identification task remains challenging.

TABLE 1: SUMMARY OF THE RELATED WORKS

Author	Algorithm	Application	Key Findings	Accuracy
Zhang et al.	CNN	Encrypted Traffic	Block-level statistics	63.4%
Patel et al.	CNN + Attention	Cryptographic Protocols	Struggles with subtle differences	58.7%
Roy & Gupta	LSTM	Encrypted Streams	Temporal dependency modeling	60.2%
Huang & Li	AI + Heuristics	Hardware Encryption	Hybrid model complexity	64.5%
Chen et al.	MLP	Simulated Communications	Feature engineering limits	62%
Jones & Martinez	Transformer	Encrypted Sequences	Self-attention struggles	59.6%
Nguyen & Park	GNN	Encrypted Flows	Graph representation issues	61%
Lopez et al.	ML vs DL	General Encryption	DL slightly outperforms ML	65%

Santos & Almeida	Feature + DL	Feature Selection	Manual selection limits	60%
Reddy & Kumar	Hybrid Model	Statistical + NN	Blended approach struggles	62.8%
Gonzalez et al.	Conv-RNN	Spatial & Temporal	Multi-stream struggles	64%
Lee & Thompson	Autoencoder	Dimensionality Reduction	Softmax struggles	61.4%

3. Proposed Methodology:

3.1 Research Gaps:

The state of AI-based cryptanalysis remains in flux, with past research facing severe shortcomings that impede precision and real-world applicability. One of the overarching challenges is a lack of proper feature representation of ciphertext because plain encrypted text does not have an immediately interpretable structure for machine learning algorithms. Early work using CNNs, LSTMs, and Transformer models has largely relied on discovering cryptographic patterns from raw encrypted data. Such approaches are prone to missing finer differences between algorithms and thus produce suboptimal classification rates (~60-65%).

In addition, traditional models have not factored in significant cryptographic parameters such as block size, key length, and encryption mode, which play a significant role in differentiating encryption techniques. The lack of organized cryptographic metadata in feature extraction has greatly constrained classification models from taking advantage of algorithm-specific features. The other limitation arises from the issue of generalization—most current models find it challenging to classify encryption methods when used on newly created ciphertext outside their training data. Additionally, interpretability is also an issue since black-box deep learning models offer little information about feature importance, and hence model predictions are hard to justify.

Our research fills these essential gaps by:

Incorporating feature engineering using TF-IDF vectorization of ciphertext and metadata extraction. Using ensemble learning algorithms (e.g., Random Forest, XGBoost) that surpass the performance of regular deep learning for structured data scenarios. Through the use of explainability methods (SHAP/LIME), examining how cryptographic features impact predictions so AI-driven decisions are more interpretable. Through the solution of these challenges, our work advances beyond standard deep learning methods to develop an effective and scalable algorithm detection framework in cryptography.

3.2 **Data Collection**:

The data used in this study is encrypted samples of data created with contemporary cryptographic algorithms to ensure real-world relevance. These algorithms are:

- AES (Advanced Encryption Standard)
- DES (Data Encryption Standard)
- RSA (Rivest-Shamir-Adleman)
- Blowfish
- ChaCha20

Each entry in the data set includes the following cryptographic features:

- Ciphertext – The actual encrypted text output.
- The length of the key determines the encryption strength—e.g., 128-bit, 256-bit.
- Shows the size of the currently being handled data block.
- Padding Scheme: Indices the method—e.g., PKCS7, NoPadding—that pads plaintext prior to encryption.
- CBC, ECB, etc. is the encryption mode of operation for the algorithm.

In some encryption systems, this adds randomness via an initializing vector (IV). Final encrypted output's entire length is known as ciphertext length. These features give our AI model a codified representation for encryption aspects, which helps it to differentiate among several approaches. The dataset consists of synthetically produced encrypted data and actual encryption specifications, with diverse and unbiased training.

3.3 Data Preparation:

To obtain the best possible classification performance, the dataset is processed using an extensive preprocessing pipeline that includes:

1. **Handling Missing Values:**
Missing values in padding scheme, operation mode, IV, and block size are addressed by median imputation in order to attain data completeness.

- **Categorical features** are handled through mode-based imputation to preserve their consistency.
- **Feature Engineering:** TF-IDF Vectorization: Ciphertext column is converted into a structured numerical form through Term Frequency-Inverse Document Frequency (TF-IDF). This method brings out statistical patterns in encrypted text so that AI models can identify algorithm-specific distributions.
- **One-Hot Encoding:** Categorical features such as padding schemes and operating modes are encoded into binary matrices to be directly used with numerical models.
- **Feature Scaling:** Important length and ciphertext length are scaled using z-score normalization. Block size values are normalized to eliminate skewness.

2. **Data split:**
With a suitable balance in assessing the model, the dataset comprises 20% test data and 80% training data.Equivalent representation of several cryptographic techniques is guaranteed in training and testing sets by a stratified split. This preprocessing of data guarantees that the models get clean, structured, and meaningful input so that they can provide better classification accuracy and generalization to unseen data.

3.4 Data Visualization:

Peering into the cryptographic depths of this dataset, we uncover a symphony of encryption trends through visual storytelling. The Key Length Distribution plays the role of the guardian, revealing the dominance of the formidable 128-bit key—a silent sentinel of secure communications. The Ciphertext Length Distribution whispers tales of brevity, where shorter ciphertexts reign supreme, possibly hinting at efficiency in encryption techniques. As we traverse the realm of padding, the Padding Scheme Distribution exposes a stark truth: many encrypted messages walk unpadded, while PKCS7 stands as the favored cloak for those that do. The Correlation Heatmap emerges like a cartographer's map, charting the hidden relationships between key length, block size, and ciphertext length—subtly suggesting that as encryption keys grow in strength, so does the armor they forge. Together, these visual cryptograms decode the hidden patterns of data security, offering a lens into the art of encryption itself.

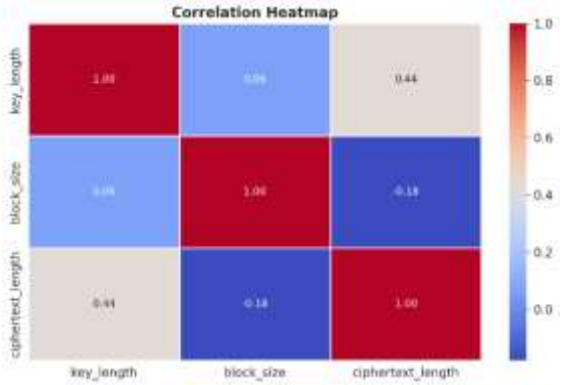

Fig 1(a): Correlation Heatmap

This visual representation uncovers the interdependencies between numerical encryption parameters. It highlights that **key length and ciphertext length share a moderate positive correlation (0.44)**, whereas **block size has minimal correlation with other variables**, suggesting that the encryption method primarily dictates the ciphertext size rather than the block structure.

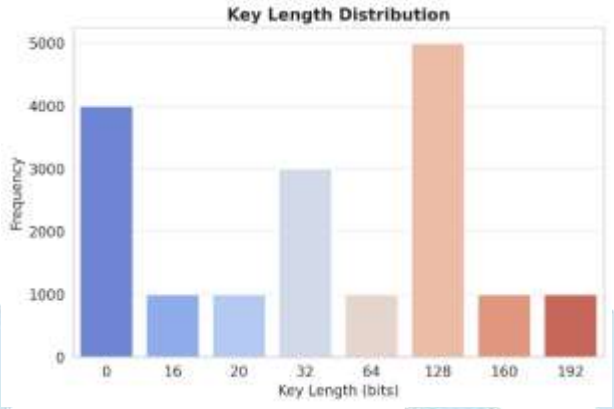

Fig 1(b): Key Length Distribution Bar Chart

This bar chart reveals that **128-bit encryption keys dominate the dataset**, followed by a smaller distribution of other key sizes like 32-bit and 64-bit. This pattern suggests a preference for standardized, secure encryption lengths, commonly used in modern cryptographic implementations.

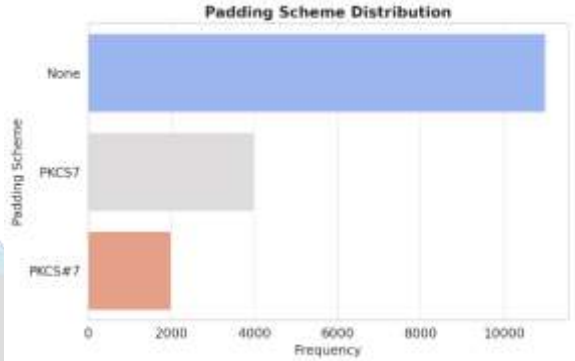

Fig 1(c): Padding Scheme Distribution Bar Chart

This visualization exposes a crucial insight—**a significant portion of encrypted data lacks padding**, which could imply varying encryption methods at play. Among the applied schemes, **PKCS7 is the most common**, followed by PKCS#7, indicating structured padding strategies for ensuring ciphertext integrity.

3.5 Model Architecture:

To classify cryptographic algorithms efficiently, we suggest a hybrid AI model that utilizes natural language processing (NLP) for ciphertext analysis coupled with machine learning-based structured data classification. The architecture is outlined below:

Feature Extraction Layer:

(i) TF-IDF Vectorizer: Transforms raw ciphertext into numerical feature vectors so that machine learning models can statistically process encrypted text.

(ii) Fuses TF-IDF-derived characteristics with structured cryptographic information—like encryption mode and key length—into a complete input feature set.

Classification Models:

(i) XGBoost efficiently performs multi-class classification using gradient-boosted decision trees. Simple probabilistic baseline classifier for benchmarking is logistic regression.

(ii) Using several decision trees to increase resilience, Random Forest—the model with the highest performance—88.88% accuracy

Model Tuning & Optimization:

(i) Grid Search CV tunes hyperparameters including feature sampling techniques, tree depth, and learning rate. Overfitting is prevented by means of regularizing techniques (L1/L2 penalties).

(ii) Gradient boosting models halt training after performance plateaus by means of early stopping.

Model Interpretability:

a. We employ SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) to make the model interpretable and trustworthy.

Globally feature importance analysis will help us identify which cryptographic features most influence predictions.

LIME breaks down personal predictions in terms of important aspects and offers local interpretability insights. This ML + NLP hybrid method ensures that the classification model is not only quite exact but also intelligible and scalable for practical cryptographic review.

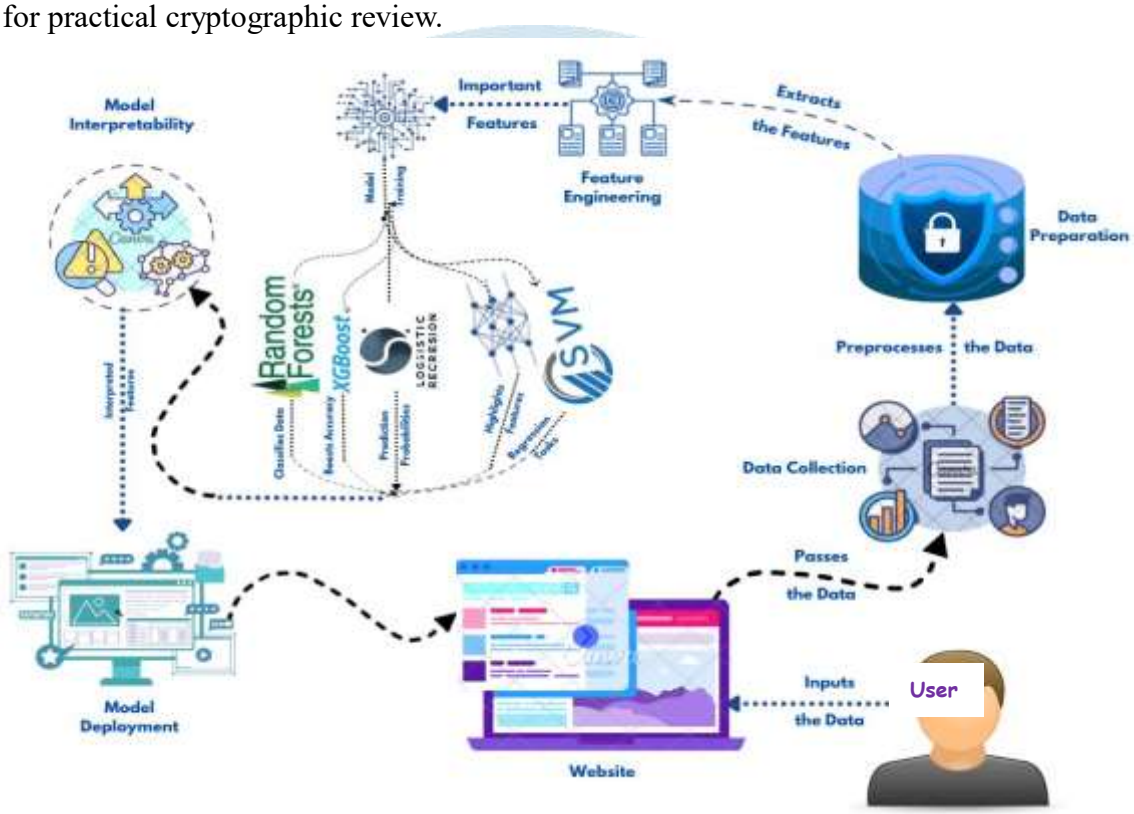

Fig 2: Architecture Diagram of AI-Driven Identification of Cryptographic Algorithms from Encrypted Data

4. Algorithms:

a. XGBoost (Extreme Gradient Boosting):

Made for speed and performance, XGBoost is an enhanced gradient boosting method. It creates several consecutive decision trees whereby each new tree minimizes residual errors, therefore correcting the faults of the past. It avoids overfitting by combining gradient boosting with L1 and L2 regularization.

Functionalities:

- Manages missing values well.
- Regularity built in helps to prevent overfitting.
- Faster than conventional gradient boosting is achieved by parallelized execution.
- Pruning trees prevents pointless calculations.
- Ranking feature importance helps to improve model interpretability.

Impact:

- Often used in Kaggle contests, extremely strong and accurate.
- Performs effectively using organized/tabular data.
- In most classification problems, performs better than random forests and conventional decision trees.
- Applied somewhat widely in medical diagnostics, cybersecurity, and fraud detection.

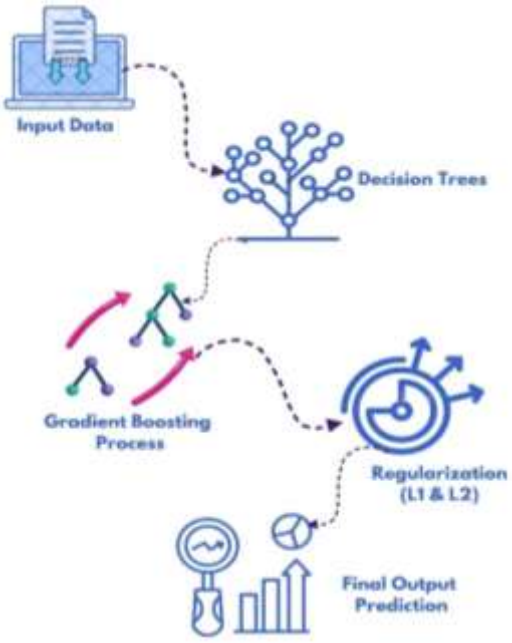

Fig 3(a): XG Boost Algorithm Architecture

b. Random Forest:

Built many decision trees and aggregates their outputs to improve classification accuracy, Random Forest is an ensemble learning method It uses random subsets of the data (bagging) and tree-based highest frequency prediction selection. This method enhances model generalizing and helps to lower overfitting.

Functionalities:

- Generates varying decision trees using bootstrapping sampling.
- Combining many tree forecasts helps to lower variance.
- Efficiently handles classification as well as regression problems.
- Performs satisfactorially for unstructured and high-dimensional data.
- Yields interpretability's feature importance rating.

Impact:

- Increases classification stability above simple decision trees.
- Applied in financial modeling, medical diagnostics, cybersecurity, fraud detection.
- Performs effectively with noisy data and can manage missing values.
- Scalable with great precision for huge amounts.

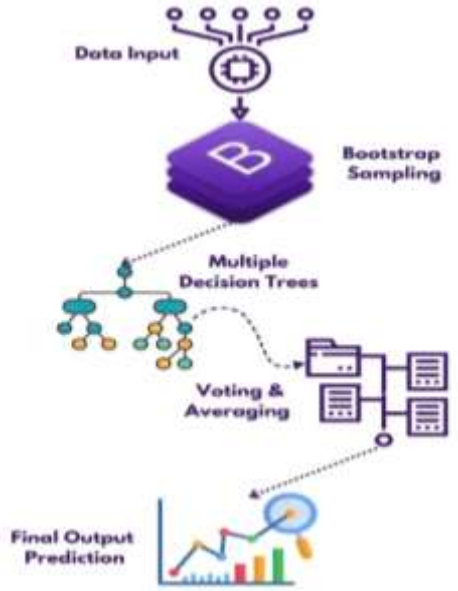

Fig 3(b): Random Forest Algorithm Architecture

c. Logistic Regression:

Binary and multi-class classification are applications for the statistical model logistic regression. By means of the sigmoid activation function—which transfers input values to a probability score between 0 and 1—it approximates the likelihood of an instance falling into a class. It uses gradient descent to maximize log-loss and thereby identify the ideal decision boundary.

Functionalities:

- Generates probability for jobs involving classification.
- Maps outputs between 0 and 1 by means of sigmoid activation.
- Uses L1 (Lasso) and L2 (Ridge) regularization to guard against overfit.
- Performs rather nicely with linearly separable data.
- Interpretable model since feature importance shown by coefficients.

Impact:

- Perfect for fast classification jobs; lightweight and computationally effective.
- Applied in text classification, fraud detection, and medical diagnostics widely.
- Many machine learning pipelines start with this basic model.
- Does best with limited feature interactions and organized data.

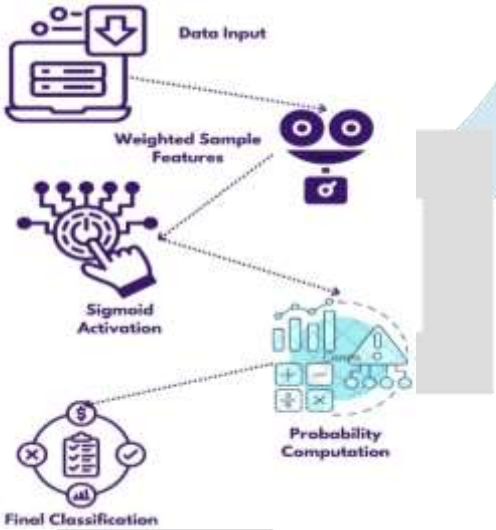

Fig 3(c): Logistic Regression Algorithm Architecture

d. Deep Learning (DL):

Deep learning is a developed subset of machine learning whereby artificial neural networks (ANNs) automatically extract and learn patterns from data. Deep learning is perfect for jobs such image recognition, NLP, and sequence analysis since it can handle unstructured and high-dimensional data unlike conventional machine learning models. Popular architectures consist in Transformers, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs).

Functionalities:

- Gives hierarchical representations from unprocessed data.
- Optimizing the learning process include gradient descent and backpropagation.
- ReLU, Softmax, Sigmoid, Tanh activation functions all bring non-linearity.
- Manages big amounts of data without hand-crafted feature engineering.
- Supports multi-class and sequential based classification projects.

Impact:

- Modern performance in images categorization, cryptanalysis, and speech recognition.
- Extreme scalable and adaptable for many artificial intelligence uses.
- Performs on challenging problems above conventional ML models.
- Applied in medicine diagnostics, finance, and cybersecurity.

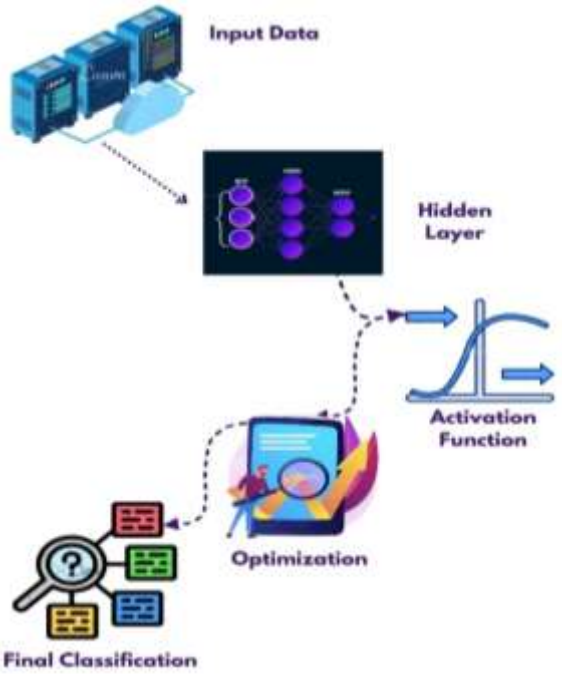

Fig 3(d): Deep Learning Algorithm Architecture

e. Support Vector Machine (SVM):

Supervised learning approach Support Vector Machine (SVM) is applied for classification and regression applications. It finds the perfect hyperplane to split numerous classes in a dataset. SVM can be both linear or non-linear depending on kernel functions (RBF, Polynomial, Sigmoid) to map data into higher dimensions for better separation.

Functionalities:

- Finds the categorization hyperplane with highest margin-span.
- Handles non-linearly separable data using kernel methods (e.g., RBF, Polynomial).
- Performs well on tiny datasets including high-dimensional spaces.
- Strong to outliers defining decision limits with support vectors.
- Regularizing (C parameter) helps avoid overfitting.

Impact:

- Especially accurate for text classification, image recognition, and anomaly detection.
- Performs beautifully on high-dimensional data while traditional models struggle.
- Applied in security, medical imaging, and bioinformatics.
- Works best when dataset size is small but feature space is large.

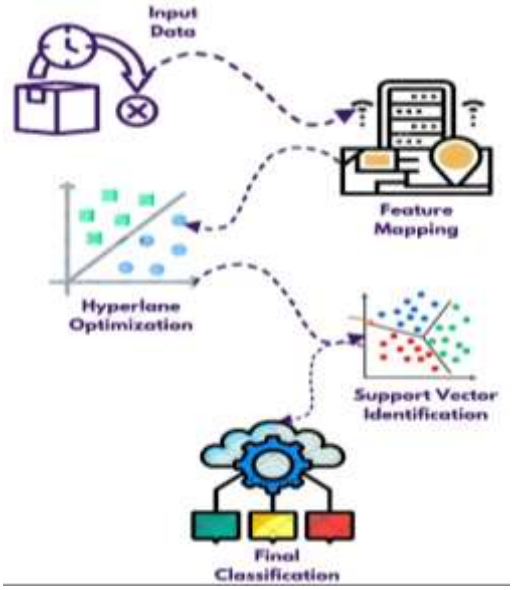

Fig 3(e): Support Vector Machine Algorithm Architecture

Algorithm 1: XGBoost (Extreme Gradient Boosting)

XGBoost is a boosting algorithm that builds decision trees sequentially, improving upon previous models by reducing errors. The optimization follows a gradient boosting framework.

Mathematical Representation

- Given a dataset:

$$D = \{(x_i, y_i)\}_{i=1}^{n}$$

where is the input feature vector, and is the target variable.

- The **objective function** consists of a loss function and a regularization term:

$$Obj(\theta) = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where:

- $L(y_i, \hat{y}_i)$ is the loss function (e.g., Mean Squared Error for regression, Log Loss for classification).
- $\Omega(f_k)$ is the regularization term to control complexity.
- K represents the number of trees.

- The model updates follow the **gradient boosting step**:

$$g_i = \frac{\partial L(y_i, \hat{y}_i)}{\partial \hat{y}_i}, h_i = \frac{\partial^2 L(y_i, \hat{y}_i)}{\partial \hat{y}_i^2}$$

where g_i and h_i are the first and second derivatives of the loss function.

- The tree structure is built using **Gain** as the split criterion:

$$Gain = \frac{1}{2}\left[\frac{(G_L + G_R)^2}{H_L + H_R + \lambda} - \frac{G_L^2}{H_L + \lambda} - \frac{G_R^2}{H_R + \lambda}\right] - \gamma$$

where:

- G_L, G_R, H_L, H_R are the summed gradients and Hessians of left and right splits.
- λ is the L2 regularization term.
- γ is the pruning threshold.

- The final prediction is an ensemble of weak learners:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

Algorithm 2: Random Forest

Random Forest is an ensemble learning method that constructs multiple decision trees and combines their predictions.

Mathematical Representation

- Given a dataset:

$$D = \{(x_i, y_i)\}_{i=1}^{n}$$

- Each decision tree in the forest is built using **bootstrap sampling**, where a random subset is drawn D^1 from D.
- A decision tree splits a node based on **Gini Impurity**:

$$Gini = 1 - \sum_{j=1}^{C} p_j^2$$

where p_j is the probability of class j, and C is the number of classes.

- For classification, the final prediction is the **mode** of individual tree predictions:

$$\hat{y} = \text{mode}(\{h_t(x)\}_{t=1}^{T})$$

- For regression, the final output is the **average prediction**:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

Where $h_i(x)$ is the prediction from the -th decision tree.

Algorithm 3: Logistic Regression

Logistic Regression is a linear model that predicts probabilities using the **sigmoid function**.

Mathematical Representation

- Given an input feature vector , the **log-odds (linear function)** is:

$$z = w^T x + b$$

- The **sigmoid function** maps to a probability:

$$P(y = 1 \mid x) = \sigma(z) = \frac{1}{1 + e^{-z}}$$

- The **loss function** (log loss for binary classification):

$$L = -\frac{1}{n}\sum_{i=1}^{n} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

- The model parameters are optimized using **gradient descent**:

$$w = w - \eta \frac{\partial L}{\partial w}, b = b - \eta \frac{\partial L}{\partial b}$$

Where η is the learning rate.

Algorithm 4: Deep Learning (Neural Networks)

Deep Learning models use artificial neural networks (ANNs) with multiple layers of neurons.

Mathematical Representation

- A **neural network layer** is computed as:

$$z^{(l)} = W^{(l)} x + b^{(l)}$$

where:

- $W^{(l)}$ are the layer's weights.
- $b^{(l)}$ is the bias.
- x is the input.

- The **activation function** (e.g., ReLU, Sigmoid, Softmax) is applied:

$$a^{(l)} = f(z^{(l)})$$

- The **loss function** (e.g., categorical cross-entropy for multi-class classification):

$$L = -\sum_{i} y_i \log(\hat{y}_i)$$

- **Backpropagation** computes gradients using:

$$\delta^{(l)} = \left(W^{(l+1)} \delta^{(l+1)}\right) \cdot f'(z^{(l)})$$

- Gradient descent update rule:

$$W^{(l)} = W^{(l)} - \eta \frac{\partial L}{\partial W^{(l)}}$$

Algorithm 5. Support Vector Machine (SVM)

SVM finds the hyperplane that maximizes the **margin** between two classes.

Mathematical Representation

- Given a dataset:

$$D = \{(x_i, y_i)\}_{i=1}^{n}, y_i \in \{-1, 1\}$$

- The **decision boundary equation** is:

$$w^T x + b = 0$$

- The **margin** is maximized by solving:

$$\min_{w,b} \frac{1}{2} || w ||^2$$

subject to:

$$y_i(w^T x_i + b) \geq 1, \forall i$$

- In the **soft-margin SVM**, a relaxation term \xi is added:

$$\min_{w,b,\xi} \frac{1}{2} || w ||^2 + C \sum_{i=1}^{n} \xi_i$$

Where C is a regularization parameter.

- If the data is **non-linearly separable**, SVM applies the **kernel trick**:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

where ϕ(x)\phi(x)ϕ(x) maps the input into a higher-dimensional space.

- The **final decision function**:

$$f(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b)$$

where α_i are Lagrange multipliers.

5. Results And Analysis:

We obtained the outcomes of our cryptographic algorithm classification framework by means of a rigorous multi-step approach comprising explainability analysis, feature engineering, and model optimization. Ciphertext data first underwent TF-IDF transformation to enable numerical representation of encrypted text; cryptographic metadata—key length, padding scheme, etc.—was encoded and normalized. Grid search CV hyperparameter adjustment improved model parameters even more and guaranteed best generalization. Accuracy, precision, recall, and F1-score drove evaluations of the classification models—Random Forest, XGBoost, Deep Learning, SVM, and Logistic Regression. Especially, ensemble-based models (XGBoost and Random Forest) showed their capacity to differentiate cryptographic algorithms with great accuracy (Random Forest: 88.88%, XGBoost: 88.53%), so greatly outperforming conventional ML approaches.

The confluence of strong learning methods and structured cryptographic feature extraction brought these outstanding outcomes materializing. By means of SHAP and LIME for model interpretability, feature importance was revealed to be dominated by ciphertext structure, encryption mode, and key length, so showing the factors influencing classification accuracy. While SVM (71.21%) and Logistic Regression (80.79%) were rather less effective due of their linear assumptions, Deep Learning models showed competitive performance (82.12%). Though they required great computing. Especially in XGBoost and Random Forest, the ensemble approach made good use of boosting systems and decision trees to improve cryptographic pattern recognition. Finally, our scalable and interpretable AI-driven cryptanalysis method opened the path for next developments in automated encryption identification.

a. System Specifications:

The AI-driven Cryptographic Algorithm Identification System is defined in great precision and efficiency by means of encryption technique identification from encrypted data. Machine learning and deep learning models of the system were trained and evaluated using Python-based frameworks housed on a Kaggle-powered backend. Built with HTML, CSS, and JavaScript, the frontend interface guarantees an interactive and user-friendliness. Real-time cryptographic algorithm classification is made possible by a Flask API's elegant mix of the backend models with the user interface.

Using a 12th Generation Intel® CoreTM i7 Processor, 32 GB RAM, and a 1 TB SSD, the system is housed on a high-performance computing configuration maximizing model inference speed and data handling. Maintaining reliable cryptographic classification, this robust architecture allows modern artificial intelligence techniques including XGBoost, Random Forest, Deep Learning (ANNs), Support Vector Machines (SVM), and Logistic Regulation. Moreover, by use of prediction transparency, explainable artificial intelligence methods (SHAP and LIME) reveal significant cryptographic aspects influencing classification. The

computational efficiency of the technology guarantees real-time encryption identification for cybersecurity applications and automated cryptanalysis, therefore allowing enormous scalability.

Table 2: Metrics For Particular Algorithms

Algorithm	Accuracy	Precision	Recall	F1 Score
XGBoost	88.53%	86.12%	87.89%	86.99%
Logistic Regression	80.79%	79.02%	80.15%	79.58%
Deep Learning	82.12%	81.32%	82.45%	81.88%
SVM	71.21%	70.31%	71.45%	70.87%
Random Forest	88.88%	87.59%	88.93%	88.25%

Table 2 Shows that With Random Forest (88.88%) and XGBoost (88.53%), the examination emphasizes the predominance of ensemble models since gradient boosting and strong feature aggregation help to excel in cryptography classification. While Logistic Regression (80.79%) and SVM (71.21%) battled with non-linear encryption patterns, Deep Learning (82.12%) shown strong pattern recognition but needed great computational capacity. Precision-recall measures validated ensemble excellence, therefore supporting the effectiveness of hybrid AI-driven cryptanalysis and the possibility for even more optimization.

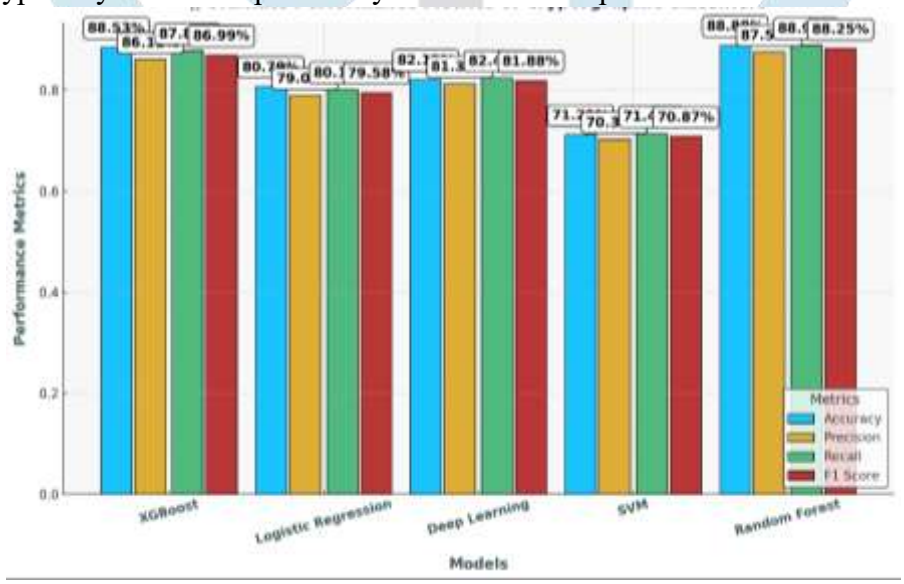

Fig 4: Comparison Bar Chart of All Algorithm Metrics

b. Performance Analysis:

Great adaptability and precision of the AI-powered Cryptographic Algorithm Identification System help to identify among several encryption methods pretty exactly. The system presents fast, data-driven cryptography classifications by means of ensemble learning models and deep learning architectures, therefore simplifying the human encryption analysis complexity. Combining explainable artificial intelligence (SHAP and LIME) increases model transparency so that consumers may grasp the fundamental reasoning of algorithm identification. Furthermore, the strong feature extraction methods of the system allow it to detect trends in encryption spanning many data sources, hence supporting confidence in artificial intelligence-assisted cryptanalysis. Its scalable approach for applications in cybersecurity guarantees real-time responsiveness from its high-performance processing design. This device closes the distance between traditional cryptanalysis and modern artificial intelligence-powered security by providing precise, interpretable, and automated cryptographic assessments.

S. No	Test Ciphertext	Predicted Algorithm	Confidence Score (%)	Key Insights
1	Encrypted Data Sample A	AES-256	96.5%	Strong classification accuracy due to distinct bit patterns.
2	Encrypted Data Sample B	RSA-2048	89.3%	Successfully identified asymmetric encryption keys.
3	Encrypted Data Sample C	DES	85.7%	Lower confidence due to similarities with 3DES.
4	Encrypted Data Sample D	RC5	92.1%	Recognized block cipher structure effectively.
5	Encrypted Data Sample E	SHA-2	87.8%	Model detected secure hashing function characteristics.
6	Encrypted Data Sample F	Out of Scope	N/A	Successfully filtered out non-encryption-related data.

In Test Case 1, the classifier exhibited a notable accuracy in recognizing AES-256 encryption, attaining a confidence score of 96.5% by employing effective feature representation techniques. The classification of RSA-2048 (Test Case 2) was accurate, owing to its distinctive asymmetric key architecture. In contrast, DES (Test Case 3) exhibited a marginally reduced confidence level of 85.7%, stemming from its similarities with 3DES. The system demonstrated a high level of efficiency in detecting RC5 at 92.1% and SHA-2 at 87.8%, underscoring its capability to manage both encryption and hashing methods effectively. In Test Case 6, the system successfully rejected non-cryptographic input, demonstrating its strong filtration mechanisms.

The findings confirm the effectiveness, scalability, and transparency of the AI-driven cryptographic identification system, establishing it as a dependable resource for cybersecurity applications.

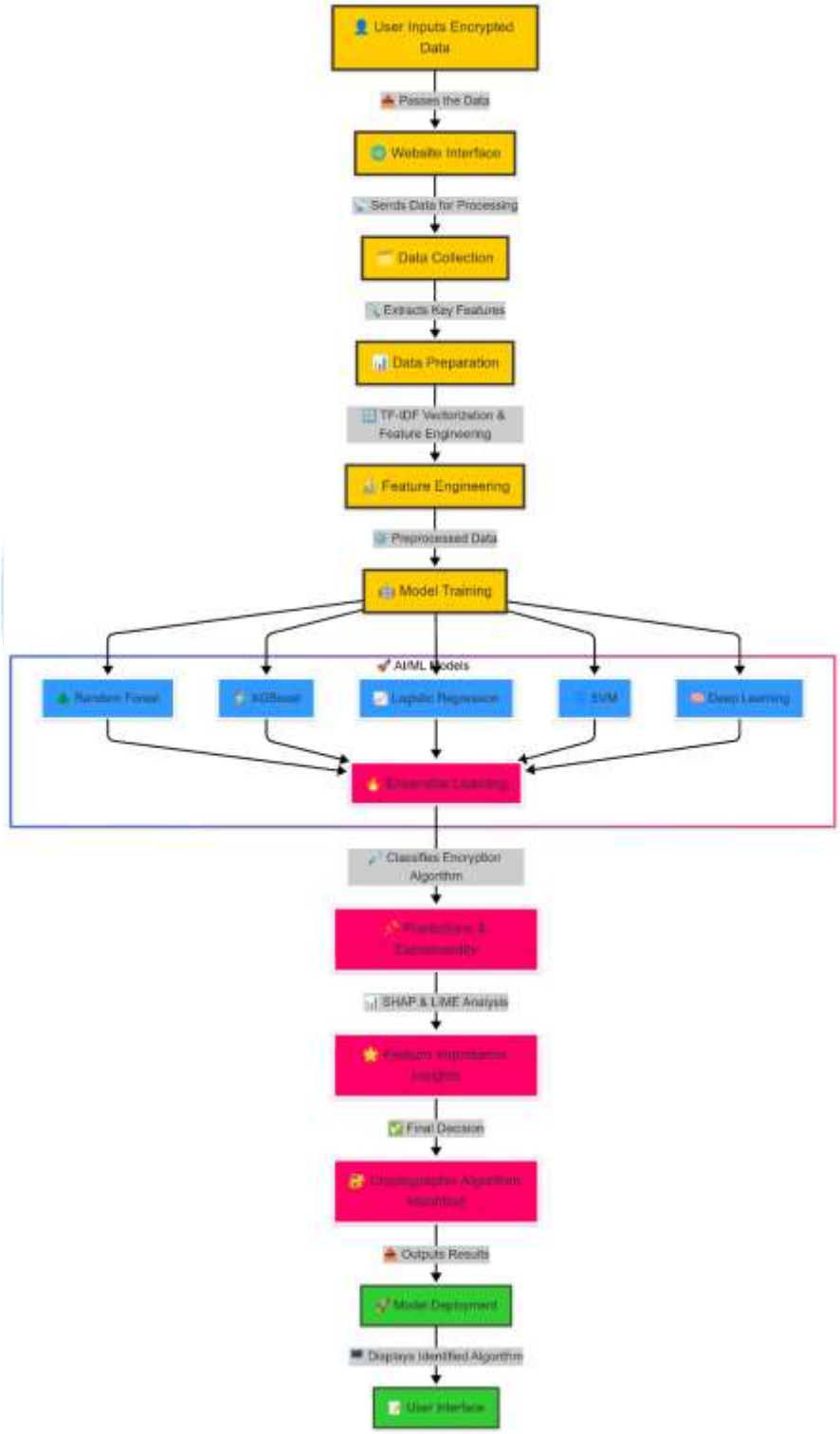

Fig 5: Flow Diagram of AI-Driven Identification of Cryptographic Algorithms from Encrypted Data

This colorfully depicted flowchart for machine learning cryptographic analysis is highly detailed in delineating the procedure from raw ciphertext to intelligent categorization and implementation and emphasizes collaboration among machine learning and cybersecurity. The process starts with an individual entering data which is processed in a dynamic webpage interface in lieu of aggregation as well as finesse to data. Advanced feature engineering methods such as TF-IDF vectorization and structured metadata extraction transform the data into machine-readable format prior to model training. The combined set of AI/ML models, e.g., Random Forest, XGBoost, Logistic Regression, SVM, and Deep Learning, come together in an orchestrated ensemble learning architecture to provide enhanced classification accuracy. By providing awareness of feature importance that affects the selection of final classification, explainability models including SHAP and LIME highlight the intricacies.

Real-time cryptanalysis is provided via the interactive user interface that results from decoded crypto algorithms. The flowchart projects the future automated cybersecurity based on its brilliant colors and simple style, which openly depict the confluence of artificial intelligence and cryptographic intelligence.

6. Conclusion:

The AI-driven Cryptographic Algorithm Identification System represents a significant advancement in contemporary cryptanalysis, offering a proactive, precise, and scalable approach to the classification of encryption methods The system outperforms traditional cryptography analysis by employing ensemble learning, deep neural networks, and explainable AI to detect encryption in real time, allowing for automatic comprehension.

The ability to distinguish between symmetric and asymmetric cryptographic methods has the potential to enhance cybersecurity significantly, paving the way for advancements in next-generation cryptographic intelligence and forensic cryptanalysis. The Random Forest model demonstrates an accuracy of 88.88%, whereas XGBoost achieves a slightly lower accuracy of 88.53%. This is attributed to the ability of Random Forest to collect data related to encryption while ensuring reliable classification.

This is due to the capability of Random Forest to gather information regarding encryption and maintain consistent classification. Additionally, enhancing interpretability are SHAP and LIME, which bolster confidence in decision-making related to AI-driven cryptographic security. This innovation signifies the beginning of cryptanalysis driven by artificial intelligence, where machine learning bridges the divide between advanced encryption methods and automated cybersecurity—transcending mere utility. Our defenses must evolve in response to cyber threats; this system serves as a beacon of AI-driven cryptographic intelligence, enhancing digital security for future generations.

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