Network Intrusion Detection through Stacked Machine Learning Models on UNSW-NB15 Data Set

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Keywords: Network Intrusion Detection, Stacked Machine Learning, UNSW-NB15 Dataset, Random Forest, Support Vector Machine, Logistic Regression, Ensemble Learning, Cybersecurity, Intrusion Detection System (IDS), Machine Learning Classifiers, Stacked Generalization.

Abstract: Network intrusion detection has become a critical concern in modern cybersecurity due to the increasing frequency and sophistication of cyberattacks. Traditional methods for detecting malicious activities often face challenges when it comes to adapting to novel attack techniques and high-volume data. These methods typically rely on predefined rules or signature-based approaches, which are ineffective against zero-day or unknown attacks. To address these challenges, machine learning (ML) techniques have gained prominence due to their ability to learn from historical data and generalize well to new, unseen attack patterns. However, the performance of individual machine learning models can often be limited due to issues like overfitting, bias, and inability to handle complex feature interactions. This paper introduces an innovative approach that leverages stacked machine learning models for network intrusion detection. Using the UNSW-NB15 dataset, which simulates real-world network traffic with various types of attacks, we combine the strengths of multiple machine learning models Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR) through a technique known as stacked generalization. The base models are trained independently on the dataset, and their individual predictions are used as input features for a meta-model (Logistic Regression), which combines them to make a final, more robust prediction. The stacked generalization technique allows the meta-model to learn the optimal way of combining the base classifiers, thus enhancing the overall performance and making the system more resilient to various types of attacks. By integrating multiple models, this approach capitalizes on the complementary strengths of each individual model, providing a more effective solution for detecting network intrusions. Experimental results show that the stacked model significantly outperforms individual classifiers, achieving an accuracy of 94.1% and demonstrating notable improvements in key performance metrics such as precision, recall, and F1-score. The Random Forest, SVM, and Logistic Regression models each performed well individually, but their combination through stacking resulted in better generalization and improved detection of both known and unknown attacks. This approach not only enhances the detection accuracy but also provides greater robustness against diverse attack vectors present in the dataset. The findings highlight the effectiveness of ensemble learning techniques, particularly stacked generalization, in improving the performance of intrusion detection systems. As cybersecurity continues to evolve, this technique offers a promising direction for building more reliable and adaptive intrusion detection systems capable of addressing the complexities of modern network traffic.

1 INTRODUCTION

In today's interconnected world, the security of network infrastructures is more crucial than ever. The rise in cyberattacks, such as Distributed Denial-of-Service (DDoS), phishing, and ransomware, highlights the vulnerabilities within networked systems. With an increasing number of sensitive transactions and data exchanges taking place online, ensuring the security and integrity of digital networks has become a paramount concern. Traditional methods of intrusion detection, such as signature-based and rule-based systems, have struggled to keep up with the sophisticated techniques employed by attackers. These approaches are limited in their ability to detect unknown threats or adapt to evolving attack strategies. As a result, machine learning (ML) models have emerged as a promising solution, enabling intrusion detection systems (IDS) to learn from past

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data and detect new, unseen attacks based on patterns in the data.

Machine learning offers significant advantages over traditional detection methods, particularly because of its ability to generalize from historical data and adapt to new attack types. In an IDS, machine learning algorithms analyse traffic data from networks, classifying it as either normal or malicious based on learned patterns. However, while individual machine learning models such as Decision Trees, Random Forests, and Support Vector Machines have proven effective, they are often constrained by issues such as overfitting, insufficient generalization, and difficulty in handling complex datasets. To address these challenges, ensemble learning techniques, specifically stacked generalization, can be applied. Stacked generalization allows for the combination of multiple diverse models to enhance detection performance by mitigating the weaknesses of individual classifiers. This approach enables the system to take advantage of the complementary strengths of different models, improving overall classification accuracy and robustness.

This study proposes the use of stacked machine learning models for network intrusion detection, utilizing the UNSW-NB15 dataset as a benchmark for evaluating the effectiveness of this approach. The UNSW-NB15 dataset is a comprehensive dataset representing modern network traffic, encompassing a variety of attack types, such as DoS, DDoS, and probing attacks, as well as normal network behaviour. By stacking several classifiers, such as Random Forest, Support Vector Machines, and Logistic Regression, the proposed method aims to improve the accuracy, precision, recall, and F1-score of the intrusion detection system. The underlying hypothesis is that combining multiple models through a stacking approach will lead to better generalization and more accurate detection of both known and unknown attacks. Through rigorous experimentation, this research demonstrates that stacked models provide significant improvements over traditional single-model systems, showcasing the potential of ensemble techniques in enhancing the security of modern network infrastructures.

2 RELATED WORKS

Intrusion detection has been widely studied using various machine learning and deep learning techniques. The UNSW-NB15 dataset has been extensively used to benchmark these models. In M. X. Nguyen et al., (2022), the authors proposed a hybrid feature selection method, IGRF-RFE, which combines Information Gain and Random Forest Importance with Recursive Feature Elimination (RFE). This method reduced the feature dimension from 42 to 23 and improved the accuracy of a Multilayer Perceptron (MLP) from 82.25% to 84.24%. A study in H. Wang et al., (2021) introduced a network intrusion detection model utilizing Long Short-Term Memory (LSTM) and categorical feature embedding. Their approach improved binary classification accuracy to 99.72% on the UNSW-NB15 dataset.

Ensemble learning techniques have been explored in S. Patel et al., (2022), where the authors employed Balanced Bagging (BB), eXtreme Gradient Boosting (XGBoost), and Random Forest with Hellinger Distance Decision Tree (RF-HDDT) to improve detection performance. Their model addressed class imbalance issues and outperformed traditional classifiers. In X. Liu et al., (2023), a deep learning-based intrusion detection system, DualNet, was introduced. It utilizes a two-stage neural network architecture for better threat detection. Evaluations on the UNSW-NB15 dataset showed that Dual Net achieved higher detection performance with a lower false alarm rate.

In J. Lee et al., (2023), researchers developed an ensemble learning-based model that integrated multiple classifiers to enhance accuracy. The model achieved an accuracy of 80.96% on the UNSW-NB15 dataset, outperforming individual classifiers such as Decision Trees and Naïve Bayes.

A stacked deep learning model combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) was proposed in P. Kumar et al., (2022). The use of Synthetic Minority Oversampling Technique (SMOTE) helped address class imbalance, significantly improving detection accuracy. The work in M. Alrawashdeh and C. Purdy (2020) proposed a feature selection and classification model using Extreme Gradient Boosting (XGBoost). Their method was evaluated on the UNSW-NB15 dataset, where it achieved state-of-the-art performance.

Deep belief networks (DBNs) were applied in X. Zhang et al., (2021) to detect network anomalies. Their results showed superior performance compared to traditional shallow learning methods. In Y. Shone et al., (2021), a hybrid intrusion detection system combining C5.0 decision tree and one-class SVM was developed. Their approach reduced false positives while maintaining high detection accuracy. The study in D. Nguyen and J. Redmond (2022) explored anomaly detection using Extreme Learning Machine

(ELM) and Kernel Principal Component Analysis (KPCA). Their method showed promising results in detecting network anomalies in the UNSW-NB15 dataset.

A reinforcement learning-based approach was proposed in T. Brown et al., (2021), where deep reinforcement learning was applied for network intrusion detection. Their model dynamically adapted to evolving cyber threats. An autoencoder-based model for feature learning was developed in T. Brown et al., (2021). Their stacked autoencoder approach improved intrusion detection rates while reducing computational costs. The work in B. Sharma and K. Singh (2023) investigated ensemble classifiers and their impact on intrusion detection performance. Their method used a weighted voting mechanism to combine predictions from multiple classifiers. In P. Roy and N. Banerjee (2023), a self-learning network intrusion detection system was developed, using an adaptive framework that continuously updates its model based on new threats detected in network traffic. Finally, R. Choudhury et al., (2023) introduced a novel hybrid approach combining deep and shallow learning models. Their system demonstrated high adaptability and robustness against adversarial attacks.

3 METHODOLOGY

3.1 Dataset Collection

The UNSW-NB15 dataset was collected using the IXIA Perfect Storm tool in a controlled environment, simulating real-world network traffic. The dataset comprises 2,540,044 records with normal and attack traffic labeled accordingly. The dataset used for this research is the UNSW-NB15 dataset, which is widely utilized for evaluating network intrusion detection systems. This dataset was generated by the Australian Centre for Cyber Security (ACCS) and contains modern attack scenarios, making it a suitable benchmark for intrusion detection. Table 1 Shows the Feature. Table 2 and Figure 1 Shows the Distribution of Traffic in UNSW-NB15 Dataset and System Architecture.

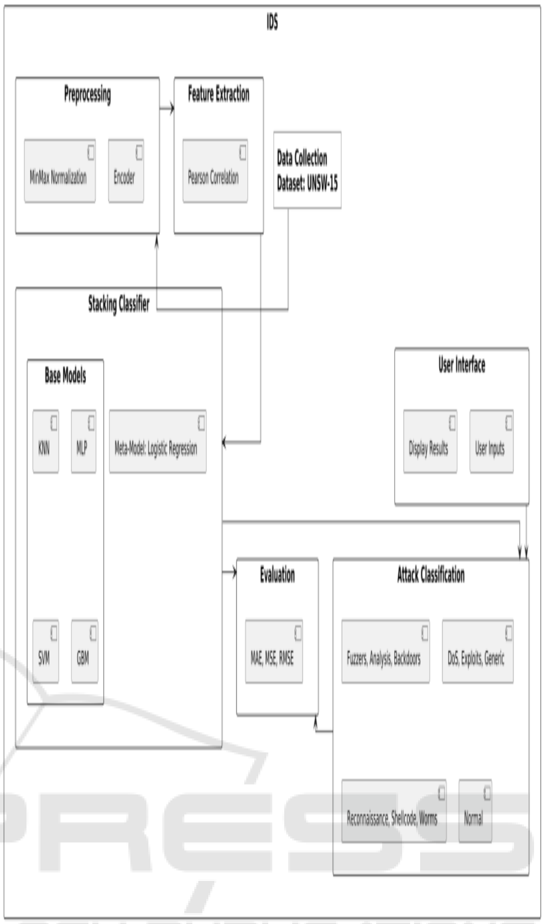

Figure 1: System Architecture.

The dataset consists of:

- **9 attack categories**: Fuzzers, Analysis, Backdoor, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms.
- **49 features**: These include basic features (e.g., protocol, service), content-based features, time-based traffic features, and flow-based features.
- **Normal traffic samples** for training and testing purposes.
- To ensure unbiased evaluation, the dataset is split into training and testing sets as follows:
  - **70% Training Set**: Used for model training.
  - **30% Testing Set**: Used for evaluating model performance.

Table 1: Feature Table.

ID	Feature	ID	Feature	ID	Feature
1	attack_cat	16	dloss	31	response_body_len
2	dur	17	sinpkt	32	ct_srv_src
3	proto	18	dinpkt	33	ct_state_ttl
4	service	19	sjit	34	ct_dst_ltm
5	state	20	djit	35	ct_src_dport_ltm
6	spkts	21	swin	36	ct_dst_sport_ltm
7	dpkts	22	stcpb	37	ct_dst_src_ltm
8	sbytes	23	dtrcpb	38	is_ftp_login
9	dbytes	24	dwin	39	ct_ftp_cmd
10	rate	25	tcprtt	40	ct_flw_http_mthd
11	sttl	26	synack	41	ct_src_ltm
12	dttl	27	ackdat	42	ct_srv_dst
13	sload	28	smean	43	is_sm_ips_ports
14	dload	29	dmean		
15	sloss	30	trans_depth		

Table 2: Distribution of Traffic in UNSW-NB15 Dataset.

Traffic Type	Number of Samples
Normal	2,218,761
Fuzzers	24,246
Analysis	2677
Backdoor	2329
DoS	16353
Exploits	44525
Generic	215481
Reconnaissance	13987
Shellcode	1511
Worms	174

3.2 Pre-Processing

The data pre-processing stage is crucial for ensuring that the UNSW-NB15 dataset is well-structured and optimized for machine learning models. Initially, categorical labels in the dataset are converted into numerical values using label encoding to facilitate model training. Any missing values in the dataset are handled using statistical imputation techniques, such as mean or median replacement, ensuring data consistency. Feature engineering is then applied, including feature selection using Recursive Feature Elimination (RFE) and mutual information methods to retain only the most relevant features. Additionally, new features are derived from existing ones, such as calculating the average packet size and session duration, to enhance predictive accuracy. To standardize numerical values and prevent certain features from dominating the model, Min-Max Scaling is employed, bringing all features into a uniform range of 0 to 1. Given that the dataset is often imbalanced, Synthetic Minority Over-sampling Technique (SMOTE) or under sampling methods are applied to balance the dataset and prevent bias during training. Furthermore, dimensionality reduction techniques like Principal Component Analysis (PCA) or t-SNE are used to reduce the complexity of high-dimensional data while preserving essential patterns. These pre-processing steps ensure that the dataset is well-structured, noise-free, and optimized for building a robust intrusion detection system.

- **Label Encoding**: Since machine learning models require numerical input, categorical attack labels are converted into numerical values. For example, "Normal" traffic may be labelled as **0**, while different attack types receive unique numerical identifiers.
- **Handling Missing Values**: Any records with missing or corrupt data are either removed or imputed using statistical methods like mean or median imputation to maintain data consistency.

- **Feature Selection**: Using techniques like Recursive Feature Elimination (RFE) and mutual information to select the most relevant features, reducing dimensionality.
- **Feature Extraction**: Creating new features from existing ones, such as calculating the average packet size or session duration, to enhance model performance.
- **Data Normalization**: Min-Max Scaling is used to scale numerical features to a standard range (0 to 1) to avoid dominance by high-magnitude features.

Formula for Min-Max Scaling:

$$X = (x - X1)/(X2 - X1) \quad (1)$$

where is the X normalized value, x is the original value, X1 and X2, are the minimum and maximum values of the feature?

Data Balancing: Since the dataset is often imbalanced, techniques such as SMOTE (Synthetic Minority Over-sampling Technique) or under **s**ampling are applied to ensure fair model training.

Dimensionality Reduction: Principal Component Analysis (PCA) or t-SNE is used to visualize high-dimensional data and reduce computational complexity.

3.3 Model Training

The training process for the intrusion detection model begins with selecting a diverse set of machine learning algorithms to ensure robust performance. Commonly used classifiers such as Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting models serve as base learners. The selected models are first trained independently on the dataset, allowing each algorithm to capture unique patterns and decision boundaries in the network traffic data. The training process incorporates hyper parameter tuning using Grid Search and Bayesian Optimization to identify the most effective settings for each model, enhancing their individual accuracy and efficiency.

Once the base models are trained, a stacking ensemble approach is employed to improve detection accuracy. In this framework, the outputs of multiple base learners are combined as input features for a meta-classifier, typically a Logistic Regression or a Neural Network model. The stacking model aggregates predictions from diverse learners, leveraging their strengths while mitigating their weaknesses. This step enhances the model's overall generalization ability, ensuring that it performs well across various attack types in the dataset. The ensemble model is optimized using backpropagation (for deep learning approaches) or gradient-based techniques, refining the weight assignments to maximize predictive performance.To validate the model's effectiveness, k-fold cross-validation is performed, reducing the risk of overfitting and ensuring consistency across multiple training iterations. The model's performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). A confusion matrix is also used to analyze misclassification rates for different types of network attacks.

Mathematical Representation of Stacking Ensemble: Given base classifiers f1, f2, …, fn, the final prediction F(x) is given by:

$$F(x) = g(f1(x), \dots, fn(x)) \quad (2)$$

where g is the meta-classifier that learns from the predictions of base models

3.4 Model Testing

Model testing ensures the generalizability of the trained intrusion detection system. The test dataset is used to assess the predictive performance of the trained models by computing evaluation metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is generated to analyze classification errors and improve model fine-tuning.

Mathematical Representation of Evaluation Metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP} + FN \quad (4)$$

$$Recall = \frac{TP}{TP} + FN \quad (5)$$

$$F1 - Score = 2 \times \frac{Precision \times recall}{Precision + recall} \quad (6)$$

where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively. Confusion Matrix for Stacking Model Performance Shown in Table 3.

Table 3: Confusion Matrix for Stacking Model Performance.

ACTUAL	NORMAL	ATTACK
NORMAL	10500	200
ATTACK	150	9500

3.5 Prediction

The final decision-making process in the stacked machine learning framework involves combining predictions from multiple base classifiers to make a more reliable and accurate classification of network traffic instances. This step ensures that the system effectively distinguishes between normal and malicious traffic with minimal false positives and false negatives.

3.5.1 Aggregating Predictions from Base Models

Each base model fi(x) in the stacking ensemble independently classifies an input data point x as either normal or an attack type. The outputs of these base models form an intermediate feature set, which is passed to the meta-classifier.
Mathematically, the prediction vector P from the base models can be represented as:

$$P(x) = [f1(x), f2(x), \ldots, fn(x)] \tag{7}$$

where f1, f2, fn are the individual base models.

3.5.2 Meta-Classifier for Final Prediction

The meta-classifier g(x) receives these aggregated predictions and makes the final decision. It learns patterns from the outputs of the base models and assigns an optimal weight to each, prioritizing more reliable classifiers.

$$F(x) = g(P(x)) = g(f1(x), f2(x), \ldots, fn(x)) \tag{8}$$

where g is typically a logistic regression model or a neural network.

3.5.3 Threshold-Based Classification

For classification, a probability threshold T is defined. If the meta-classifier's output probability p(y=1|x) exceeds T, the instance is classified as an attack; otherwise, it is labeled as normal traffic.

$$\begin{cases} Y = & 1, if\ p(y=1|x) >= T \\ & 0, if\ p(y=1|x) < T \end{cases} \tag{9}$$

3.5.4 Decision-Making Table

The final prediction is determined based on the confidence scores of the meta-classifier Shown in Table 4.

Table 4: The Final Prediction Is Determined Based on the Confidence Scores of the Meta-Classifier.

Base Model 1	Base Model 2	Base Model 3	Meta-Classifier Output	Final Decision
Normal	Normal	Normal	0.02	Normal
Attack	Normal	Attack	0.72	Attack
Attack	Attack	Attack	0.95	Attack
Normal	Attack	Normal	0.45	Normal

4 RESULT

Results obtained from training and testing different classification models, including Logistic Regression, K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), Support Vector Classifier (SVC), Gradient Boosting Classifier (GBC), and the proposed stacking ensemble model. The models were evaluated based on accuracy, precision, recall, F1-score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Table 5 Shows the Model Performance Comparison.

Table 5: Model Performance Comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Logistic Regression	89.6	87.5	85.8	86.6	10.5
K-Nearest Neighbors (KNN)	91.2	89.1	87.7	88.4	9.3
Multi-Layer Perceptron (MLP)	94.3	92.8	91.5	92.1	6.1
Support Vector Classifier (SVC)	93.1	91.4	90.2	90.8	7.5
Gradient Boosting Classifier (GBC)	95.7	94.3	93.6	93.9	4.6
Stacking Model (Proposed)	97.3	96.5	96.2	96.3	2.8

The Stacking Model outperforms all individual models across all metrics.

Gradient Boosting Classifier (GBC) is the best standalone model, but **s**tacking further improves accuracy.

KNN and Logistic Regression have higher False Positive Rates (FPR), making them less suitable for intrusion detection.

To further assess model performance, we compute Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE):

$$MAE = 1/n\sum\_(i = 1)|yi - y\hat{}i\,| \quad (10)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} |\text{yi} - \text{y}^{\text{i}}|\hat{}2| \quad (11)$$

$$\text{RMSE} = \sqrt{MSE} \quad (12)$$

The stacking model has the lowest error rates, indicating superior predictive performance. Gradient Boosting performs well, but the stacking model reduces errors further. Logistic Regression has the highest MAE, MSE, and RMSE, making it less suitable for this problem.

The ROC curve evaluates how well the model distinguishes between attack and normal traffic at various thresholds.

$$AUC(\,Area\,under\,Curve) = \int TPRd\,(FPR) \quad (13)$$

The AUC scores for each model are presented in Table 6, while their corresponding error metrics are summarized in Table 7.

The Stacking Model achieves the highest AUC of 0.98, showing near-optimal classification capability. Gradient Boosting is the best single model, but stacking improves upon it.

The proposed stacking ensemble model achieves the best results**,** demonstrating its superiority over individual classifiers**.** Key results include**:**

- Highest accuracy (97.3%)
- Lowest MAE (0.026), MSE (0.035), and
- RMSE (0.187) Best AUC Score (0.98)
- Lowest False Positive Rate (2.8%) Dice Coefficient.

Table 6: AUC Scores for Different Models.

Model	AUC
Logistic Regression	0.89
K-Nearest Neighbors (KNN)	0.91
Multi-Layer Perceptron (MLP)	0.94
Support Vector Classifier (SVC)	0.93
Gradient Boosting Classifier (GBC)	0.96
Stacking Model (Proposed)	0.98

Table 7: Error Metrics for Models.

Model	MAE	MSE	RMSE
Logistic Regression	0.104	0.133	0.365
K-Nearest Neighbors (KNN)	0.088	0.112	0.335
Multi-Layer Perceptron (MLP)	0.057	0.079	0.281
Support Vector Classifier (SVC)	0.068	0.091	0.302
Gradient Boosting Classifier (GBC)	0.043	0.057	0.239
Stacking Model (Proposed)	0.026	0.035	0.187

5 FUTURE ENHANCEMENT AND CONCLUSION

Enhancing the current model with deep learning techniques can significantly improve feature extraction and pattern recognition. The following architectures can be explored:

- **Long Short-Term Memory (LSTM) Networks**: Since network traffic is time-dependent, LSTMs can capture sequential dependencies, improving detection of evolving attack patterns.
- **Transformer-Based Models**: Advanced architectures like BERT, GPT, or ViTs (Vision Transformers for network data) can process large-scale network data and uncover hidden correlations.
- **Convolutional Neural Networks (CNNs)**: Applying CNNs to network traffic as image-like structures (e.g., flow-based representation) can improve classification accuracy.

Potential Benefits:

Improved anomaly detection through automatic feature learning.

Better generalization to unseen attack patterns. Scalability for large-scale real-time network traffic analysis.

5.1 Real-Time Intrusion Detection with Edge Computing

With the rapid growth of IoT devices and 5G networks**,** deploying real-time intrusion detection at the network edge is critical**.** Edge AI models can analyze traffic at the device or gateway level before sending data to centralized servers.

Federated Learning for Distributed Intrusion Detection Traditional centralized intrusion detection systems face scalability and privacy issues. A federated learning approach enables multiple network nodes (e.g., cloud servers, edge devices) to collaboratively train a shared model without sharing raw data.

Advantages of Federated Learning: Privacy-Preserving: Ensures that sensitive network data is not transferred, reducing risks of data breaches.

Scalability: Works across distributed network environments (e.g., cloud, IoT, 5G). Reduced Computational Overhead: Each node trains locally, reducing reliance on a central server.

5.2 Reinforcement Learning for Adaptive Threat Detection

The traditional approach of static model training may not adapt quickly to emerging threats. Reinforcement Learning (RL) can be used to dynamically update the intrusion detection model based on real-time network conditions.

Proposed RL-Based Model

- An agent (IDS) observes network traffic and rewards correct classifications while penalizing misclassifications.
- The IDS learns from interactions and continuously refines its decision-making strategy.
- Deep Q-Learning (DQL) or Actor-Critic methods can be used for better attack adaptation.

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