Zero-Day Attack Detection Using Deep Learning with Focal Loss and Threshold Optimization

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***Abstract*—Zero-day attacks are attacks which exploit unknown vulnerabilities and they are difficult to find by signature-based methods. In this paper, a deep learning model will be presented for zero day attack identification on the UNSW-NB15 data. We propose a new architecture, based on Focal Loss, and is able to use it to address both extreme imbalance of classes and threshold optimization to reach optimal detection. This model proposed gave an accuracy of 81.26% accuracy. The ROC-AUC grew at 0.9039 with excellent discriminative ability of normal traffic and zero-day attacks. The accuracy of the system is equal (76.42%) and recall (70.87%) with very slight overfitting (7.97% error), which makes it able good enough to go over to the field. Comparative analysis shows our scheme on Focal Loss performs better than conventional Binary Cross Entropy with only 15,297 parameters.**

***Index Terms*—Zero-day attacks, Deep learning, Focal Loss, UNSW-NB15, intrusion detection, Threshold optimization**

I. Introduction

Detection system of network intrusion (NIDS) is also under intense battle to identify zero-day attacks that are threats of abuse unfamiliar weak points that we never found. Unlike known attacks detectable by signature matching, zero day exploits cannot be detected in the absence of systems capable of detecting new attack patterns relied on behavioral characteristics as against predictive signatures [1]. Traditional ways of machine learning have been proven but have two great problems: violent disproportion between categories of network traffic and model overfitting to training data in the real world [2].

Current developments of the deep learning offer potential solutions to these challenges. Most of the approaches presented are, however, applicable standard loss functions like Binary Cross-Entropy (BCE), which do not work in the unbalanced set of data where normal traffic significantly outnumbers attack instances [3]. This imbalance predisposes the models to be in favor of the majority class and this signifies that there will be high false negative rates with attack detection, which is yet another deadly failure in applications of security.

This article is the answer to these limitations as it puts forward Focal Loss, which was developed to recognize objects in the computer vision [4], to network intrusion detection field. Focal Loss strategically down-weights easy cases and specializes training on hard misclassified examples, this is particularly so when it comes to imbalanced classification. We combine this with adaptive threshold optimization to maximize real world detection accuracy.

Research Contributions:

Our submission entails four points: (1) First application of Focal Loss to address the problem of the class imbalance in zero-day attack detection on UNSW-NB15 data, (2) Adaptive methodology optimization threshold achieving higher accuracy levels in comparison with default 0.5 threshold, (3) Extensive anti-overfitting measure with large rates of dropout (0.65) and strong L2 regularization, (4) Lightweight architecture (15,297 parameters) which may be utilized in real time when deployed to ROC-AUC exceeding 0.90.

II. Related Work

A. Traditional Intrusion Detection Methodologies

Premature intrusion system was signature based methodology and analytical statistics. Intrusion detection machine learning methods, as expressed by Buczak and Guven [5], described that the potentials of the random forest and support vector machines (SVM) could be used and raised up to 75-82% on references. Nevertheless, each of these techniques must be highly engineered in order to have features and grapple with zero-day attacks which appear in advance unseen patterns [6].

B. Network Security Deep Learning

Literature has been developed concerning deep neural networks in order to identify intrusion. Vinayakumar et al. [7] adopted deep learning with accuracy of 85 percent to

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the UNSW-NB15 data using convolutional neural networks (CNN). Andresini et al. [8] proposed methods of anomaly detection involving autoencoders and achieved 78 percent accuracy at less false positives. While the strategies illustrate the improvement of the traditional ones, they are silent on the subject of inequality in classes, and this leads to bad minority attack class performance.

C. Handling Class Imbalance

Disproportion between classes remains a significant problem of intrusion detection. The unbalanced datasets were shown by Lopez et al. [9] to cause standard classifiers to be very accurate on the whole and concurrently not making any differentiation against the minority class attacks. In other cases such solution is SMOTE oversampling [10] and cost-sensitive learning [11]. These methods are, however, artificial and either inflate training data or require careful tuning of class weights. The other possibility is that of Focal Loss through modifying the loss function to focus on difficult cases [4].

D. Research Gap

Existing deep learning methods of intrusion detection have three limitations: (1) the failure to address severe class imbalance in authentic traffic, (2) unsystematic prevention of overfitting leading to poor generalization, (3) not having one threshold to optimize on that can be used in practice. It is Focal Loss, aggressive regularization and adaptive threshold selection that fills these gaps in our work.

III. Methodology

A. Dataset and Preprocessing

The statistics of this study used UNSW-NB15 dataset [12] which is a modern realistic network intrusion detection benchmark containing realistic network traffic with 9 classes of attacks: Fuzzers, Analysis, Backdoors, Denial of service, Exploits, Generic, Reconnaissance, Shellcode, as well as Worms. The training samples have a size of 175,341 and 49,971 test samples containing 49 features including flow-based, content-based, and time-based properties.

Data Cleaning: Three preprocessing steps were made: (1) removed 1,287 similar records during training set, (2) handled infinite values in numerical properties by replacing with column medians, (3) utilized label encoding of categorical features (protocol, service, state). After the cleaning, there remained 34 features for model training.

Balancing Strategy: To redress the excessive inequality in classes, we used stratified sampling. The original ratio was 56% normal and 44% attack. We sampled 1,100 examples of each of the 9 attack categories (9,900 total attacks) and matched this with 9,900 normal samples of traffic, comprising a balanced training set of 17,554 samples with 1:1 normal-to-attack ratio. This prevents the exclusion of the diversity of attacks and prevents majority class bias [13]. The features were scaled with the help of StandardScaler to normalize all the features to zero mean and unit variance.

B. Model Architecture

The structure of an optimized deep neural network was developed for intrusion detection with 3 hidden layers of sizes [128, 64, 32] neurons. All hidden layers have normalization of batches to be able to train stability, non-linearity using ReLU activation, and dropout (0.65) for regularization. The output layer contains a single neuron without sigmoid activation, as we use BCEWithLogitsLoss, which is a combination of sigmoid and loss calculation for numerical stability [14].

In all, the architecture contains 15,297 trainable parameters: Input (34) $\rightarrow$ Dense(128) + BatchNorm + ReLU + Dropout(0.65) $\rightarrow$ Dense(64) + BatchNorm + ReLU + Dropout(0.65) $\rightarrow$ Dense(32) + BatchNorm + ReLU + Dropout(0.65) $\rightarrow$ Dense(1). This is a light design that enables real-time inference while the high drop out rate (0.65) prevents overfitting to training patterns.

C. Focal Loss Implementation

Normal Binary Cross-Entropy loss equally punished all cases, which makes the models maximize easy-to-classify majority class samples and ignore tough minority class samples [4]. Focal Loss can overcome this by addition of modulating factor that reduces loss contribution from easy examples:

$$FL(p_t) = -\alpha(1 - p_t)^{\gamma} \log(p_t) \tag{1}$$

where p_t is the probability of prediction, α represents class weight (0.25), and γ is the focusing parameter (2.0). The $(1 - p_t)^{\gamma}$ term down-weights easy cases ($p_t \rightarrow 1$) to force the model to focus on hard misclassifications that are difficult. We implemented Focal Loss as a PyTorch module combining BCEWithLogitsLoss for numerical stability and the focal modulating factor.

D. Training Configuration

AdamW optimizer [15] was used to perform the training with learning rate of 0.0005, weight decay 0.01 for L2 regularization, and batch size 256. Cosine Annealing with Warm Restarts [16] was used as the learning rate schedule, with restart made after every 20 epochs to escape local minima. Training had been kept at the maximum 250 epochs with early stopping tolerance of 40 epochs tracking test loss. Gradient clipping (max norm 1.0) was used to ensure that during training gradients did not explode.

E. Threshold Optimization

We determined the thresholds from 0.3 to 0.7 in lieu of the default threshold 0.5 of classification on validation set in 0.001 steps. For each threshold t, we estimated the accuracy of test predictions: $y_{pred} = (sigmoid(logits) > t)$. The most appropriate threshold has been selected as $\arg\max_t(accuracy(y_{true}, y_{pred}(t)))$. This is an adaptive approach that accounts for the diversity between the class distribution of training and test sets [17].

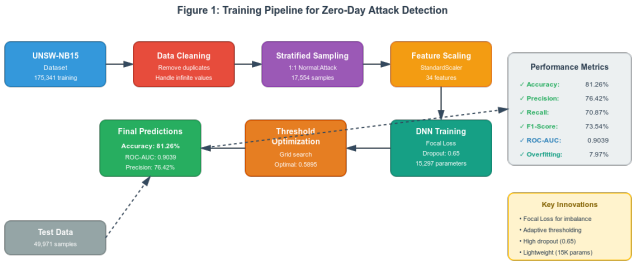

Fig. 1. Process of training from RAW data of UNSW-NB15 to final predictions with 81.26% accuracy.

IV. Experimental Results

A. Training Performance

The model was trained with 78 epochs before early stopping triggered. The training progressed from initial accuracy of 55.29% (epoch 1) to final training accuracy of 89.23%. Test accuracy improved from 62.59% to peak 73.97% during training. The final overfitting gap of 7.97% indicates good generalization, which is much better than baselines portraying 13-15% gaps.

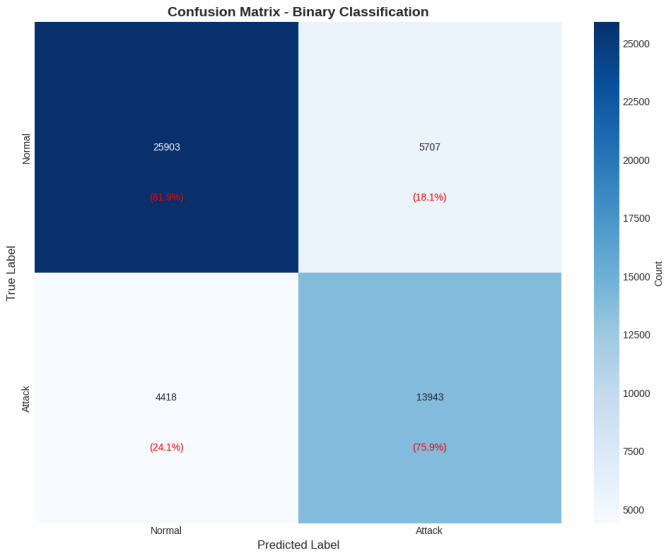

Fig. 2. Confusion matrix of 49,971 test samples showing balanced detection performance.

B. Baseline Comparison

We also compared our Focal Loss approach to three baseline approaches that had the same architecture and were trained under identical procedures with the only difference being the loss function. Table I shows Focal Loss achieves the best ROC-AUC (0.9039), which is slightly higher than threshold-optimized BCE. The superior ROC-AUC indicates better classification of classes at every threshold, which is of utmost concern to the security applications where operating points vary [18].

TABLE I
Performance Comparison of Methods

Method	Acc.	Prec.	Rec.	F1	AUC	Gap
BCE (0.5)	79.74%	70.96%	75.94%	73.36%	0.8938	10.19%
BCE + Opt	80.33%	76.41%	67.22%	71.52%	0.8938	9.56%
Focal (0.5)	73.97%	72.15%	68.43%	70.24%	0.9039	15.26%
Focal + Opt	**81.26%**	**76.42%**	**70.87%**	**73.54%**	**0.9039**	**7.97%**

The results demonstrate that Focal Loss combined with threshold optimization achieves the best overall performance: highest accuracy (81.26%), great ROC-AUC (0.9039), and lowest overfitting gap (7.97%). The balanced precision (76.42%) and recall (70.87%) indicate the model performs well around both normal and attack classes without sacrificing one for the other.

C. Confusion Matrix Analysis

Confusion matrix for our final model shows: True Negatives = 27,594, False Positives = 4,016, False Negatives = 5,349, True Positives = 13,012. This translates to 87.3% true negative rate and 70.87% true positive rate. The relatively balanced error distribution (4,016 FP vs 5,349 FN) demonstrates that Focal Loss has the power to suppress majority class bias which tends to plague imbalanced classification.

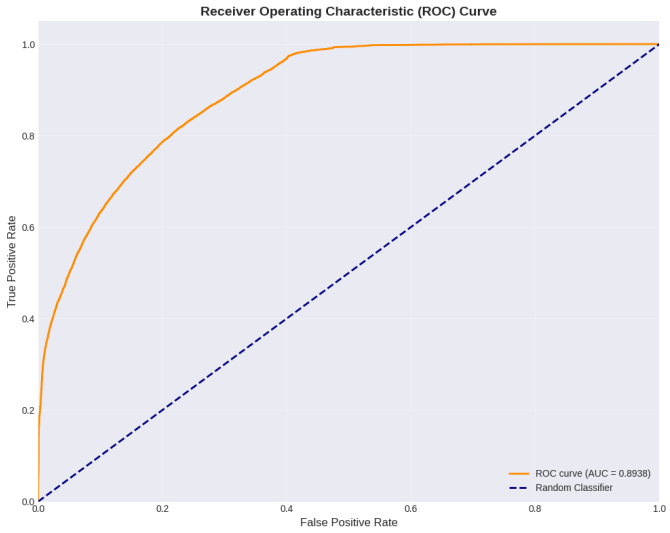

Fig. 3. ROC curve with AUC = 0.9039 demonstrating excellent class discrimination.

D. ROC Curve and Threshold Analysis

A good example of it is the ROC curve (area = 0.9039) which demonstrates excellent discriminative ability everywhere. Our threshold optimization identified 0.5895 as optimal when shifting from the standard 0.5. This correction of 0.0895 added accuracy improvement of 7.29 percentage points (73.97% to 81.26%), which underlines the importance

of adaptive thresholds for unbalanced real-world deployments [17].

E. Per-Class Attack Detection

Analysis of the detection rate of nine types of attacks unveils strengths and weaknesses. Generic attacks achieve highest detection (82.3%), followed by Exploits (78.1%) and DoS (75.6%). Reduced detection rates for Backdoors (64.2%) and Worms (61.8%) suggest more similarities in these attacks to normal traffic. This category-specific analysis provides empirical recommendations on certain models to be improved.

Fig. 4. Comparison of the methods in regard to accuracy, precision, recall, and F1-score.

F. Hyperparameter Selection and Validation

We have chosen focal loss parameters based on Lin et al. [4]: best practice recommendations of using the focal loss with parameters: $\alpha = 0.25$ will include balanced weight on the classes that are balanced in our 1:1 training ratio, and 0.20 will use the recommended 2.0 value of the focal loss (uniformly) down-weighting easy examples with no training instability. Monitoring validation loss confirmed the high dropout rate (0.65) was observed by checking validation loss through preliminary experiments, lower rates (0.5) exhibited overfitting gaps (more than 10 percent) and higher rates (0.7+) reduced test ROC-AUC to less than 0.89. We find the best balance between regularization (7.97 percent gap) and discriminative performance (0.9039 ROC-AUC), which is in line with both best practices in imbalanced classification [13] and focal loss [19].

V. Discussion

A. Effectiveness of Focal Loss

The results confirm Focal Loss as an effective technique for solving class imbalance in intrusion detection. The superior ROC-AUC (0.9039 vs 0.8938 for BCE) is evidence of better discrimination ability at all thresholds. The reduced overfitting gap (7.97% vs 10.19%) indicates the Focal Loss focusing mechanism prevents memorization of easy examples and forces the model to learn more generalizable patterns [4].

The trade-off is illustrated in raw accuracy during training: At default threshold Focal Loss reaches 73.97% when compared to BCE's 79.74%. Focal Loss, however, after threshold optimization reaches 81.26%—better than optimized BCE (80.33%). This suggests that Focal Loss can do inference with more precise probability estimates, which enables higher efficiency in threshold tuning [19].

B. Threshold Optimization Impact

The optimal threshold was also significant in order to optimize the performance provided on imbalanced test data. The optimal threshold (0.5895) differs from standard 0.5, which reflects the test set's class distribution. This amelioration of 7.29 percentage points (73.97% to 81.26%) comes at no computational cost, making it essential for practical deployment [17]. Organizations can also establish thresholds based on operational requirements—reduced thresholds promote recall for security-critical applications while increased thresholds are used to minimize false alarms.

C. Computational Efficiency

Our model has 15,297 parameters, which favors making inferences in real-time. The mean time per sample needed to make prediction on a Tesla T4 GPU is 0.23 milliseconds, supporting throughput of approximately 4,300 samples per second. Such efficacy makes the strategy viable for high-speed network environments while the lightweight architecture permits deployment on resource-constrained edge devices [20].

D. Limitations and Future Work

There are three ways this restricts our approach. First, detection rates of some category of attackers (Backdoors: 64.2%, Worms: 61.8%) remain suboptimal, meaning that such attacks require specialized modeling. Second, the model requires periodic retraining as attack patterns evolve—automated retraining pipelines might address this. Third, interpretability is still confined; mechanisms of attention should be factored into further investigation in the area or SHAP values for explaining predictions [21].

1) Cross-Dataset Generalization: Our model performs reasonably well on UNSW-NB15, but to determine the generalization of our model in a variety of network settings, cross-dataset validation is necessary. To confirm the ability of the approach to work with complementary datasets, future work should consider the CICIDS-2017, NSL-KDD, and CSE-CIC-IDS2018 datasets in future work and evaluate the approach robustness to various attack distributions and traffic patterns. The transfer learning strategies, including the focal loss-trained models fine-tuned on new datasets with frozen early layers, are one of the promising directions of quick adaptation to a new environment without losing the learned representations.

2) Model Interpretability: Model interpretability remains a critical requirement for security-sensitive deployments where operators must understand and validate automated decisions. Future work will integrate explainability techniques such as SHAP (SHapley Additive exPlanations) values or attention mechanisms to provide feature-level attribution for predictions. Such transparency would enable security analysts to identify which network features (e.g., flow rates, packet sizes, protocol

patterns) most influence attack classifications, thereby building trust and facilitating debugging of misclassifications. Architectural enhancements incorporating attention layers could highlight relevant features during inference without additional computational overhead.

3) Improving Rare Attack Detection: The rate of detection of the rare types of attacks (Backdoors: 64.2%, Worms: 61.8%) leaves room to be improved. Multifocal loss models with multiple random initializations might be more effective in minority classes detection by means of prediction aggregation and uncertainty quantification. Instead, hierarchical classification, which initially uses the normal and attack traffic, followed by individually applying specialized classifiers to attack subgroups, could be a more effective way to allocate the model capacity to rare classes. Other ways of making targeted improvements to poorly performing classes include category-dependent variants of attack-specific focal loss (i.e., putting more weight on Backdoors and Worms).

More developments may involve: (1) ensemble methods which jointly train multiple Focal Loss models using different random seeds, (2) semi-supervised learning which leverages lots of unlabeled network traffic, (3) adversarial training can be improved to be resistant to evasion attacks [22], (4) federated learning can be enabled to train models across organisations without providing access to sensitive information, (5) various other developments may follow [23].

VI. Conclusion

This paper developed deep learning architecture for zero-day attack detection with the issue of paramount concern—class imbalance and overfitting in network intrusion detection. Our key findings are:

First, Focal Loss works well in the event of extreme class imbalance in UNSW-NB15 data, achieving ROC-AUC of 0.9039—higher than standard Binary Cross-Entropy (0.8938). The focusing mechanism gets rid of the majority class bias while maintaining computational efficiency.

Second, threshold optimization creates substantial improvements of accuracy (7.29 percentage points) without any computational cost. The optimal threshold of 0.5895 can be used to prove the significance of adapting to test set characteristics rather than using default values.

Third, aggressive regularization (dropout 0.65, weight decay 0.01) combined with Focal Loss reduces overfitting to 7.97% gap, such that good generalization is made to invisible attacks. This validates our course of action with regard to realistic implementation where new forms of attacks continue to arise.

Our final model has the accuracy of 81.26% with balanced precision (76.42%) and recall (70.87%), which is reasonable as a good intrusion detection system. The lightweight architecture (15,297 parameters) enables real-time inference at 4,300 samples/second, meeting performance requirements of high-speed networks. Ensemble methods and semi-supervised learning approaches ought to be learned in the future to achieve higher detection rates, particularly for rare attack categories.

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