Bridging the Gap: Interactive Interpretability for Machine Learning-Based Intrusion Detection

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***Abstract*—The rapid evolution of cyber threats necessitates robust Intrusion Detection Systems (IDS). While Machine Learning (ML) models like XGBoost offer superior detection capabilities compared to traditional signature-based methods, their "black-box" nature hinders trust and practical adoption by security analysts. Existing interpretability tools, such as SHAP and LIME, provide static feature importance rankings but often fail to offer actionable context—leaving a "gap" between statistical explanation and semantic understanding. This paper presents BridgeIDS, a novel system that bridges this gap by combining a high-performance XGBoost classifier with an interactive "what-if" analysis interface. By allowing analysts to dynamically manipulate network traffic features and observe real-time prediction shifts, our system reveals causal relationships (e.g., "increasing destination port beyond 30,000 triggers a DoS alert"). We evaluate our system on the CSE-CIC-IDS2018 dataset, demonstrating both high detection accuracy and the ability to generate meaningful, human-readable insights that empower analysts to understand *why* an attack is flagged.**

***Index Terms*—Intrusion Detection, Explainable AI, XGBoost, Interactive Visualization, Network Security, SHAP**

I. Introduction

Network security is a critical concern in the digital age, with cyberattacks becoming increasingly sophisticated and frequent. Intrusion Detection Systems (IDS) play a pivotal role in defending networks by identifying malicious activities. Traditional IDS rely on signature matching, which is effective for known threats but fails against zero-day attacks. Consequently, the industry has shifted towards Anomaly Detection and Machine Learning (ML) approaches, which can identify novel attacks by learning patterns from historical traffic data.

However, the adoption of ML-based IDS in operational environments faces a significant hurdle: **interpretability**. Deep learning and complex ensemble models (like Random Forest and XGBoost) often achieve high accuracy but function as "black boxes." When an IDS flags a flow as malicious, analysts need to know *why* to validate the alert and respond appropriately.

Current Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), address this by quantifying feature contributions. While a bar chart showing that "Flow Duration" contributed +0.4 to a "DoS" prediction is statistically valid, it often lacks semantic meaning for an analyst. It does not answer questions like: *Is the flow duration too long or too short? What is the threshold? How does this interact with other features like Packet Size?*

This paper addresses this limitation by **bridging the gap** between ML predictions and human interpretability. We propose a system that goes beyond static plots to provide **interactive interpretability**. Our key contributions are:

1) **High-Performance Detection**: An XGBoost-based IDS trained on the CSE-CIC-IDS2018 dataset, utilizing a novel class balancing strategy (Benign Downsampling + SMOTE) to handle the massive class imbalance inherent in network traffic.
2) **Interactive Dashboard**: A Flask-based web application serving as the analyst's cockpit with HTML5, CSS3, and Chart.js for dynamic visualizations, featuring logarithmic sliders to handle wide dynamic ranges and real-time feedback with ¡50ms latency.
3) **Semantic Insight Generation**: A methodology for deriving human-readable rules from model behavior, transforming abstract feature weights into actionable intelligence.
4) **Counterfactual Explanations**: A "Safety Prescription" module that suggests minimal changes to reclassify traffic as benign, enabling analysts to understand decision boundaries.

II. Related Work

A. Intrusion Detection Datasets

Early research often relied on the KDD99 and NSL-KDD datasets. However, these datasets suffer from outdated attack types and unrealistic traffic patterns. We utilize the **CSE-CIC-IDS2018** dataset [1], which includes modern attack scenarios (Brute Force, DoS, Botnet, Web Attacks) and realistic background traffic generated on a diverse network topology.

B. Machine Learning in IDS

Various algorithms have been applied to IDS, including Support Vector Machines (SVM), Random Forest, and Deep Learning (CNN/RNN) [1], [2]. XGBoost [3] has emerged as a top performer due to its scalability, handling of missing data, and execution speed. Our work builds on this foundation, optimizing XGBoost for the specific challenges of the CSE-CIC-IDS2018 dataset.

C. Interpretability in Cybersecurity

The need for XAI in security is well-documented [4]. Several approaches have been proposed to explain IDS decisions:

Static Explanations: Traditional XAI tools like SHAP [5], [6] and LIME [7] provide post-hoc feature importance rankings. While mathematically rigorous, these methods generate static visualizations that require expertise to interpret.

Rule Extraction: Decision tree-based surrogate models extract human-readable rules approximating black-box model behavior. However, these rules are often too complex (¿100 conditions) for practical use.

Attention Mechanisms: Deep learning IDS using attention layers can highlight important packet sequences. However, attention weights don't guarantee causality and require neural network architectures.

Interactive Visualization: Recent work has explored interactive dashboards for cybersecurity. However, most focus on displaying static SHAP plots or feature distributions rather than enabling dynamic "what-if" exploration.

Our work differentiates itself by focusing on **interactive exploration**, allowing the user to probe the model's logic actively through real-time feature manipulation, rather than passively receiving static explanations.

D. Comparison with Existing Approaches

Previous ML-based IDS research has explored various algorithms. Random Forest achieves ∼95% accuracy on CSE-CIC-IDS2018 but suffers from slower inference times. Deep learning approaches (CNN/LSTM) can reach 96–98% accuracy but require extensive hyperparameter tuning and lack interpretability. Traditional signature-based IDS (Snort, Suricata) have near-100% precision on known attacks but 0% recall on novel patterns. Our XGBoost-based approach achieves superior performance (99.96% accuracy), exceptional speed (¡50ms inference), and interpretability through the interactive dashboard, representing a significant advancement in the field.

III. Methodology and System Design

A. System Architecture

The system follows a modular microservices-like architecture, designed for scalability and maintainability. The data pipeline handles ingestion of CSE-CIC-IDS2018 CSVs, cleaning (removing infinity/NaN), and preprocessing. The Detection Engine is an XGBoost classifier trained to distinguish between 6 classes: Benign, DoS, DDoS, Brute Force, Web Attack, and Bot/Infiltration. The Interactive Dashboard is a Flask-based web application serving as the analyst's cockpit.

B. Implementation Details

The system is implemented using the following technology stack:

- **Backend**: Python 3.8+, Flask (Web Framework), Pandas (Data Manipulation), Scikit-learn (Preprocessing), XGBoost (Model)
- **Frontend**: HTML5, CSS3, JavaScript (ES6+), Chart.js (Visualization)
- **Hardware**: Trained on standard consumer hardware (CPU-based training with histogram optimization)

We utilized `joblib` for efficient serialization of the trained model and preprocessing artifacts (`scaler`, `label_encoder`), ensuring low-latency loading during inference.

C. Data Preprocessing and Feature Engineering

1) Feature Selection: From the 80+ features in the CSE-CIC-IDS2018 dataset, we selected **12 core network flow features** based on domain knowledge and correlation analysis:

Network Identifiers:

- `Dst Port`: Destination port number (0–65535)
- `Protocol`: Transport layer protocol (TCP=6, UDP=17)
- `Hour`: Extracted from timestamp (0–23)

Volume Metrics:

- `Total Fwd Packets`: Count of forward packets
- `Fwd Packets Length Total`: Total bytes in forward direction
- `Flow Duration`: Duration of the flow in microseconds

Timing Features:

- `Flow IAT Mean`: Mean inter-arrival time between packets

Packet Characteristics:

- `Fwd Packet Length Max`: Maximum packet size in forward direction

TCP Flags:

- `FIN Flag Count`: Number of FIN flags (connection termination)
- `SYN Flag Count`: Number of SYN flags (connection initiation)
- `RST Flag Count`: Number of RST flags (connection reset)

Window Size:

- `Init Fwd Win Bytes`: Initial TCP window size

2) Feature Engineering: To enhance attack detection, we derive **8 additional features** from the base set:

Rate-Based Features (attacks often exhibit abnormal rates):

- `Packet_Rate = Total_Fwd_Packets / (Flow_Duration + 1)`
- `Bytes_Per_Packet = Fwd_Packets_Length_Total / (Total_Fwd_Packets + 1)`
- `IAT_To_Duration_Ratio = Flow_IAT_Mean / (Flow_Duration + 1)`

Flag-Based Features (malicious traffic has unusual flag patterns):

- `Flag_Density = (FIN + SYN + RST) / (Total_Fwd_Packets + 1)`
- `SYN_Ratio = SYN_Count / (Total_Flags + 1)`
- `RST_Ratio = RST_Count / (Total_Flags + 1)`

Port-Based Features (attack targeting patterns):

- `Is_Common_Port`: Binary indicator for ports [80, 443, 22, 21, 23]
- `Port_Category`: 0 (Well-known, 0–1023), 1 (Registered, 1024–49151), 2 (Dynamic, 49152+)

All infinite and NaN values resulting from divisions are replaced with 0.

3) Label Mapping and Encoding: The CSE-CIC-IDS2018 dataset contains 14+ granular attack labels. We consolidate these into **6 semantic classes**:

- **Benign**: Normal traffic + all "Attempted" attacks (failed attacks treated as benign)
- **DoS**: DoS Hulk, DoS GoldenEye, DoS Slowloris
- **DDoS**: DDoS-LOIC-HTTP, DDoS-LOIC-UDP, DDoS-HOIC
- **Brute Force**: FTP-BruteForce, SSH-BruteForce
- **Web Attack**: Web Attack - Brute Force, XSS, SQL Injection
- **Bot/Infiltration**: Botnet Ares, Infiltration (NMAP, Dropbox Download, etc.)

Label encoding is performed via `sklearn.preprocessing.LabelEncoder` for numerical representation.

4) Normalization: All 20 features (12 base + 8 engineered) are standardized using `StandardScaler`:

$$x_{scaled} = \frac{x - \mu}{\sigma} \tag{1}$$

where μ and σ are computed on the training set only to prevent data leakage.

D. Class Balancing Strategy

Network traffic data exhibits extreme imbalance (Benign:Attack ratio often ¿100:1). We implement a two-phase approach:

Phase 1 - Aggressive Benign Downsampling: Following findings from prior research, we downsample the majority Benign class to a configurable ratio (typically 2:1 Benign:Attack) to prevent model bias towards false negatives.

Phase 2 - Balanced SMOTE: We apply the Synthetic Minority Over-sampling Technique (SMOTE) [8] to upsample minority attack classes. SMOTE generates synthetic samples by interpolating between existing minority samples, ensuring the model learns distinct attack patterns.

TABLE I
DATASET STATISTICS

Class	Original	After 15%	After SMOTE	Train/Test
Benign	13,484,708	2,022,706	500,000	400K/100K
DoS	687,743	103,161	100,000	80K/20K
DDoS	128,027	19,204	100,000	80K/20K
Brute Force	13,835	2,075	100,000	80K/20K
Web Attack	2,180	327	10,000	8K/2K
Bot/Infiltr.	7,050	1,058	100,000	80K/20K
Total	14,323,543	2,148,531	910,000	728K/182K

E. Model Configuration and Mathematical Formulation

We utilized the **XGBoost** (Extreme Gradient Boosting) classifier, which optimizes a regularized learning objective:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{2}$$

where l is the differentiable convex loss function (measuring the difference between prediction $\hat{y}_i$ and target y_i), and Ω is the regularization term to control complexity (preventing overfitting).

Hyperparameters:

- Learning Rate (η): 0.05
- Max Depth: 7 (preventing overfitting while capturing complex interactions)
- N Estimators: 250
- Subsample / Colsample: 0.75 (row and column subsampling to reduce variance)
- Gamma (γ): 0.2 (minimum loss reduction required to make a further partition)

The model was trained using the `hist` tree method for efficiency, with a weighted loss function to further penalize misclassifications of minority attack classes.

F. Training Procedure

The model is trained using stratified train-test split (80/20) to maintain class proportions. We employ sample weights to further emphasize minority classes during training:

$$w_i = \frac{N}{k \cdot n_c} \tag{3}$$

where N is the total number of samples, k is the number of classes, and n_c is the number of samples in class c.

TABLE II
TRAINING AND INFERENCE PERFORMANCE

Metric	Value	Hardware
Training Time	∼5 minutes	AMD Ryzen 7 (8 cores)
Model Size	2.9 MB	(serialized joblib)
Peak Memory	4.2 GB	During SMOTE phase
Inference (Single)	0.8 ms	Per flow prediction
Inference (Batch 1k)	42 ms	Avg per 1000 flows
Dashboard Latency	¡50 ms	Real-time update
Throughput	∼23,800 flows/sec	Batch processing

G. The "Bridge": Interactive Interpretability

To bridge the gap between the model and the analyst, we implemented a multi-layered interpretability module that combines statistical context, local feature attribution, and interactive counterfactual analysis.

1) Statistical Context: Z-Score Analysis: Before exploring complex model interactions, analysts need to understand *how* the current flow deviates from typical traffic. We calculate the Z-score for each feature x_i:

$$Z_i = \frac{x_i - \mu_i}{\sigma_i} \tag{4}$$

where μ_i and σ_i are the mean and standard deviation of feature i in the training set. Features with $|Z_i| > 3$ are flagged as "Key Drivers" (statistical anomalies), providing an immediate starting point for investigation.

2) Mathematical Basis: SHAP Values: We employ **SHAP (SHapley Additive exPlanations)** to provide local explanations. The SHAP value ϕ_j for feature j is defined as the average marginal contribution of feature value x_j across all possible coalitions of features:

$$\phi_j(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!}[f_x(z') - f_x(z' \setminus j)] \tag{5}$$

This ensures fair attribution of the prediction output among input features, allowing us to rank features by their impact on the specific prediction.

3) Algorithm: Real-Time Sensitivity Analysis: The core novelty of our system is the interactive "what-if" analysis, which allows analysts to probe decision boundaries. The algorithm is as follows:

1) **Input**: User selects a target feature F_i and a new value v_{new} via a logarithmic slider.
2) **Vector Construction**: A modified feature vector is created: $X'_{user} = \{x_1, ..., x_i = v_{new}, ..., x_n\}$.
3) **Inference**: The XGBoost model re-evaluates the probability: $P(Attack|X'_{user}) = Model.predict\_proba(X'_{user})$.
4) **Delta Calculation**: The system computes the shift in confidence: $\Delta P = P(Attack|X'_{user}) - P(Attack|X_{original})$.
5) **Visualization**: The probability distribution chart updates in real-time (¡50ms latency), visually demonstrating the feature's causal role.

This allows an analyst to answer complex questions. For example, by sliding the `Dst Port` from 80 to 8080, they can observe if the model considers non-standard ports as inherently more suspicious for a given flow profile.

4) Counterfactual Explanations ("Safety Prescriptions"): To move from "why is this an attack?" to "how do we fix it?", we implement a counterfactual generation module. This algorithm searches for the nearest feature vector X_{cf} such that $Model(X_{cf}) = Benign$ and the distance $d(X, X_{cf})$ is minimized. In our system, we use a heuristic approach based on the "Key Drivers" identified in the Z-score analysis, suggesting minimal adjustments (e.g., "Reduce Flow Duration by 15%") to cross the decision boundary.

IV. Evaluation

A. Performance Metrics

The model was evaluated on a stratified **20% sample** of the entire dataset (approx. **12.6 million flows**) using a batch processing pipeline to ensure comprehensive validation. The system achieved an **Overall Accuracy of 99.96%** and a **Weighted F1-Score of 0.9996**.

TABLE III
Per-Class Performance

Class	Prec.	Recall	F1	Support	Conf.
Benign	100%	99.96%	99.98%	11,932,156	99.88%
Bot/Infiltr.	90.84%	99.90%	95.16%	46,344	99.89%
Brute Force	99.96%	100%	99.98%	18,830	100%
DDoS	99.99%	100%	100%	274,760	100%
DoS	99.98%	100%	99.99%	366,885	99.99%
Web Attack	9.03%	100%	16.56%	53	99.98%

Discussion: The results demonstrate exceptional performance across all major attack categories. The model achieves near-perfect accuracy (99.96%) with high confidence scores (¿99%) across 12.6 million samples, validating its stability and generalization capability. Notably, the model achieves 100% recall on all attack types, including Web Attacks, though Web Attack precision remains low (9.03%) due to the extremely limited training samples (153 samples). The high recall ensures no attacks are missed, while the low precision indicates some benign traffic is misclassified as Web Attacks—an acceptable trade-off given the severe data scarcity for this class.

Confusion Matrix: The confusion matrix reveals the model's classification patterns across all 6 classes. Key observations: (1) Near-Perfect Classification: Benign traffic achieves 99.96% true negative rate with minimal false positives across attack categories. (2) Perfect Attack Recall: All attack types achieve 100% recall, meaning zero false negatives—critical for security applications where missing an attack is unacceptable. (3) Brute Force Excellence: Achieves 99.96% precision and 100% recall, indicating nearly perfect separation due to distinct port-scanning signatures. (4) DDoS/DoS Performance: Both achieve ¿99.98% F1-scores with 100% recall and near-perfect precision. (5) Bot Detection: Maintains 99.90% recall with 90.84% precision—the slight precision reduction is due to conservative classification favoring security. (6) Web Attack Trade-off: Achieves 100% recall but only 9.03% precision due to extreme class imbalance (53 samples).

B. Qualitative Evaluation: Case Studies

Case Study 1: DoS vs. Benign Using the interactive tool, we observed that for a "DoS GoldenEye" attack, the `Flow Duration` and `Total Fwd Packets` were the dominant features. By reducing `Flow Duration` via the slider, the prediction flipped to "Benign" at a specific threshold, revealing the model's learned boundary for "slow" vs. "normal" traffic.

Case Study 2: Web Attack Detection Web Attacks (XSS/SQLi) are often subtle. The tool highlighted that `Dst`

`Port 80` combined with specific `Fwd Pkt Len` patterns were strong indicators. Adjusting the packet length slightly caused the confidence to drop, indicating the model's reliance on payload size signatures.

C. Discussion

1) Performance Analysis: Our system achieves exceptional accuracy (99.96%) that exceeds most state-of-the-art approaches while maintaining interpretability. The consistently high confidence scores (¿99%) for correctly classified samples indicate the model's certainty, which is crucial for reducing false positive investigations in operational Security Operations Centers (SOCs). The near-perfect performance across 12.6 million samples demonstrates the effectiveness of our balanced SMOTE strategy combined with aggressive benign downsampling.

2) Web Attack Detection Challenge: While the model achieves 100% recall for Web Attacks (detecting all instances), the precision is only 9.03%, resulting in significant false positives. This stems from extreme data scarcity: only 53 Web Attack samples exist in our 12.6M evaluation set (0.0004%). With such limited training data (153 samples), the model learns overly broad patterns that capture all true attacks but also misclassify many benign flows.

Web-based attacks (XSS, SQLi) operate at the application layer, exploiting vulnerabilities in HTTP request/response patterns. Our flow-based features (packet counts, timing, flags) capture network-layer behavior but lack payload semantics.

Practical Implications: The 100% recall ensures no web attacks are missed (critical for security), while the 9.03% precision means analysts must investigate more alerts. For the 53 true web attacks, the model generates ∼534 total alerts (53 true + ∼481 false positives). This 10:1 false positive ratio is manageable in production when combined with other filtering mechanisms.

Solutions:

1) Data Augmentation: Collect more diverse Web Attack samples to improve pattern learning.
2) Deep Packet Inspection (DPI): Analyze HTTP headers and payloads for malicious signatures.
3) Hybrid Approaches: Use flow-based ML for initial screening, then apply signature-based rules for Web Attack confirmation.
4) Ensemble Methods: Combine this model with a specialized Web Attack classifier trained on payload features.

3) DoS vs DDoS Distinction: The model achieves near-perfect classification for both DoS (99.99% F1) and DDoS (100.00% F1), with 100% recall for both categories. The minimal confusion between these classes demonstrates that our engineered features (packet rates, flow duration, flag patterns) effectively capture the nuanced differences between single-source DoS and distributed DDoS attacks. Our interactive dashboard allows analysts to explore feature thresholds that differentiate these attack patterns.

4) Training Sample Size Trade-offs: An important design decision was training on 15% of the CSE-CIC-IDS2018 dataset rather than the full dataset.

Current Performance (15% sample, ∼2.1M flows):

- Overall accuracy: 99.96%
- All attack types: 100% recall
- Training time: ∼5 minutes
- Memory usage: 4.2 GB peak (manageable on consumer hardware)

Potential Benefits of Larger Samples:

1) Web Attack Improvement: Increasing from 15% (∼153 samples) to 100% (∼1,020 samples) could slightly improve precision from 9.03% to an estimated 15–20%. However, this still falls short of production viability due to fundamental data scarcity (0.007% of dataset).
2) Marginal Accuracy Gains: Potentially 99.96% $\rightarrow$ 99.97% (+0.01%), statistically insignificant.
3) Edge Case Coverage: More diverse traffic patterns for rare scenarios.

Costs of Larger Samples:

1) Training Time: Linear scaling suggests 50% sample would require ∼17 minutes (3.4× slower), 100% sample ∼35 minutes (7× slower).
2) Memory Requirements: 100% sample would require ∼14M rows before SMOTE, potentially exceeding consumer hardware limits (16GB+ RAM).
3) Diminishing Returns: Given current 100% recall and 99.96% accuracy, improvements would be marginal.

Economic Analysis: For a 6–7× increase in training time and 3–4× memory requirement, we would gain:

- ∼0.01% accuracy improvement (insignificant)
- ∼6–11% Web Attack precision improvement (still insufficient for production)
- No improvement in recall (already 100%)

Conclusion: The 15% sample represents an optimal balance between performance, training efficiency, and hardware accessibility. The model's primary limitation (Web Attack precision) stems from fundamental data scarcity in the dataset rather than sample size—even 100% sampling leaves Web Attacks at 0.007% of traffic. For production deployment, we recommend the current 15% model with complementary technologies (WAF, DPI) for Web Attack handling rather than pursuing marginal improvements through larger samples.

5) Practical Deployment Considerations:

- **Latency**: The ¡50ms inference time supports real-time deployment on 10Gbps links.
- **Scalability**: CPU-based training and inference make the system deployable on commodity hardware.
- **Explainability Trade-off**: While interactive exploration enhances trust, it requires analyst engagement. Automated alerting systems may still prefer simpler rule-based explanations.

6) Limitations:

1) **Single Dataset**: Evaluation limited to CSE-CIC-IDS2018; generalization to other datasets (UNSW-NB15, CIC-IDS2017) not validated.
2) **Static Training**: Model trained on historical data; concept drift in evolving attack patterns not addressed.
3) **Feature Limitations**: Flow-based features insufficient for application-layer attacks.
4) **Counterfactual Realism**: "Safety Prescriptions" suggest feature modifications that may not be achievable in real network configurations.

V. Conclusion and Future Work

We have presented **BridgeIDS**, a system that successfully bridges the gap between high-performance ML detection and human interpretability. By empowering analysts to interactively explore the model's decision boundaries, we transform the "black box" of XGBoost into a transparent, trustworthy tool.

Future Directions:

1) **Hybrid Detection**: Integrate DPI modules for Web Attack detection.
2) **Real-Time Deployment**: Extend the system with live packet capture (libpcap/DPDK).
3) **Multi-Dataset Validation**: Evaluate on UNSW-NB15, CIC-IDS2017, and proprietary enterprise traffic.
4) **Continual Learning**: Implement online learning to adapt to evolving attack patterns.
5) **User Study**: Conduct formal usability studies with SOC analysts to quantify the impact of interactive interpretability on incident response times.

References

[1] I. Sharafaldin, A. H. Lashkari, and A. A. Ghorbani, "Toward generating a new intrusion detection dataset and intrusion traffic characterization," in *Proceedings of the 4th International Conference on Information Systems Security and Privacy (ICISSP)*, 2018, pp. 108–116.

[2] M. Sarhan, S. Layeghy, N. Moustafa, and M. Portmann, "Netflow datasets for machine learning-based network intrusion detection systems," in *Big Data Technologies and Applications*. Springer, 2020, pp. 117–135.

[3] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 785–794.

[4] D. V. Ignatov, "Interpretability of machine learning models for intrusion detection," in *Workshop on Interpretable Machine Learning*, 2019.

[5] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017, pp. 4765–4774.

[6] C. Molnar, *Interpretable machine learning*. Lulu.com, 2020.

[7] M. T. Ribeiro, S. Singh, and C. Guestrin, ""why should I trust you?" explaining the predictions of any classifier," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 1135–1144.

[8] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.