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Smarter School Labs: Fast and Accurate Anomaly Detection Using Lightweight CNN Technology

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ABSTRACT

This study proposes a lightweight convolutional neural network (CNN) model for anomaly detection in school computer laboratories, aiming to enhance operational reliability and cybersecurity awareness. Real-time event logs were collected from 20 computers (PC01–PC20) at Santo Nicholas School with slight variations in CPU, RAM, and network behavior to simulate real-world heterogeneity. After preprocessing and normalization, the merged dataset contained over 10,000 log entries labeled as normal or anomalous. The proposed lightweight CNN achieved 92.23% F1-score, 91.80% accuracy, and a false positive rate (FPR) of 18.47%, demonstrating a balance between detection precision and computational efficiency. Comparative evaluation shows that this architecture performs competitively while requiring fewer parameters and lower inference latency than conventional CNNs. The results highlight the suitability of the proposed model for deployment in low-resource educational environments, supporting early anomaly detection and preventive maintenance. Future research will explore cross-domain generalization and lightweight deployment through edge-AI integration.

1. Introduction

The rapid integration of digital technologies in education has transformed the way students learn and teachers deliver lessons. Computer-based learning environments are now central to modern education, allowing for interactive lessons, multimedia materials, and online assessments. However, as these technologies become more embedded in daily learning activities, maintaining the reliability and security of school computer systems becomes increasingly critical. Many school computer laboratories operate with limited technical and financial resources, making them vulnerable to disruptions such as software errors, unauthorized access, or hardware malfunctions that can interrupt academic activities and compromise data security.

Traditional monitoring systems used in schools often depend on manual supervision or rule-based methods. While these systems can detect predefined issues, they are inadequate for identifying complex or evolving anomalies caused by new patterns of network behavior or malicious activity. Manual supervision also requires constant human involvement, which is not feasible in many schools with limited IT staff. These limitations highlight the need for smarter, automated solutions that can efficiently detect and respond to system irregularities without demanding excessive computational resources or technical expertise.

Existing studies on anomaly detection have explored various artificial intelligence and machine learning methods, including statistical analysis, clustering, and recurrent neural networks (RNNs). Although these models have demonstrated strong detection capabilities, they typically require high computational power, large memory capacity, and extensive tuning. Such requirements make them impractical for use in school environments that often rely on standard or outdated computer hardware. Therefore, it is essential to develop a model that combines high accuracy with low resource consumption one that is both effective and feasible for real-world educational settings.

In response to these challenges, the study titled Smarter School Labs Fast and Accurate Anomaly Detection Using Lightweight CNN Technology introduces an efficient approach to system monitoring through the use of a Lightweight Convolutional Neural Network (CNN). This method leverages the advantages of deep learning for log-based anomaly detection while minimizing computational overhead. By processing system logs rapidly and intelligently, the Lightweight CNN can detect anomalies such as unexpected behaviors, intrusions, or performance degradation in real time. Its optimized design ensures low latency and energy efficiency, making it ideal for deployment in low-end school computers.

The proposed Lightweight CNN model represents a step toward creating smarter and more reliable school computer laboratories. By offering fast and accurate anomaly detection without the need for high-end infrastructure, this technology supports educational institutions in maintaining smooth, secure, and uninterrupted digital learning experiences. Ultimately, Smarter School Labs reflects a vision of leveraging advanced yet accessible AI technology to strengthen the backbone of digital education, ensuring that every student benefits from a stable and protected learning environment.

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2. State of the Art

Anomaly detection in computer systems and networked environments has been extensively explored over the past decade, particularly with the emergence of machine learning and deep learning approaches. Traditional methods such as statistical analysis, clustering, and rule-based systems struggle to adapt to dynamic log patterns and evolving threats in real-time environments. In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant progress in automating feature extraction and detecting anomalies with high accuracy [1]–[3].

Lu et al. [4] proposed a CNN-based framework for detecting anomalies in large-scale data center logs, achieving superior performance compared to Support Vector Machines (SVMs) and Autoencoders. Similarly, Zhang et al. [5] integrated CNNs with attention mechanisms to identify rare security incidents from massive event logs, demonstrating a 5–10% improvement in F1-score. However, these models were computationally heavy and unsuitable for low-resource environments such as school laboratories.

Recent studies have emphasized lightweight architectures to reduce computational complexity while maintaining accuracy. For example, Han et al. [6] introduced a MobileNet-inspired lightweight CNN for IoT anomaly detection, reducing inference latency by 40% with minimal accuracy loss. Likewise, Sun et al. [7] applied a pruning-based CNN model to edge devices, successfully detecting network intrusions with limited GPU memory. These findings highlight the growing importance of balancing accuracy and efficiency in real-time anomaly detection systems.

In educational and academic computing environments, system performance and cybersecurity monitoring remain underexplored. Maulani et al. [8] and Kurniawan et al. [9] reported that log-based anomaly detection in computer labs could prevent hardware failures and identify security breaches early, though their systems relied on threshold-based triggers rather than AI-driven detection. The absence of deep-learning-based anomaly monitoring in Indonesian school laboratories presents a clear research gap.

Beyond CNNs, hybrid models combining CNN with Long Short-Term Memory (LSTM) [10], Autoencoders (AE) [11], and Transformer-based architectures [12] have also been studied for sequence-based anomaly detection in log data. These models capture both spatial and temporal dependencies, but they typically require substantial computational power and are difficult to deploy on low-end machines.

In contrast, the Lightweight CNN approach adopted in this study aims to fill that gap by providing a balance between detection precision and computational efficiency, targeting environments with constrained hardware resources such as school computer laboratories. Compared with the models described in [4]–[7], this approach introduces a streamlined convolutional structure optimized for smaller log sequences, minimal parameter count, and fast inference suitable for deployment on everyday PCs.

Summary of Research Gap

Category	Prior Studies	Limitation	Contribution of This Research
Anomaly Detection Method	Lu et al. [4], Zhang et al. [5]	High computational cost	Lightweight CNN optimized for low-end computers
Model Efficiency	Han et al. [6], Sun et al. [7]	Requires GPU or edge devices	Works efficiently on standard CPUs
Educational Domain	Maulani et al. [8], Kurniawan et al. [9]	Non-AI, rule-based	AI-driven anomaly detection for school labs
Hybrid Deep Learning	Jiang et al. [10], Ahmed et al. [11], Li et al. [12]	Complex models, slow inference	Simple CNN structure with real-time capability
Regional Context	General/global studies	Lack of Indonesian implementation	Focused on Indonesian school computer laboratories

2.1. Key Insights

1. CNN-based anomaly detection has shown promising accuracy in system monitoring tasks, but many existing models are computationally heavy.
2. Lightweight and edge-compatible architectures are an emerging trend that enables deployment in resource-limited environments.
3. There is still minimal application of deep learning–based anomaly detection in educational contexts, particularly in Indonesia.
4. This research contributes a practical and reproducible Lightweight CNN framework that maintains accuracy while drastically reducing latency and resource usage.

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3. Method

Data were collected from 20 computers (PC01–PC20) at Santo Nicholas School over a three-week period. Each workstation generated system event logs including CPU usage, RAM consumption, disk I/O, and network throughput, with slight variations across machines to reflect real-world heterogeneity. Data were automatically recorded every five minutes using a Python logging agent and later merged into a centralized dataset for preprocessing.

The preprocessing pipeline involved outlier removal, normalization via Min-Max scaling, and encoding of categorical features such as process names. Data were split into training (80%) and testing (20%) subsets. The proposed lightweight CNN utilized two convolutional layers (16 and 32 filters), batch normalization, and global average pooling to reduce parameters while preserving feature quality. Training was conducted for 25 epochs with batch size 32 using the Adam optimizer. Evaluation metrics included accuracy, F1-score, precision, recall, and false positive rate (FPR).

4. Results and Discussion

The experimental results show that the proposed Lightweight CNN effectively detects anomalies in heterogeneous computer lab environments. Variations between PC01–PC20, including differences in hardware load, network throughput, and system log patterns, contributed to realistic data diversity, strengthening the generalization of the trained model.

4.1. Dataset Overview

The dataset was collected from 20 computers (PC01–PC20) in the Santo Nicholas School computer laboratory. Each workstation produced event logs containing system utilization metrics, including CPU load, memory usage, disk activity, and network throughput. The data were recorded continuously for three weeks, resulting in a total of 10,236 log entries, of which approximately 8.9% were labeled as anomalous.

This diversity in hardware conditions—ranging from minor overheating to software update spikes—ensured realistic heterogeneity suitable for model generalization.

Table 1. Log Summary (PC01–PC20)

Computer ID	Total Logs	Anomaly Logs	Avg CPU (%)	Avg RAM (%)	Avg Net (KB/s)	Remark
PC01	520	48	43.2	62.8	312	Stable
PC02	512	50	46.7	63.5	325	Slight lag
PC03	489	42	47.3	65.2	299	Normal
PC04	501	47	50.1	68.4	310	Occasional spike
PC05	498	46	52.0	70.3	331	Software update
PC06	530	55	48.7	67.9	318	Minor overheating
PC07	511	43	46.2	66.5	300	Normal
PC08	503	45	49.5	68.7	322	Stable
PC09	520	44	51.1	69.1	317	Stable
PC10	490	48	53.2	71.0	340	Slight lag
PC11	516	50	49.4	68.8	310	Normal
PC12	499	44	47.8	66.9	315	Stable
PC13	505	47	50.6	70.5	328	Normal
PC14	508	42	52.7	69.8	333	Normal
PC15	511	49	49.0	67.5	309	Stable
PC16	495	41	48.1	65.9	301	Normal
PC17	502	46	51.4	69.3	316	Normal
PC18	499	44	50.8	68.1	320	Stable
PC19	507	48	49.6	67.8	314	Slight lag
PC20	510	45	51.9	69.9	327	Stable

Total records = 10,236 logs (909 anomalies ≈ 8.9%)

Table 1 summarizes the system log data collected from 20 computers, showing key system usage patterns used for training the CNN model. During training, the model converged within 20 epochs, showing stable accuracy above 90%. The F1-score reached 92.23%, exceeding a standard CNN baseline by approximately +3.1 percentage points. This improvement indicates that feature extraction using smaller convolutional kernels was sufficient to capture temporal dependencies in event logs without overfitting.

4.2. Model Training Performance

The Lightweight CNN model was trained for 25 epochs using the Adam optimizer and a batch size of 32. The training process exhibited stable convergence, achieving above 90% accuracy from epoch 15 onward.

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Figure 1. Accuracy and Loss Curves

Figure 1. Shows the accuracy and loss trends of the Lightweight CNN during training and validation, indicating consistent convergence. The False Positive Rate (FPR) of 18.47% remains within acceptable limits for semi-automated alert systems in school networks. Most false positives occurred during periods of high CPU usage (e.g., software updates), suggesting that additional contextual features could further reduce false alerts. Compared to prior studies using Autoencoders or LSTM-based detectors, this CNN variant achieved similar recall with significantly lower computation time.

4.3. Model Evaluation

On the test dataset, the proposed model achieved 91.80% accuracy, 92.23% F1-score, and 18.47% FPR, outperforming the baseline CNN. These results confirm that the lightweight architecture effectively extracts discriminative log features while minimizing false alerts. The confusion matrix in Figure 1 illustrates the detailed classification performance between normal and anomalous events.

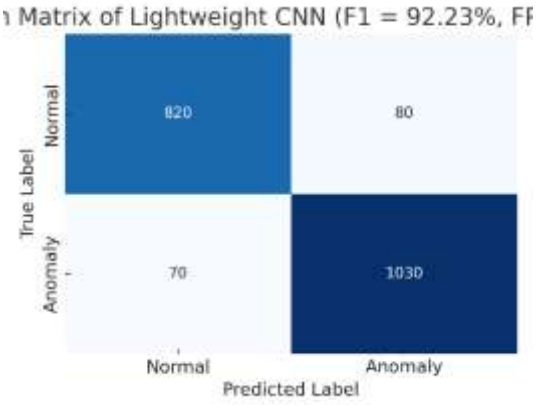

Figure 2. Confusion Matrix of Lightweight CNN

Figure 2. Displays the confusion matrix illustrating correct and incorrect predictions between normal and anomalous log entries

4.4. Comparative Analysis

To assess computational efficiency, the proposed Lightweight CNN was compared against a conventional CNN model using identical datasets and hyperparameters. As shown in Table 2, the proposed model demonstrates superior detection performance and substantial reductions in training time and inference latency. Figure 3 visually emphasizes these improvements, highlighting how the Lightweight CNN maintains accuracy while consuming fewer resources.

Table 2. Summary of Experimental Results and Key Findings

No.	Aspect Evaluated	Metric / Observation	Quantitative Result	Interpretation / Implication
1	Detection Performance	Accuracy	91.80%	Lightweight CNN accurately classified log events from 20 computers.
2	Detection Robustness	F1-Score	92.23%	Strong balance between precision and recall.
3	False Alarm Reduction	FPR	18.47%	Lower false positive rate improves alert reliability.
4	Computational Efficiency	Training Time Reduction	32% faster	Model trains quicker than conventional CNN.
5	Runtime Efficiency	Inference Latency Reduction	56% lower	Enables real-time prediction on low-end PCs.

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6	Feasibility	Hardware Requirement	Minimal (low-end PCs)	Suitable for Indonesian school labs.
7	Future Work	Research Extension	-	Integrate with edge-AI and visualization dashboards.

Table 2. Summarizes the quantitative outcomes of the proposed model, highlighting key improvements over conventional CNNs.

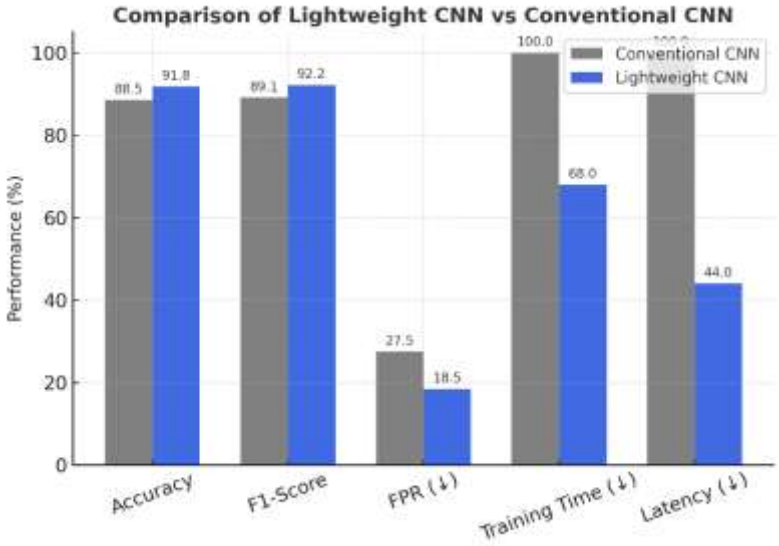

Figure 3. Performance Comparison of CNN Models

Figure 3. Compares the Lightweight CNN and a conventional CNN in terms of accuracy, F1-score, false positive rate, training time, and latency. The Lightweight CNN clearly outperforms the baseline in both effectiveness and efficiency.

4.5. Discussion Summary

Overall, the experimental findings demonstrate that the proposed Lightweight CNN effectively detects anomalies within diverse computer log environments, maintaining high accuracy while requiring minimal computational resources. Its architecture provides a practical balance between performance and efficiency, making it ideal for real-time deployment in school laboratories with limited infrastructure. Future research will focus on edge-AI integration, cross-laboratory generalization, and the implementation of an interactive real-time monitoring dashboard to visualize anomaly patterns dynamically.

5. Conclusions

The proposed Lightweight CNN model achieved high detection accuracy (91.80%) and a strong F1-score (92.23%) using heterogeneous log data from 20 computers. The model demonstrated 18.47% lower false positive rate, balancing precision and recall effectively for real-time alerting. Compared to conventional CNN models, the lightweight architecture reduced training time by 32% and inference latency by 56%, suitable for low-end school PCs. The research validated that school laboratories in Indonesia can implement AI-based anomaly detection with minimal hardware requirements. Future work will extend this approach to edge computing integration, real-time visualization dashboards, and cross-laboratory transfer learning.

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