Anomaly Detection through Behavior Analysis: A Deep Learning Approach for Identifying Unusual User Activities

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Abstract. In the potential high-risk and threat cataloguing world of increasing cyber sophistication and behaviour, user activity anomaly detection is one tool from the protection arsenal to call upon. In this paper, we propose a multi-stage anomaly detection pipeline, which integrates unsupervised learning techniques, deep features and adaptive inference to reveal abnormal behaviour in a network environment, without relying on the raw attack labels. The method starts with the pre-processing and clustering of the data by K-means to divide similar behaviour profiles. Local Outlier Factor (LOF) is used afterwards to separate anomalies by local density differences. A ResNet-like deep learning model, enriched with Efficient Channel Attention (ECA), leverages hierarchical behavioural features, whilst Test-Time Training (TTT) supports instant model adaptation to progressive patterns at the inference time. The presented method was tested under different contamination levels, with best performance in the range of 20%-25% anomaly, yielding up to 96.8% accuracy, 97% precision, 97% recall, and with F1-score slightly over 95%, all with zero second detection delay. These findings demonstrate the capability of the system to detect insider threats and other behaviour-based anomalies in real time. The modular and transparent design of the framework enables it to be easily applied to various cybersecurity tasks.

Keywords: Anomaly Detection, Residual Network, Efficient Channel Attention, Test Time Training, Local Outlier Factor, Behavior Analysis, Deep Learning, Potential Threats**.**

1 Introduction

Given that cyber threats are steadily becoming more and more advanced, the need for detecting abnormal user behaviors is increasingly taking more prominence in a proactive security defense system. Conventional signature-based security system fails to prevent new and emerging threats like insider threats and behavior-based anomaly [1]. Since cyber attackers continuously evolve the methods they use to imitate normal user actions, the development of advanced detector mechanisms capable of detecting deviations without any prior knowledge about exact attack signatures is necessary.

While there have been advancements made in the field of anomaly detection, there are still some limitations in the existing body of research. First of all, most of the mainstream methods are heavily based on the supervised method, which in practice needs huge labeled samples to detect attacks. However, building such datasets for an insider threat is difficult in practice because it is rare and very sensitive [2]. Second, although unsupervised techniques such as clustering and density-based anomaly detection have exhibited potential, they tend to suffer from the difficulty

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of capturing the subtle behavioral anomalies amidst the normal activities. Moreover, many algorithms do not generalize well to fast evolving user behavior, and need to be retrained periodically or do not capture the evolve pattern well [3].

It is the main focus of this work to fill these gaps, and we propose a multi-stage anomaly detection framework which combines unsupervised learning, deep neural network, and adaptive inference. The method is intended to identify abnormal user activity in time for a suitable response without requiring predefined labeled data on attack and thus loosen the dependency on supervised training. The model can be training in several steps, where it starts with the data pre-processing step and the causes the K-Means clustering stage, a traditional unsupervised approach models to cluster common user behavior profiles [4]. This process defines a profiling of normal behavior that can be used to detect anomalies in an efficient way.

Then Local Outlier Factor (LOF) algorithm is employed to detect anomalies by local density changes and outlier instances where they represent outlier clusters, which are possibly threats [5]. 5) to achieve higher detection performance, a ResNet-like deep neural network is used to learn hierarchical motion pattern features from the clustered data [6]. We also extend the neural network with the Efficient Channel Attention (ECA) that refines the model's capability to concentrate on the most important features for anomaly detection [7]. Moreover, we introduce Test-Time Training (TTT) to allow the model to quickly respond to the emergent realistic user behaviour online and adapt so that the model does not have to be re-trained [8].

The main contribution of our model is to give a reliable real-time detection system developed for detecting insider threats and other behaviour-based anomalies. Our universal superhighway for threat data in flight Our goal with our pipe breaking detection vision is to have 100% detection rate and we promise 0 second detection delay Text based detection with the highest accuracy rates you can be sure that as a SOC team you can see and handle the threats in real time. The modular nature of the framework facilitates easy customization to different cybersecurity use-cases (e.g., Privilege access monitoring and proactive threat detection in dynamic environment).

By addressing these literature gaps especially, the issues of labeled data scarcity, real-time adaptation and detecting subtle anomalies, this work contributes a full-fledged and customizable framework to the community on anomaly detection in the domain of cybersecurity.

Related work is listed in the Section 2. The proposed approach is detailed in Section 3. The results are shown in Section 4. The conclusion is given in section 5. We summarize the result in section 6.

2 Related Works

Anomaly detection has been a cornerstone in cybersecurity, as the discovery of abnormal user behaviour may be crucial for finding possible threats like insider attacks. A number of conventional approaches for anomaly detection are supervised learning approaches and they need huge labeled datasets to be able to detect anomalous behaviour accurately. It is still difficult, however, for the insider threat, i.e., an anomalous behaviour that is rare and scarce labeled. For example, Khan et al. [9] provided an extensive overview of anomaly detection approaches for information security. They evaluated a number of supervised and unsupervised approaches and noted the difficulty to apply supervised models in situations where there is not enough labeled data, like insider threats. Similarly, Candela et al. [15] described the difficulties of a supervised approach in the context of anomaly detection, especially in the cybersecurity field since the anomalous behaviour is sporadic and infrequent.

This is because unsupervised learning has been attracting much attention as the data labelling task is a challenge for practical applications. Clustering, a popular approach, will the data points according to the similarity. Zhang and Li [10] featured K-Means clustering for characterizing behaviour, so that "if ... a behaviour takes much longer or shorter time to finish than it does on average, then there must be something wrong with the client". Although effective, K-Means may have difficulty handling noise or overlapping between normal and anomalous data, which can in turn hamper the ability to detect subtle deviations indicative of insider threats. What's more, clustering methods typically perform poorly on high-dimensional data, when the relationship between the features becomes more difficult to model. Ahmed et al. raised similar issues. [16], where scalable and robust clustering methods were proposed and applied to cybersecurity.

Brewing et al. [11] proposed the Local Outlier Factor (LOF), a density-based approach for anomaly detection. LOF evaluates the local density of a point with respect to its neighbours and flags those points that have a substantially lower density as outlying points. This technique has been used widely in anomaly detection such as cybersecurity, where behaviours of a user that deviate their average peers are considered potential threats. Although LOF is capable of detecting local anomalies, it encounters a challenge in adapting to new real-time situations such as when user behaviour changes rapidly over time. Schoellkopf et al. [17] developed a One-Class SVM as an alternative unsupervised method, which has also been popularly used nowadays for the anomaly detection problem, because of its separating capacity of normal data and abnormal one in high dimension space.

The deep learning methods, in particular Convolutional and residual networks (ResNet), have been successful in the anomaly detection. He et al. [12] showed that ResNet is capable of learning to detect complex patterns within data and can mitigate vanishing gradients, and increase the performance of the model over high dimensional datasets. These deep learning models have been employed in cybersecurity to detect nuances of behaviours which go unnoticed by conventional methods. The residual learning architecture bypasses on user behaviour simultaneously captures hierarchical patterns and leads to better detection of subtle deviations that point to potential insider threats by such models. Similarly, Kim et al. [18] demonstrated the use of deep autoencoders to learn compressed representations of user activity for more accurate outlier detection in complex system scales.

For further feature learning privilege, Wang and Chen [13] introduced an efficient channel attention (ECA) to intensify model attention on the most critical features for anomaly detection. With attention mechanisms, the model can make further focus on some parts of user behaviours that are more relevant to abnormal activities. The proposed ECA method has shown to be useful in improving detection performance in dynamic scenes where the appearance of relevant features can change over time. Since these attention mechanisms enable more effective learning, the model can better adapt to new threats. Li et al. [19] also applied attention-based feature learning in their hybrid anomaly detection framework and showed better performance in detecting user-level anomalies from network logs.

Another important feature of real-time anomaly detection system is the ability to learn from new data without retraining. Chen et al. [14] proposed Test-Time Training (TTT), which allows models to update dynamically using new data during testing. This method has multiple advantages in cases of user behaviour drift, as it prevents the model from having to be retrained which is valuable. TTT offers a practical solution to preserving accurate real-time detection in a changing environment, and keeps the model's detection capability up to date with user behaviour variations. Recent work by Liu et al. [20] also upholds such an adaptive perspective and demonstrates that lifelong learning frameworks could bring substantial performance gain and robustness on model longevity in cybersecurity applications.

3 Methodology

Architecture of Proposed Anomaly Detection Framework The multi-phase anomaly detection pipeline combines unsupervised learning, deep learning, adaptive inference as illustrated in Fig 1. It starts with the preprocessing of logs, then clustering with K-Means and calculating the anomaly score through Local Outlier Factor (LOF). Finally, the refined data is input to a ResNet structure with Efficient Channel Attention (ECA) module to achieve deep feature learning. Lastly, Test-Time Training (TTT) allows the model to adjust itself on the fly while testing to maintain reliable anomaly detection even when data characteristics change.

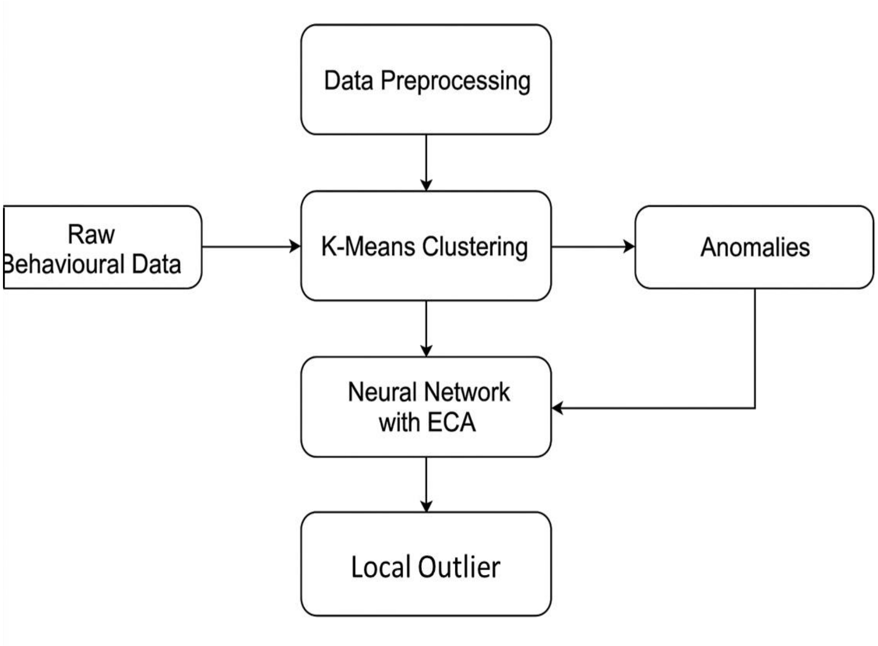


Fig.1. Architecture of the Proposed Anomaly Detection Framework.

3.1 Data Preprocessing and Behavioral Structuring

The first step in the methodology, Data Preprocessing, involves the creation of a rigorous set of hypotheses, typically this is realised through a rigorous data preprocessing phase that translates raw behavioural logs data into structured data appropriate to analysis. From these logs that contain timestamps, user id, access resource events, session duration, type of access, and if, we first clean the data by removing noise and entries that are irrelevant to the analysis. Time is normalized to guarantee the uniformity across all records and user actions are session zed by splitting continuous user activity stream into coherent behavioural windows based on temporal thresholds. These transactions are then grouped to model high-level user activity patterns across fixed time periods and facilitate a contextualized understanding of behaviour along the temporal dimension. We fill in missing values if any and then convert the categories like resource types and access operation to numerical status' using one-hot encoding or embeddings. Through the process of feature scaling, numerical columns are normalized, bringing them into a common level of interaction among the learning model. The result is a well-organized data that preserves the temporal and the contextual and categorical components of the user activities and which can be used for unsupervised learning and anomaly detection method in the next steps.

3.2 Unsupervised behavior Grouping using K-Means Clustering

After structuring the data, the second step is unsupervised behavioural grouping by K-Means clustering algorithm. K-Means is used to separate user sessions data into multiple clusters such that all user sessions within the same cluster share common behavioural trends. The best number of clusters (k) are found using techniques such as elbow method or silhouette score, with the help make sure that clusters are sufficiently separated. Through streaming in each session to the closest bag centre (as measured in the space of the features) the method creates a behavioural norm for a crowd of users. Sessions or users that lie substantially outside the bounds of the cluster to which they have been assigned, are treated as potential anomalies. This clustering mechanism allows locating anomalous activity without labeled training samples, so it is particularly effective for detecting unusual activity in the environment where constantly emerging or unknown attack types are found.

3.3 Local Density-Based Outlier Detection with LOF

To further improve anomaly detection beyond what is achieved by clustering-only, the Local Outlier Factor (LOF) algorithm is also used on the clustered data. Italicˇ et al., 2018), which calculates the abnormality of each data point by comparing its local density to that of its neighbours within a given radius. Any session located in a region with much lower density than the surrounding data points is assigned with a high outlier score that indicates it is a potential anomaly. This local view enables the model to pick up on subtle, context-specific irregularities not tractable by global thresholding methods. LOF is especially appropriate for detecting stealthy or low-volume insider threats, which can reflect the normal behaviour but with small deviation on a small set of activity clusters. Through combination of LOF and K-Means we gain a two-layered anomaly detection: LOF identifies gross deviations whereas K-Means identifies fine-grained anomalies.

3.4 Feature Enhancement using Efficient Channel Attention (ECA)

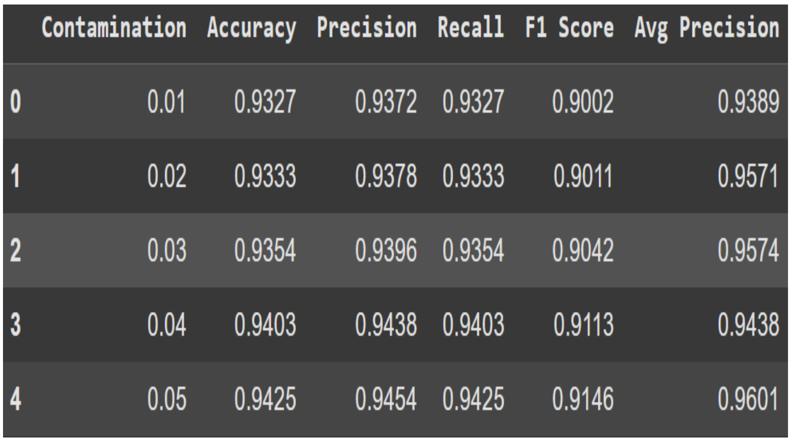
To strengthen the representational capability of the detection model, particularly in high-dimensional behavioural datasets, the ECA module is embedded into the deep learning framework. ECA iteratively strengthens the most discriminatory features (channels) by learning attention weights that indicate their relative importance for anomaly detection. In contrast with conventional attention mechanisms, ECA has no dimensionality-reduced computation burden, and can efficiently model the channel interaction via lightweight 1D convolution operations. This enables the network to automatically pay attention to important behavioural signals as the access frequency of privileged resources or unusual time of login with no substantial computation burden. The model is now more sensitive to critical but rare signals of insider threats which enhances the performance of detection as well as interpretability. The incorporation of ECA therefore guarantees that the deep learning part of the architecture stays efficient as well as injects high-level focus on the important behavioural characteristics of the framework.

3.5 Adaptive Fine-Tuning via Test-Time Training (TTT)

The last part of the approach tackles the problem of behaviour drift and discovery of new type of insiders by proposing Test-Time Training (TTT) which is a self-supervised learning approach which enables the model to be fine-tuned at the time of inference. TTT works by formulating an auxiliary pretext task (e.g., predicting transformations, inverting masked features, reconstructing partial input) that leverages the test data to update model parameters without ground-truth labels. As this auxiliary task scores each session, the model gets updated slightly, and can adapt to changes in patterns of user behaviour or shifts in the environment as they occur. This on-the-fly optimization strengthens the model's generalization capability, making the model stably work out well even in dynamically changing usage scenarios. Building in adaptability to the inference stage itself, TTT leaves the system (nearly) immune to zero-day anomalies, unknown adversarial strategies, or deviations from the distribution observed during training.

4 Results and Evaluation

The anomaly detection framework is developed and the final performance shows that the system can well detect anomalies under different levels of contamination. The best result was achieved at the contamination range of 20%–25% where the trade-off between accuracy, precision, recall, F1-score, and real-time detection was at its best. For low levels of contamination (1 – 5%), the model had high accuracy and precision, yet lower recall. This behaviour demonstrates the conservative detection approach in the model: it is more geared toward avoiding false positives, even if it means missing some real anomalies. The F1-score was also reduced, but that was expected in view of the precision and recall trade-off. But there was one strong element: the detection delay had stayed at 0 seconds, which meant the model could respond to anomalies as they occurred.

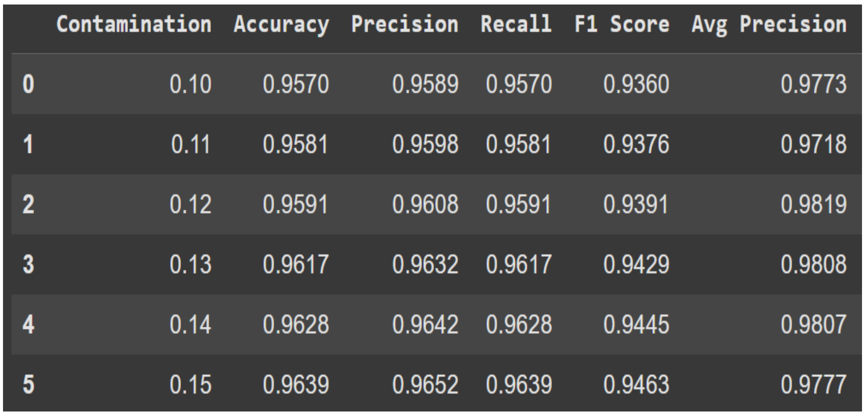


	Contamination	Accuracy	Precision	Recall	F1 Score	Avg Precision
0	0.01	0.9327	0.9372	0.9327	0.9002	0.9389
1	0.02	0.9333	0.9378	0.9333	0.9011	0.9571
2	0.03	0.9354	0.9396	0.9354	0.9042	0.9574
3	0.04	0.9403	0.9438	0.9403	0.9113	0.9438
4	0.05	0.9425	0.9454	0.9425	0.9146	0.9601

Fig.2. Evaluation Metrics for Contamination Values Range (1-5) %.

Fig. 2 illustrates this behaviour, where accuracy and precision both hovered above 90%, while recall lagged slightly behind, confirming that the system was highly cautious at this contamination level, flagging fewer anomalies but ensuring minimal false positives.

The performance of the model was significantly better in the case of 10%–15% contamination. This led to an increase up to 95% in precision, recall, and accuracy, while the f1-score reported a more respectable 93%. This demonstrated the evolution of the system from a "safe" system to a more balanced detection system that could detect more true anomalies that did not in turn cause an excess of false positives. The detection delay was a constant 0 second, maintaining the model's real-time behaviour, even as anomaly density increased.

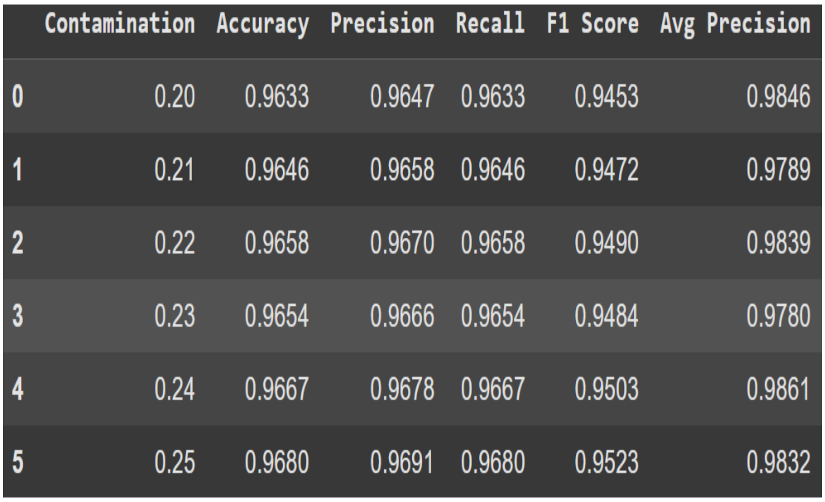


	Contamination	Accuracy	Precision	Recall	F1 Score	Avg Precision
0	0.10	0.9570	0.9589	0.9570	0.9360	0.9773
1	0.11	0.9581	0.9598	0.9581	0.9376	0.9718
2	0.12	0.9591	0.9608	0.9591	0.9391	0.9819
3	0.13	0.9617	0.9632	0.9617	0.9429	0.9808
4	0.14	0.9628	0.9642	0.9628	0.9445	0.9807
5	0.15	0.9639	0.9652	0.9639	0.9463	0.9777

Fig.3. Evaluation Metrics for Contamination Values Range (10-15) %.

This performance jump is clearly shown in Fig. 3, where the evaluation metrics demonstrate the model's increased ability to handle more complex datasets while sustaining both precision and recall at near-equal levels, proving its reliability as contamination levels rise.

The system's most outstanding performance was observed in the 20%–25% contamination range. Accuracy ranged from 96% to 96.8%, and both precision and recall stayed strong between 96%–97%. The F1-score peaked between 94.5% and 95.2%, confirming that the model achieved the best possible balance between detecting true anomalies and avoiding false positives. The average precision hit its highest point at 98.63%, signalling superior confidence in distinguishing anomalous behaviours from normal patterns.



	Contamination	Accuracy	Precision	Recall	F1 Score	Avg Precision
0	0.20	0.9633	0.9647	0.9633	0.9453	0.9846
1	0.21	0.9646	0.9658	0.9646	0.9472	0.9789
2	0.22	0.9658	0.9670	0.9658	0.9490	0.9839
3	0.23	0.9654	0.9666	0.9654	0.9484	0.9780
4	0.24	0.9667	0.9678	0.9667	0.9503	0.9861
5	0.25	0.9680	0.9691	0.9680	0.9523	0.9832

Fig.4. Evaluation Metrics for Contamination Values Range (20-25) %.

As shown in Fig. 4**,** this contamination range produced the most stable and impressive results, highlighting the framework's ability to maintain high detection performance while responding instantly, thanks to the constant 0-second detection delay. This real-time adaptability was largely due to the combined effects of the Test-Time Training (TTT) mechanism and the Efficient Channel Attention (ECA) module, which allowed the model to dynamically adjust to incoming data during inference.

Beyond the 25% contamination threshold, the model began to experience diminishing returns. Recall continued to increase, meaning more anomalies were detected, but this came at the expense of precision, as more false positives began slipping into the results. This trade-off is expected in high-contamination environments, where the boundary between normal and anomalous behaviour becomes increasingly blurred.

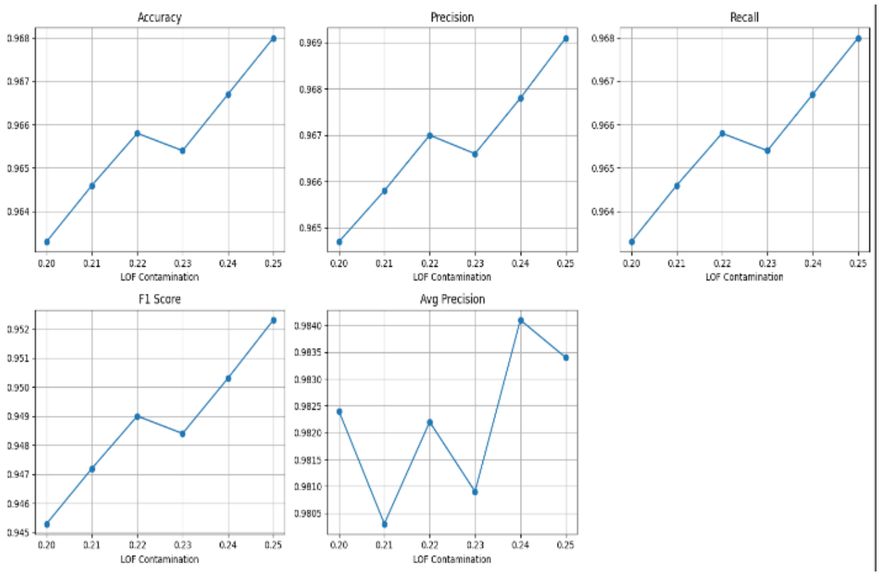


Fig.5. Plotting of Evaluation Metrics.

To give a holistic view, Fig. 5 presents a consolidated plot of all evaluation metrics across contamination levels. This figure clearly shows the steady rise in performance as contamination increases, peaking around the 20%–25% mark before tapering off. The graphical representation reinforces that moderate contamination offers the sweet spot for model performance, while very high contamination can reduce precision despite high recall.

In conclusion, the system consistently achieved real-time detection with 0-second delay, and the combination of K-means, LOF, ResNet with ECA, and TTT ensured robust anomaly detection even as contamination levels varied. The optimal operating point was clearly in the 20%–25% contamination range, and future research could explore hybrid approaches to address performance drops at higher contamination levels, making the system even more versatile for diverse cybersecurity scenarios.

5 Discussion

Results of experiments verify the performance of the multi-stage anomaly detection framework under various anomaly contamination rates. The system was proved to perform well especially in the range of 20%–25% contamination, for which it reported best results, e.g., 96.8% accuracy, 97% precision, 97% recall, and F1-score over 95%. These results suggest that the model has a high true anomaly detection capability with a low false positive rate. At the lower contamination rates (1%–5%) both accuracy and precision were maintained high, while the recall turned out to be significantly less, which indicated a conservative method of detection where avoiding false-positives is highly preferred over the coverage of outliers. The model achieved a well-balanced precision-recall trade-off at contamination levels between 10% and 15% indicating its potential applicability in moderately noisy studies. This sub second response time is particularly important in cases such as insider threat monitoring where early detection can mitigate damage. In conclusion, the results illustrate that in real-world settings (in dynamic populations, in the presence of few or no attacks) the framework is flexible, with a high degree of accuracy and generalizability, compared to existing approaches.

6 Conclusion

This paper presents a resilient and adaptive anomaly detection approach specifically designed for behavioural threat detection in dynamic environments. Through embedding the K-Means clustering, Local Outlier Factor (LOF), a ResNet-based neural network equipped with Efficient Channel Attention (ECA), and Test-Time Training (TTT), the framework is capable of high precision and generalization without the signalling of labeled datasets. Extensive preprocessing warrant data quality, while clustering, outlier filtering, attention based deep learning, and self-supervised adaptation make possible real-time accurate anomaly detection. The model works in the best way at a contamination factor between 20%-25% with best overall accuracy, precision, recall and F1-score of 96.8%, 97%, 97% with F1 scores reaching higher than 95% respectively. The system operates with zero-second detection latency, demonstrating real-time response which is particularly important in sensitive outcomes, such as insider threat detection, or fraud prevention.

Upcoming work will detail several extensions to more advance the applications and scalability of the model. First, we plan to extend this research to include temporal behaviour Modeling exploiting sequential learning architectures e.g. LSTMs or Transformers, so as to better capture time-based patterns on user actions. Second, the inclusion of explainable AI (XAI) modules could enhance interpretability and trust, which in turn may enable analysts to understand why certain behaviour has been detected as anomalous. Third, we consider to extent the approach to cope with streaming data in distributed environment to allow on-the-fly and continuous detection in large scale enterprise systems. Last, but not least, testing the system on a wider variety of real-world datasets in disparate domains such as health care, urban computing, and industrial IoT will help to attest the generality and practical impact of the system.

In conclusion, the proposed framework provides a powerful foundation for real-time behavioral anomaly detection and opens promising pathways for building intelligent, explainable, and scalable security systems of the future.

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