Doctoral School of Information and Biomedical Technologies Polish Academy of Sciences (TIB PAN)

SUBJECT:
KAN-based anomaly detection in IoT and engineering systems

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DESCRIPTION:
In the era of advanced IoT system development and the increasing role of systems in securing technology infrastructure, data processing, and transmission, modern solutions for detecting anomalies and external attacks are critical to the reliable operation of IoT systems. The primary challenge of anomaly detection, particularly in critical environments of infrastructure and complex large-scale IT systems, is often the absence or only residual characteristics of these anomalies - it is unclear whether the cause is a failure of system components or an external attack. In such cases, it is essential to react quickly and reconfigure the system in a way that does not compromise its operation, even in emergency mode.

The lack of complete information about the nature of anomalies in the initial stages of detection makes it challenging to train machine learning (ML) models and deep learning (DL) models, which are commonly used in so-called Anomaly (Intrusion) Detection Systems (ADS/IDS). These methods are used to identify suspicious patterns in monitoring data from IoT systems, which requires large training datasets. Unsupervised learning methods solve the problem of costly and time-consuming data annotation (using unlabelled data), but the efficiency and accuracy of such systems are generally not high. Another proposal is federated learning methods (FL) without the need for data centralisation.

In recent years, so-called “oversampling” methods have often been used in anomaly detection, which allow the training dataset to be enlarged in case of a shortage of labelled data or handling data imbalances. Generative adversarial networks (GANs) are used to detect generative “patterns” of anomalies. However, these methods are generally computationally expensive and negatively impact ITS performance, failing in cases where minor differences exist between data patterns depicting normal system fluctuations and disturbed system fluctuations.

Given the limitations of the ML and DL models and their variants, there is a need to build and analyse models that can better generalise, capture complex nonlinear relationships in data, and offer computational performance suitable for real-time IoT deployments. A promising alternative is the Kolmogorov-Arnold network (KAN). Unlike traditional DL and ML models,

which rely on fixed activation functions, KANs use learnable one-dimensional functions at their edges, allowing them to approximate complex, multidimensional functions with fewer parameters and greater interpretability. This makes KANs particularly suited to the unpredictable and evolving nature of attack and anomaly detection, where patterns of these attacks can change rapidly and feature relationships that are often non-linear, as is often the practice case.

The purpose of this work is to develop KAN-based models for anomaly detection in IoT systems, along with a comprehensive comparative analysis with existing ML, DL, and FL models. The work involves designing a reliable case study that utilises an implementable system for speech analysis, image analysis, or wireless network operation (e.g., LoRa WAN) in the monitoring and management of safe intelligent transportation in cities.

REQUIREMENTS:

- MSc degree in computer science, mathematics, AI, or related field
- High programming skills in Python
- Experience with ML, DL and FL tools and model evaluation frameworks
- Knowledge of current research on anomaly and intrusion detection methods
- Advanced level of English (spoken and written);

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