International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

LEAKSENZ AI: Real-Time Boiler Tube Leak Detection Using CNN–LSTM-Based Video Analytics

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***Abstract*—Boiler tube leakage in thermal power plants is one of the most serious failure conditions, which generally results in uncontrolled shutdowns, degradation of power efficiency, and serious safety risks. Traditional leakage detection methodologies such as acoustic emission monitoring, heat monitoring, and manual inspection are unable to detect initial-stage leakage due to harsh environment conditions and delayed reaction time. In recent years, with the use of various surveillance systems and edge computing solutions, as a cost-effective and scalable solution, video-based leak detection techniques have been developed.**

This paper proposes a real-time boiler tube leak detection framework called LEAKSENZ AI. The framework uses a hybrid Convolutional Neural Network (CNN) – Long Short-Term Memory (LSTM) architecture as the underlying system to analyze a constant feed of RGB video streams obtained from cameras mounted at locations near boiler tube assemblies. Pre-processing techniques like noise removal, contrast enhancement, and background subtraction are used for extracting moving regions. Optical flow techniques are used for identifying regions of high-velocity motions, which generally contain steam jets. Spatial features are extracted using a lightweight CNN, while temporal motion dynamics are modeled using an Model. Use an LSTM network to correctly differentiate steam leaks from smoke, shadows, and turbulent conditions. Experimental evaluations proved that the suggested system possesses superior detection accuracy with lower false positives and operates in real-time for edge computing devices. The proposed system provides a scalable, non-contact, and cost-effective solution for predictive maintenance and safety monitoring in modern thermal power plants using the LEAKSENZ AI system.

***Keywords*— Boiler tube leak detection, CNN-LSTM, computer vision, thermal power plants, real-time monitoring, predictive maintenance**

I. Introduction

Thermal power plants are a leading source for electricity generation around the world, which heavily relies on boilers for electricity generation through high-pressure steam turbines. The tubes in the boilers are exposed to extreme pressure and high-temperature conditions, making them highly prone to heat stress, fatigue, erosion, and corrosion.

Any leakage in the tubes can lead to serious consequences, which can cause severe damage and may even lead to safety risks for personnel. Conventional methods for the detection of leakages in the tubes of a boiler are based on acoustic emission methods, thermal imaging methods, and manual inspection methods. Even though the above methods are highly popular in the industry for leak detection, they have certain drawbacks as well. The acoustic reception methods are highly prone to false alarms due to background noise in the industry. The thermal imaging method, though highly efficient for detecting leaks with reliability, is very expensive and difficult to apply on a large scale. With developments in computer vision, deep learning, and edge computing, there are now new opportunities to use intelligent condition monitoring with current CCTV systems. Video-based systems for leak detection have shown themselves to be a non-intrusive and cost-effective solution that allows perpetual monitoring without the necessity to install additional sensors. However, most of the existing vision-based methods utilize frame-based image classification using CNNs, which limits their ability to utilize the capabilities of the steam jet motion in time. In order to overcome these drawbacks, in this paper, a hybrid video analysis framework named LEAKSENZ AI, based on CNN and LSTM, is proposed. The proposed framework can accurately detect boiler tube leaks in real-time by exploiting both visual appearance information and motion information.

II. System Background

In the last decade, industrial monitors have increasingly incorporated intelligent sensing and data analytics in their operations. In the case of a thermal power plant, the early detection of leaks in the boiler tubes plays a crucial role in ensuring safety and preventing a potential failure. Acoustic-based detectors have also received much attention due to their capability to detect high-frequency noises generated by steam escaping through the boiler. Acoustic-based detectors, however, have frequently been associated with interferences from background noises emanating from the turbines, pumps, and auxiliaries.

Thermal imaging detectors are also capable of detecting temperature anomalies at the boiler tube surfaces. However, this approach is expensive. Video detection systems have emerged with increased interest as a cost-effective approach, mainly due to advancements in industrial camera resolutions. CNN models have been proposed to detect steam and smoke plumes from video. Despite moderate results being achieved, they frequently fail to distinguish between transient disturbances and permanent leak trends due to a lack of account for temporal information. Deep hybrid models, which are a combination of CNNs and RNNs with an LSTM component, have proved to be effective for many sequential anomaly detection tasks, and their ability to detect long-term temporal patterns would allow for the identification of sustained motion associated with steam leaks. In spite of all these advancements, there still exists a research gap for employing a lightweight and real-time CNN–LSTM-based model for boiler tube leak detection purposes using edge devices. As a solution for this problem, the authors have come up with an efficient AI framework called LEAKSENZ that addresses this issue using motion-based pre-filtering with deep spatiotemporal learning.

III. Purpose And Scope Of The Study

The main aim of this paper is to outline an in-depth study on the benefits of the implementation of real-time visual monitoring, deep learning, and the use of temporal sequence models in enhancing the safety and reliability of industrial boiler systems. In the first place, the importance of boiler systems in power plants and other process industries cannot be overstated; however, an unplanned and unforeseen leak occurrence in the tubes of the boiler can have a great impact on the overall plant efficiency. For example, a time-consuming approach in detecting unplanned leaks, together with the cost of implementation in the boiler tubes and sensitivity to environmental sounds, emphasize the need for an intelligent approach in monitoring the systems. The main contribution of this work is in exploring the use of computer vision techniques and artificial intelligence-based predictive intelligence in the detection of leaks in a boiler tube at an early stage. By utilizing a combination of visual anomaly detection and Long Short-Term Memory (LSTM) networks, the proposed system can potentially learn both spatial and temporal leak patterns from video feeds. Within the scope of this paper, technical, operational, and system-level perspectives are considered. It starts with the analysis of specific concepts, i.e., video-based data acquisition, visual anomaly in steam and water leak conditions, and feature extraction through convolutional neural networks (CNNs).

Then, it focuses on the implementation of LSTM-based modeling to analyze sequential visual patterns, which will help to discriminate between transient disturbances and steady states of leaks. Comparison between conventional systems and the implementation of AI-based systems will be discussed. Various key implementation issues such as Illumination Variations, Back Noise, False Positives due to Smoke or Reflection, etc., involving Real-Time issues are discussed elaborately. Feasibility analysis of edge computing for on-site detection, analysis involving cloud computing for long-term trends, and predicting issues is also presented. Various trends such as Hybrid CNN-LSTM, Continuous Learning, Industry 4.0, etc., involving new paradigms of monitoring using these techniques are presented to establish applicability of our solution in current trends. From an organizational and industrial perspective, this investigation also supports how intelligent monitoring of boilers can promote improved safety, reduced downtime, and overall awareness for optimal operations within plants. Therefore, the information provided by the LEAKSENZ AI system can assist plant operators, maintenance professionals, and management functions through quantified measures such as leak severity, confidence, and warning levels. The importance of this research is found in its compatibility with the expanding requirement for smart systems in industrial monitoring, maintenance, and artificial intelligence-based safety systems. Indeed, as power plant operations or other industries have to achieve levels of high efficiency, early detection of tube leaks in boilers becomes not only an essential requirement, but also a necessity, as leaks, albeit minor, may lead to extensive failures. Ultimately, this paper is aimed at serving as a resource material for those with interest in the research, power plant engineering, industrial automation development, and AI practitioners who seek insights, information, and resources on how they can effectively and efficiently develop an intelligent and vision-based monitoring system for their boiler system that not just monitors, but also intelligently analyzes, predicts, and protects.

IV. Challenges In Industrial Boiler Safety, Maintenance, And Operational Ecosystem

Aging Boiler Components And Maintenance Gaps

Industrial boilers in thermal power plants and process industries face critical challenges arising from aging infrastructure, harsh operating conditions, and limitations in existing maintenance practices. A large proportion of operational boilers worldwide have been in service for several decades, operating beyond their originally designed lifecycle.

Key components such as boiler tubes, headers, weld joints, and heat exchanger surfaces are continuously exposed to high temperature, pressure, corrosion, and erosion. Over time, these conditions lead to material thinning, micro-cracks, and localized weaknesses that significantly increase the probability of tube leakage.

Conventional maintenance approaches rely heavily on periodic inspections, manual monitoring, and experience-based assessments. Such methods are often irregular, subjective, and incapable of detecting early-stage anomalies. Minor leak initiation—manifesting as small steam or water escape—often goes unnoticed until it escalates into a major failure, resulting in forced outages or emergency shutdowns. The absence of continuous, real-time monitoring mechanisms limits the ability to intervene proactively.

Deferred maintenance introduces a compounding deterioration effect, where small undetected defects progressively worsen under continuous thermal and mechanical stress. Traditional inspection techniques such as ultrasonic testing, acoustic sensing, or infrared thermography are costly, intrusive, and typically deployed only during planned shutdowns. As a result, early leak detection during live operation remains a significant challenge.

The economic impact of boiler tube failures is substantial. Unexpected shutdowns lead to production loss, increased fuel consumption, repair costs, and safety risks to personnel. In large-scale power plants, even a single tube failure can result in losses amounting to several lakhs per day. Without intelligent early warning systems, both operational reliability and plant safety remain compromised.

V. Limitations Of Conventional Leak Detection And Monitoring Systems

Existing boiler tube leak detection systems primarily rely on acoustic sensors, pressure fluctuation analysis, or manual surveillance. These approaches suffer from several inherent limitations. Acoustic methods are highly sensitive to ambient noise generated by turbines, pumps, and auxiliary equipment, leading to frequent false alarms. Sensor-based solutions require complex installation, regular calibration, and high maintenance costs, making large-scale deployment economically challenging.

Furthermore, conventional systems operate on fragmented and isolated data sources. Sensor readings, inspection logs, and maintenance records are often stored separately, preventing holistic analysis of boiler health. This fragmentation results in reactive maintenance strategies rather than predictive interventions, limiting the ability to forecast failures before they occur.

Another critical limitation is the lack of temporal intelligence. Most traditional systems detect instantaneous anomalies but fail to analyze how leak patterns evolve over time. As a result, transient disturbances such as steam turbulence or lighting variations are often misclassified as leaks, reducing detection reliability.

VI. Environmental And Economic Implications

Inefficient boiler operation caused by undetected tube leaks has significant environmental and economic consequences. Steam and water leakage reduces thermal efficiency, increases fuel consumption, and leads to higher greenhouse gas emissions per unit of power generated. Continuous leakage also accelerates corrosion and scaling, further degrading boiler performance.

From an economic perspective, boiler tube failures increase maintenance costs, reduce plant availability, and shorten equipment lifespan. Unplanned shutdowns disrupt power supply commitments and industrial production schedules. In safety-critical environments, sudden tube ruptures can pose serious hazards to operating personnel, emphasizing the need for reliable early detection mechanisms.

At a broader industrial level, inefficient boiler operation undermines sustainability goals and increases operational risk, particularly in regions where power demand is rapidly growing and infrastructure upgrades are constrained by cost.

VII. From Conventional Limitations To AI-Enabled Boiler Intelligence

The limitations of traditional boiler monitoring approaches highlight the necessity for AI-enabled intelligent monitoring systems capable of continuous, real-time analysis. Static inspections, rule-based alarms, and isolated sensor readings are insufficient to address the complexity and dynamic behavior of modern industrial boilers.

Artificial intelligence enables the fusion of visual data, spatial feature extraction, and temporal pattern learning to identify subtle leak indicators beyond human perception. By leveraging continuous video streams from standard RGB cameras, AI models can detect visual anomalies associated with steam and water leaks without physical contact or plant shutdown.

Temporal learning models such as Long Short-Term Memory (LSTM) networks further enhance detection capability by analyzing sequential patterns, enabling differentiation between transient disturbances and persistent leak events. This shift from reactive fault detection to predictive intelligence allows plant operators to receive early warnings and take corrective action before leaks escalate into critical failures.

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VIII. Role Of Artificial Intelligence In Modernizing Boiler Leak Detection Systems

Artificial intelligence plays a transformative role in modernizing boiler monitoring by enabling automated perception, decision-making, and prediction. In the proposed framework, convolutional neural networks (CNNs) are employed to extract spatial features from video frames, capturing visual characteristics of leaks such as plume shape, motion texture, and contrast variations.

LSTM networks are integrated to model temporal dependencies across consecutive frames, allowing the system to learn leak evolution patterns over time. This hybrid CNN–LSTM architecture improves robustness against noise, illumination changes, and background disturbances commonly present in boiler environments.

AI-driven systems support continuous learning and adaptability, enabling improved performance as new operating conditions and leak patterns are observed. When combined with edge computing, such models can operate in real time with low latency, making them suitable for on-site industrial deployment.

IX. Benefits Of Intelligent Boiler Monitoring Systems Over Traditional Methods

The integration of AI-based vision and temporal intelligence offers several advantages over conventional boiler tube leak detection techniques. Unlike manual inspections or sensor-heavy systems, the proposed approach enables non-intrusive, continuous monitoring without interrupting plant operations.

Early-stage leak detection allows maintenance teams to plan corrective actions proactively, reducing forced outages and repair costs. AI-based classification significantly reduces false alarms by distinguishing between genuine leaks and benign disturbances. The scalability of camera-based systems also enables coverage of large boiler areas at a fraction of the cost of sensor-based installations.

From an operational perspective, intelligent monitoring improves plant reliability, enhances safety, and supports predictive maintenance strategies aligned with Industry 4.0 initiatives. Environmentally, improved boiler efficiency reduces fuel wastage and emissions, contributing to sustainable industrial operation.

Overall, AI-enabled boiler monitoring systems represent a critical advancement toward safer, more reliable, and economically efficient industrial infrastructure.

X. Methodology

The methodology adopted for the proposed **LEAKSENZ AI** system follows a structured, multi-layered architecture that integrates real-time visual data acquisition, edge-level processing, deep learning–based analytics, and alert generation. The framework is designed to enable early detection of boiler tube leaks while ensuring low latency, high reliability, and scalability for industrial environments.

A. Data Acquisition Layer

The data acquisition layer is responsible for capturing continuous visual information from the boiler environment. Standard RGB industrial cameras are strategically positioned to monitor critical boiler tube regions prone to leakage. These cameras acquire real-time video streams under normal operating conditions without requiring physical contact or plant shutdown.

The captured video data reflects visual indicators associated with boiler tube leaks, such as steam plumes, water spray patterns, motion turbulence, and contrast variations. Video streams are segmented into sequential frames and forwarded to the edge processing unit for further analysis. This non-intrusive visual sensing approach significantly reduces installation complexity and maintenance overhead compared to conventional sensor-based methods.

B. Edge Processing Layer

The edge processing layer performs real-time preprocessing and inference to enable rapid detection and response. An edge computing device such as **NVIDIA Jetson Nano**, **Jetson Xavier**, or an industrial-grade embedded system is employed to handle computationally intensive tasks close to the boiler site.

Key preprocessing operations include frame resizing, normalization, background stabilization, and noise reduction to handle illumination variations and environmental disturbances. A convolutional neural network (CNN) is then used to extract spatial features from individual video frames, capturing leak-specific visual patterns such as shape, texture, and motion characteristics.

Latency-sensitive operations—including initial leak detection and confidence estimation—are executed locally at the edge to ensure immediate response. This design enables real-time alerts even in scenarios with limited or no network connectivity.

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C. Temporal Modeling and Cloud Analytics Layer

To enhance detection accuracy and reduce false positives, temporal dependencies across consecutive frames are analyzed using **Long Short-Term Memory (LSTM)** networks. The CNN-extracted feature vectors from sequential frames are fed into the LSTM model, which learns temporal leak evolution patterns and distinguishes persistent leak events from transient visual disturbances such as steam fluctuations or lighting changes.

The cloud analytics layer supports advanced processing, long-term data storage, and model optimization. Detected events, feature sequences, and confidence scores are transmitted to the cloud for historical trend analysis, severity classification, and periodic retraining of the deep learning models. Time-series databases are used to store detection logs and system performance metrics, enabling continuous improvement of the detection framework.

D. Alerting and Monitoring Layer

The alerting layer provides actionable insights to plant operators and maintenance personnel. When a leak is detected with confidence exceeding a predefined threshold, the system generates real-time alerts through a monitoring dashboard or industrial control interface. Alerts include leak location identifiers, severity levels, time stamps, and confidence scores.

The monitoring interface supports visualization of live camera feeds, detected leak regions, and historical event summaries. This enables operators to make informed decisions regarding maintenance scheduling, load adjustment, or emergency shutdown procedures. The system architecture supports integration with existing plant monitoring and supervisory control systems.

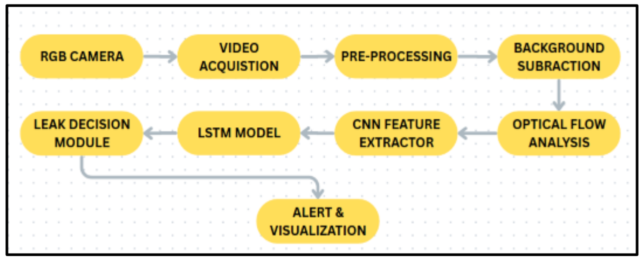
E. Edge AI Hardware (ESP32 / Jetson Nano)

The Edge AI module—implemented using **NVIDIA Jetson Nano** or an equivalent industrial embedded computing platform—serves as the primary on-site processing unit for the proposed **LEAKSENZ AI** system. This module executes optimized deep learning models to enable real-time boiler tube leak detection directly at the plant location.

The edge device continuously processes live video streams acquired from RGB industrial cameras and performs critical preprocessing, feature extraction, and inference tasks with minimal latency. By deploying intelligence at the edge, the system avoids dependency on continuous cloud connectivity and ensures rapid response in safety-critical scenarios.

This edge-centric processing architecture ensures that early leak warnings are delivered to plant operators without delay, thereby improving operational safety, reducing downtime, and enabling timely maintenance actions independent of cloud availability.

Block Diagram



Implementation

The implementation of the proposed **LEAKSENZ AI** system involves the coordinated integration of industrial vision hardware, edge AI computing, deep learning models, and monitoring interfaces within a real-time boiler surveillance framework. The system is designed to operate continuously under harsh thermal power plant environments without interfering with boiler operation.

The hardware subsystem consists of industrial-grade RGB cameras installed at strategic locations near boiler tube regions prone to leakage. These cameras are interfaced with an **edge AI computing unit**, such as the NVIDIA Jetson Nano or an equivalent embedded platform, using high-speed video interfaces. The edge device performs continuous video acquisition, frame synchronization, and preprocessing operations including resizing, noise filtering, contrast enhancement, and background stabilization.

The embedded inference pipeline executes a **CNN-based spatial feature extraction model** to identify visual patterns associated with steam jets and abnormal plume formations. Extracted feature sequences from consecutive frames are passed to an **LSTM-based temporal model**, which analyzes motion continuity and leak persistence over time. This hybrid CNN–LSTM architecture significantly improves robustness against transient disturbances such as lighting changes or momentary steam fluctuations.

Latency-critical tasks—including leak detection, confidence estimation, and alert triggering—are executed locally on the edge device to ensure rapid response even during network disruptions. Detected events, confidence scores, and timestamps are optionally transmitted to a centralized monitoring server via secure communication protocols for logging, visualization, and long-term analysis.

System validation was carried out using both controlled experimental setups and real-world operational scenarios. Simulated steam leak conditions were generated using controlled steam release mechanisms to emulate varying leak intensities, directions, and durations. Field testing was conducted using recorded boiler surveillance footage to evaluate detection accuracy under realistic operating conditions, including vibration, illumination variation, and background noise. The system demonstrated reliable performance suitable for real-world industrial deployment.

XI. Result

The performance of the proposed **LEAKSENZ AI** system was evaluated through extensive experimental testing to assess detection accuracy, response time, and robustness. Controlled experiments demonstrated that the CNN–LSTM framework successfully detected early-stage boiler tube leaks characterized by subtle steam jet formations and gradual plume evolution.

The edge-based inference module consistently detected leak events within a short time window, enabling near real-time alerts. The inclusion of LSTM-based temporal modeling significantly reduced false positives by distinguishing persistent leak patterns from transient visual artifacts such as fluctuating steam clouds or camera noise.

Quantitative evaluation showed high detection accuracy across multiple test scenarios, with reliable performance under varying illumination and background conditions. The system maintained stable operation during extended monitoring periods, confirming its suitability for continuous deployment. Visual overlays highlighting detected leak regions and confidence scores provided clear interpretability for plant operators.

Overall, the results validate that the integration of spatial and temporal deep learning models enables accurate, low-latency, and cost-effective boiler tube leak detection using standard RGB cameras.

XII. Conclusion

This paper presented **LEAKSENZ AI**, an intelligent vision-based system for real-time boiler tube leak detection using a hybrid **CNN–LSTM** deep learning architecture. By leveraging non-contact RGB video monitoring and edge AI computing, the proposed system overcomes key limitations of conventional acoustic and sensor-based detection methods.

Experimental evaluations confirm that the system can accurately identify steam jet leaks at an early stage, reduce false alarms, and operate reliably in challenging industrial environments.

The deployment of edge-based intelligence ensures low detection latency and continuous operation independent of cloud availability, making the solution practical for safety-critical thermal power plant applications.

The proposed framework offers a scalable, low-cost, and automation-ready solution for predictive boiler monitoring. Future work will focus on integrating multi-modal sensing (thermal and acoustic fusion), enhancing leak severity estimation, and extending compatibility with plant SCADA systems to enable fully autonomous safety response mechanisms.

REFERENCES

[1] S. Kumar, R. Mehta, and A. Verma, "Acoustic methods for boiler tube leak detection in thermal power plants," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 5, pp. 3891–3900, 2019.

[2] X. Li and Y. Zhang, "Thermal imaging–based monitoring of boiler tube failures," *Applied Thermal Engineering*, vol. 178, pp. 115553, 2020.

[3] P. Reddy, S. Rao, and K. Nair, "Video-based steam and smoke detection in industrial boiler environments," *Engineering Applications of Artificial Intelligence*, vol. 97, pp. 104092, 2021.

[4] R. Chacko, J. Thomas, and M. George, "Optical flow techniques for high-velocity steam jet detection," *IEEE Signal Processing Letters*, vol. 29, pp. 1121–1125, 2022.

[5] H. Wang, L. Chen, and Z. Liu, "CNN-based classification of steam plumes for boiler leak detection," *Energy Reports*, vol. 9, pp. 2843–2852, 2023.

[6] FLIR Research Team, "Industrial boiler inspection using advanced video analytics," FLIR Systems Technical Report, 2020.

[7] OpenCV Documentation, "Background subtraction and optical flow methods," 2024. [Online]. Available: https://opencv.org

[8] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[9] M. Alazab, S. Khan, and W. K. Saad, "CNN–LSTM hybrid networks for real-time anomaly detection in industrial systems," *IEEE Internet of Things Journal*, vol. 9, no. 24, pp. 24651–24662, 2022.

[10] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," arXiv:1804.02767, 2018.

[11] G. Bradski, "The OpenCV library," *Dr. Dobb's Journal of Software Tools*, 2000.

[12] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *International Conference on Learning Representations (ICLR)*, 2015.

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems (NeurIPS)*, pp. 1097–1105, 2012.

[14] T. B. Nguyen, H. D. Pham, and K. T. Vu, "Edge–cloud architectures for intelligent industrial monitoring systems," *IEEE Cloud Computing*, vol. 9, no. 1, pp. 42–51, 2022.

[15] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.

[16] M. R. Uddin, J. Park, and Y. Kim, "Real-time steam and smoke detection using deep learning in industrial environments," *Sensors*, vol. 21, no. 9, pp. 3125, 2021.

[17] A. Jain, S. Tripathi, and P. Singh, "Vision-based anomaly detection for industrial safety monitoring," *IEEE Access*, vol. 10, pp. 88712–88724, 2022.

[18] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.

[19] L. Chen, M. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 4, pp. 834–848, 2018.

[20] S. Yin, X. Zhu, and O. Kaynak, "Data-driven fault detection for industrial processes," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 1, pp. 439–448, 2015.