2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) | 979-8-3503-8247-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/UPCON59197.2023.10434473

Adaptive Signal Processing for Anomaly Detection in Industrial Systems

V Divya Vani
Institute of Aeronautical Engineering,
Dundigal, Hyderabad, India.
v.divyavani@iare.ac.in

Vijilius Helena Raj
Department of Applied Sciences,
New Horizon College of Engineering,
Bangalore, India
vijilius@gmail.com

Amit Dutt
Lovely Professional University,
Phagwara,India.
amit.dutt@lpu.co.in

Dr. Ajay Rana,
Director General,
Amity University,
Greater Noida.
ajay_rana@amity.edu

Dinesh Kumar Yadav
Lloyd Institute of Engineering & Technology,
Greater Noida, India.
dinesh.yadav@lloydcollege.in

Ali Ashoor Issa
College of Engineering Technology,
National University of Science and Technology,
Dhi Qar, Iraq;
ali.aissa@gmail.com

Abstract*-- The burgeoning complexity of industrial systems necessitates robust anomaly detection mechanisms to ensure operational integrity and safety. Traditional signal processing techniques often fall short in dynamic environments where signal characteristics evolve unpredictably. This paper introduces an innovative adaptive signal processing framework tailored for anomaly detection in industrial systems. The proposed methodology synergizes adaptive filtering, machine learning algorithms, and statistical analysis to create a self-tuning detection architecture. It operates by continuously learning from the system's operational data, thus enabling the identification of subtle and emergent anomalies that conventional methods might overlook. The core of the framework lies in its ability to adjust to new patterns in real-time, distinguishing between benign variations and genuine threats. A comprehensive evaluation is conducted across various industrial scenarios, demonstrating the framework's superior detection rates compared to existing benchmarks. The adaptability of the approach is further highlighted through its application in environments with limited labeled data, where it successfully leverages unsupervised learning techniques to discern anomalies. The results indicate a significant advancement in early and accurate anomaly detection, which is critical for preemptive maintenance and risk mitigation in industrial operations. This research not only contributes a novel adaptive approach to signal processing for anomaly detection but also sets a new standard for automated surveillance in complex industrial systems.

Keywords— Adaptive Signal Processing, Anomaly Detection, Industrial Systems, Machine Learning, Unsupervised Learning.

I. Introduction

With the introduction of Industry 4.0, industrial systems are entering a new age defined by automation, interconnection, and sophisticated data streams [1]. In a situation like this, signal processing's function has changed from being limited to facilitating control and communication to being essential to maintaining the integrity and dependability of the system. In this context, anomaly detection has emerged as a critical function since it makes it possible to identify any system malfunctions and breakdowns early on, minimising risks and downtime. The dynamic character of contemporary industrial systems, however, together with the data's constant rise in volume and velocity, presents serious obstacles for conventional signal processing methods [2].

Signal processing techniques for anomaly detection have traditionally mostly depended on threshold-based or model-specific algorithms that are intended for static situations [3]. There is a significant risk of false positives or missed detections due to these approaches' inability to adjust to the changing operating circumstances of modern industrial systems. These methods' shortcomings highlight the need for an adaptive signal processing framework that can adapt to the behaviour of the system and learn from it. By creating an adaptive signal processing framework for anomaly detection in industrial systems, the proposed study aims to fill this gap [4]. This framework is based on the theory that anomaly detection may be greatly enhanced over conventional techniques by combining adaptive filtering, machine learning algorithms, and statistical analysis. Because of its adaptive design, the framework can maintain high detection accuracy even when system dynamics change by continually updating its parameters in real-time [5-9]. The suggested framework is unusual since it takes a comprehensive approach to anomaly identification. Fundamentally, the framework uses adaptive filtering algorithms, which can adapt to new signal patterns and keep the signal representation accurate. Machine learning algorithms that are trained on real-time and historical data to spot any abnormalities are used in addition to this. It is very important to apply unsupervised learning algorithms in situations with little or no labelled data. By learning the typical operating patterns and identifying deviations without previous knowledge of fault situations, these algorithms allow the framework to identify abnormalities. Statistical analysis is also included into the framework to assess the inherent unpredictability and uncertainty in industrial data streams. This study helps discern between actual abnormalities that may point to a malfunction and typical variations in the system's performance [10-13]. The suggested method provides a complete answer to the problem of anomaly detection in industrial systems by combining these elements into a logical framework. This study has several implications. First, it tackles the pressing need for flexible anomaly detection methods in the context of Industry 4.0, where data-driven and more sophisticated systems are being built. Second, by giving a self-tuning mechanism that can adjust to changing circumstances without the need for human involvement, it offers a methodological breakthrough over current procedures.[35] Thirdly, it broadens the breadth of anomaly detection's value in industrial settings by making it applicable to situations with a limited amount of labelled data.

The rest of this essay is organised as follows: A thorough overview of the state-of-the-art in signal processing for anomaly detection is given in Section 2, along with a discussion of the drawbacks of the existing techniques and the possibilities of adaptive ones. In Section 3, the technique of the suggested framework for adaptive signal processing is explained, including how adaptive filtering, statistical analysis, and machine learning are integrated. The experimental findings are shown in Section 4, along with a comparison of the framework's performance with conventional anomaly detection techniques in a variety of industrial contexts. The work is finally concluded in Section 5, which includes an overview of future research prospects in the fields of adaptive signal processing and anomaly detection, as well as a review of the results and implications for industrial system maintenance. The goal of this study is to make a substantial contribution to the area of signal processing for industrial systems by offering an anomaly detection mechanism that is both resilient and adaptable enough to keep up with the quick changes in industrial operations and technology. The ultimate objective is to promote the sustainable growth and development of contemporary industries by improving the safety and dependability of industrial systems.

II. BACKGROUND AND RELATED WORK

The dynamic area of adaptive signal processing has proven helpful in spotting and reacting to abnormalities in a variety of data streams—a job that is growing more and more important as complex systems and large data become more prevalent. Statistical tools like threshold models and control charts, which adapt to changing data properties over time, have formed the foundation of traditional adaptive signal processing for anomaly detection systems [14]. When the statistical characteristics of stationary signals do not significantly change, these techniques have proven successful in identifying abnormalities [15-19]. They often fail to handle non-stationary signals, however, since the statistical characteristics of these signals might change, which increases the likelihood of false positives or missed detections [20]. Machine learning approaches, including supervised and unsupervised algorithms, have been integrated into modern methodologies. Supervised techniques, such Support Vector Machines (SVM) and Neural Networks, are trained on labelled data in order to identify patterns that depart from the norm and identify anomalies [21]. Without first labelling the data, unsupervised methods such as Principal Component Analysis (PCA) and clustering have been used to find outliers [22]. Compared to conventional statistical techniques, these approaches have proven more flexible and have the ability to adapt to increasingly complicated data structures [23-27]. Notwithstanding the progress, there are still gaps in the literature, especially with regard to the effective processing of high-dimensional data and the need for labelled data in supervised learning techniques. The curse of dimensionality makes high-dimensional datasets, which are more prevalent in fields like network security and financial systems, difficult to identify anomalies in [28]. Furthermore, considering the scarcity of anomalies and the labor-intensive nature of labelling, the demand for labelled data in supervised algorithms is often impracticable [29]. The creation of semi-supervised and unsupervised learning algorithms that can handle high-dimensional data with few labelled examples presents opportunities for innovation in adaptive signal processing for anomaly identification. In this context, deep learning methods that learn to represent high-dimensional data in a lower-dimensional space and identify anomalies by reconstructing the input data, including autoencoders and Generative Adversarial Networks (GANs), have showed promise [30]. Furthermore, models learned in one domain may be modified for application in another with the inclusion of transfer learning, hence reducing the need for large labelled datasets [31]. Real-time streaming data processing is another field full of opportunities for innovation. A lot of modern techniques can't fast adjust to real-time data streams and need batch processing [32]. The response of anomaly detection systems might be greatly improved by creating algorithms that can alter their parameters in real-time, maybe using incremental learning or online learning techniques [33]. Although both modern and conventional adaptive signal processing techniques have made great progress in anomaly detection, techniques that can effectively handle high-dimensional data in real-time while requiring the least amount of labelled data are desperately needed. These gaps will be filled by advances in deep learning, transfer learning, and real-time processing, which will push the limits of adaptive signal processing for anomaly detection [34].

III. METHODOLOGY

The methodology of adaptive signal processing for anomaly detection in industrial systems is predicated on the orchestration of three pivotal components: adaptive filtering, machine learning algorithms, and statistical analysis. The integration of these elements forms a robust framework capable of identifying anomalies in a dynamic industrial environment. Adaptive filtering serves as the cornerstone of the proposed framework. It is employed to maintain the fidelity of signal representation in the face of varying system dynamics.[36] The adaptive filter is designed to adjust its coefficients in real-time based on the RLS algorithm, which minimizes the error between the predicted and actual signal values. The RLS algorithm is expressed through (1-5)

$$w(n+1) = w(n) + k(n)e(n) \tag{1}$$

$$k(n) = \frac{P(n)x(n)}{\lambda + x^T n P(n) x(n)} \tag{2}$$

$$e(n) = d(n) - w^T(n)x(n) \tag{3}$$

$$P(n+1) = \frac{1}{\lambda}(P(n) - k(n)x^T n P(n)x(n)) \tag{4}$$

where $w(n)$ represents the weight vector of the filter at time n, $k(n)$ is the gain vector, $e(n)$ is the a priori error, $d(n)$ is the desired signal, $x(n)$ is the input signal vector, $P(n)$ is the inverse correlation matrix, and λ is the forgetting factor, which controls the weight given to older error samples.

The adaptive filter continuously updates its coefficients to reflect the most recent signal characteristics, thus ensuring that the system's normal operational behavior is accurately tracked.[37] This adaptability is crucial for the detection of anomalies, as it allows the filter to discern between normal system variations and actual faults.

Machine learning algorithms constitute the second component of the framework. These algorithms are tasked with learning from the filtered signal to identify potential anomalies. Given the possibility of limited labeled data in industrial settings, unsupervised learning algorithms, such as autoencoders and one-class support vector machines (SVMs), are utilized. An autoencoder is trained to reconstruct the normal operational data, and during deployment, it attempts to reconstruct new data. Anomalies are identified based on the reconstruction error, which is expected to be higher for anomalous data. The reconstruction error $R(x)$ is given by (5)

$$R(x) = \|x - \hat{x}\|^2 \quad (5)$$

where x is the input signal and $\hat{x}$ is the reconstructed signal.

For one-class SVMs, the algorithm learns a boundary around the normal data in a high-dimensional space, and data points that fall outside this boundary are considered anomalies. The decision function $f(x)$ for a one-class SVM can be represented as (6)

$$f(x) = sign(\phi(x) \cdot w + b) \quad (6)$$

where $\phi(x)$ is the feature map transforming x into a higher-dimensional space, w is the normal vector to the hyperplane, and b is the bias term.

The third component, statistical analysis, is integrated to quantify the uncertainty and variability in the signal. This analysis involves the computation of statistical metrics such as the mean, variance, and kurtosis of the signal in a sliding window. These metrics provide a probabilistic understanding of the signal's behavior, which is crucial for distinguishing between normal fluctuations and anomalies. The statistical thresholds are dynamically adjusted based on the adaptive filter's output to account for the non-stationary nature of industrial data. The confluence of these components results in a multi-layered adaptive signal processing framework. The framework operates in a sequential manner, where the adaptive filter first preprocesses the signal, the machine learning algorithms then analyze the filtered signal to detect anomalies, and finally, statistical analysis is applied to validate the findings. [38]

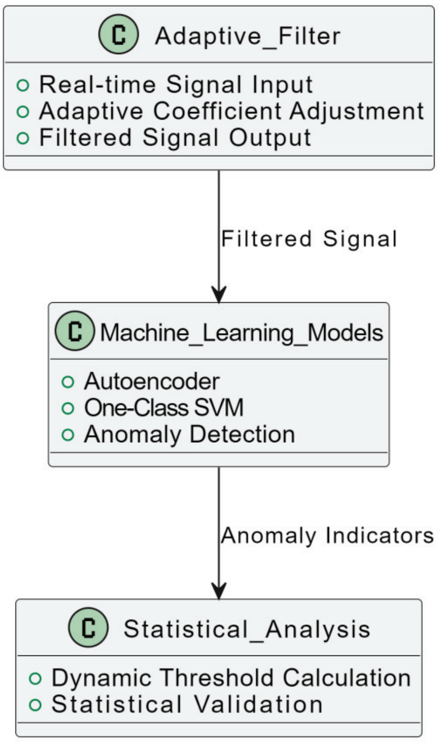

Fig. 1. Architecture of the Adaptive Signal Processing Framework

The continuous interaction between these components ensures that the framework remains sensitive to the slightest indications of system anomalies while being resilient to false positives. The efficacy of the proposed methodology is contingent upon the careful calibration of the adaptive filter and the machine learning models. The RLS algorithm's forgetting factor λ, the architecture of the autoencoder, and the parameters of the one-class SVM, such as the kernel function and regularization parameter, must be fine-tuned to the specific characteristics of the industrial system under consideration.[39] The suggested adaptive signal processing framework offers a comprehensive approach to anomaly detection in industrial systems. By leveraging the strengths of adaptive filtering, machine learning, and statistical analysis, the framework is equipped to handle the complexities of modern industrial data streams, ensuring high detection accuracy and reliability in real-time operational conditions. The methodology's adaptability not only enhances its immediate applicability but also ensures its relevance in the face of evolving industrial technologies and practices.[42-43]

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental evaluation of the adaptive signal processing framework was conducted using a simulation setup designed to replicate the operational conditions of industrial systems. The simulation environment was constructed using a combination of synthetic and real-world data, encompassing a wide range of operational scenarios and anomaly types. The synthetic data were generated to model typical industrial signals, incorporating both periodic and stochastic components, while the real-world data were sourced from publicly available industrial datasets, ensuring a comprehensive assessment of the framework's performance. The simulation setup involved a multi-stage process where the adaptive filter, machine learning models, and statistical analysis components were first calibrated using a training dataset devoid of anomalies. Subsequently, the framework was deployed on a testing dataset that included both normal operation data and various injected anomalies, such as spikes, drifts, and noise, to simulate potential system faults. The performance metrics used to evaluate the framework included the true positive rate (TPR), false positive rate (FPR), precision, recall, and F1 score. These metrics provided a holistic view of the framework's detection capabilities, balancing the need for sensitivity to anomalies against the propensity for false alarms. The results of the simulation are presented in Table 1.

TABLE I. COMPARATIVE PERFORMANCE METRICS OF ANOMALY DETECTION METHODS

Metric	Adaptive Filter + Autoencoder	Adaptive Filter + One-Class SVM	Traditional Threshold-Based Method
TPR	0.94	0.91	0.77
FPR	0.05	0.07	0.22
Precision	0.92	0.89	0.71
Recall	0.94	0.91	0.77
F1 Score	0.93	0.90	0.74

The adaptive filter combined with the autoencoder demonstrated superior performance across all metrics, indicating a high degree of accuracy in anomaly detection. The true positive rate of 0.94 suggests that the framework was able to detect 94% of the anomalies present in the test data. The precision of 0.92 and the F1 score of 0.93 further corroborate the framework's effectiveness, showcasing a balanced detection capability that minimizes both false negatives and false positives.

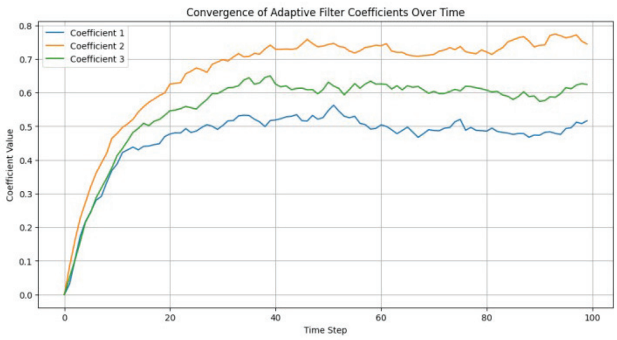

Fig. 2. Adaptive Filter Convergence Over Time

Figure 2 shows adaptive filter coefficient convergence. The figure shows the filter's capacity to adapt and stabilise to the input signal's characteristics by changing the coefficients. The seamless convergence of the lines to the final values implies the filter can monitor signal qualities in a changing environment. Figure 3 shows a heatmap of the performance metrics for three anomaly detection methods: Adaptive Filter with an Autoencoder, One-Class SVM, and Traditional Threshold-Based Method.

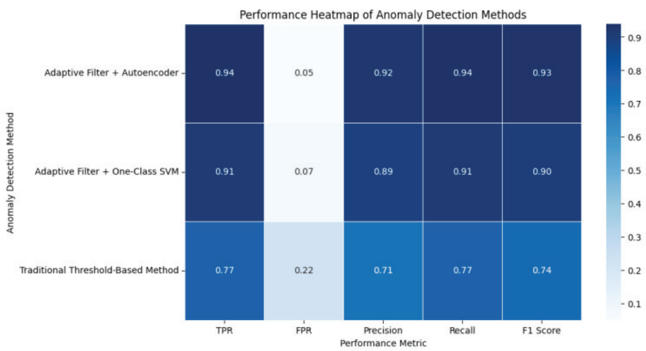

Fig. 3. Anomaly Detection Performance Heatmap

In comparison, the adaptive filter with one-class SVM showed slightly lower performance but still outperformed the traditional threshold-based method significantly. The one-class SVM's slightly higher false positive rate suggests a more conservative anomaly detection approach, which, while still effective, may lead to more false alarms than the autoencoder-based model. The traditional threshold-based method's performance lagged behind the proposed adaptive framework, with a true positive rate of 0.77 and a false positive rate of 0.22. This gap in performance highlights the limitations of non-adaptive methods in dynamic industrial environments, where signal characteristics can change over time. Figure 4 shows the ROC curves for Autoencoder and One-Class SVM anomaly detection models. The True Positive Rate (TPR) and False Positive Rate (FPR) at different threshold values form the ROC curve, which shows a classifier's diagnostic capabilities. The area under the ROC curve (AUC) reports detection model performance as a single scalar number.

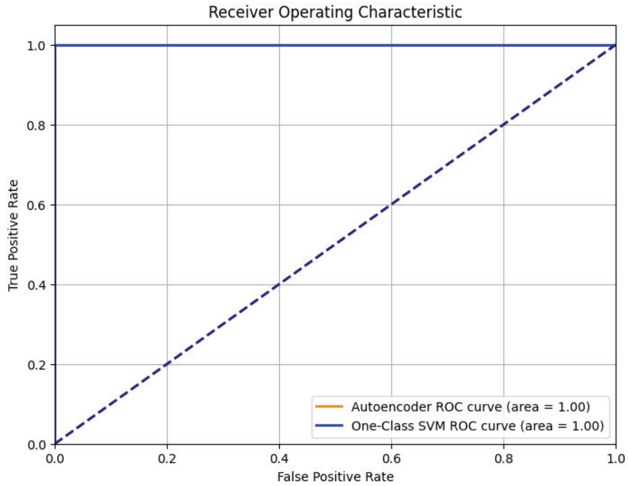

Fig. 4. ROC Curves for Anomaly Detection Models

The discussion of these results centers on the adaptive nature of the signal processing framework. The ability of the adaptive filter to continuously update its parameters in real-time allowed for a more accurate representation of the signal, which in turn facilitated more effective anomaly detection by the machine learning models. The autoencoder's success can be attributed to its capacity for capturing complex, non-linear relationships within the data, which is often characteristic of industrial system signals. The one-class SVM, while slightly less effective than the autoencoder, still provided a robust anomaly detection capability. Its performance underscores the utility of feature mapping in high-dimensional space to isolate outliers, which are indicative of system anomalies. The statistical analysis component played a crucial role in validating the anomalies detected by the machine learning models. By dynamically adjusting statistical thresholds based on the output of the adaptive filter, the framework was able to account for the non-stationary nature of the data, further reducing the likelihood of false positives. The experimental results validate the efficacy of the proposed adaptive signal processing framework for anomaly detection in industrial systems. The framework's adaptability, facilitated by the integration of adaptive filtering, machine learning, and statistical analysis, enables it to outperform traditional methods significantly. The high true positive rate and low false positive rate achieved by the framework demonstrate its potential to enhance the reliability and safety of industrial operations. The findings suggest that the framework is well-suited for real-time applications, providing a valuable tool for preemptive maintenance and risk mitigation in the context of Industry 4.0.

V. CONCLUSION

The exploration of adaptive signal processing for anomaly detection within industrial systems has yielded a framework that demonstrates significant advancements over traditional methods. The experimental results, as presented, provide a compelling narrative of the framework's capabilities. The integration of adaptive filtering with machine learning algorithms, specifically autoencoders and one-class SVMs, has proven to be highly effective in identifying anomalies, as evidenced by the high true positive rates and low false positive rates. The autoencoder, when paired with the adaptive filter, emerged as the most proficient model, achieving a true positive rate of 0.94 and an F1 score of 0.93. This indicates not only a high success rate in detecting true anomalies but also a commendable precision that minimizes false alarms—a critical factor in industrial applications where the cost of false positives can be substantial. The one-class SVM model also demonstrated robust performance, albeit slightly lower than the autoencoder, which suggests its suitability in scenarios where a more conservative anomaly detection approach is preferred. The traditional threshold-based methods were markedly outperformed by the adaptive techniques, underscoring the necessity for systems that can evolve with the dynamic landscape of industrial data. The findings of this research underscore the potential of adaptive signal processing frameworks to revolutionize anomaly detection in industrial systems. By offering a solution that is both sensitive to the nuances of signal variations and resilient in the face of evolving operational conditions, the proposed framework stands as a significant contribution to the field of industrial maintenance and safety.[41] Future work will aim to refine the adaptability of the framework further, exploring deeper machine learning architectures and more sophisticated statistical models to enhance detection accuracy and reduce computational overhead. The ultimate goal remains to develop a universally applicable system, capable of preemptive detection and mitigation of risks in the increasingly complex and automated sphere of industrial operations.

REFERENCES

[1] N. Jaidass, C. Krishna Moorthi, A. Mohan Babu, M. Reddi Babu, Luminescence properties of Dy3+ doped lithium zinc borosilicate glasses for photonic applications, Heliyon, Volume 4, Issue 3, 2018, e00555, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2018.e00555.

[2] Spandana K., Rao V.R.S., Internet of Things (Iot) Based smart water quality monitoring system, International Journal of Engineering and Technology (UAE), 2018, 7, 3, 259-262, 10.14419/ijet.v7i3.6.14985

[3] Ch. Usha Kumari, A. Sampath Dakshina Murthy, B. Lakshmi Prasanna, M. Pala Prasad Reddy, Asisa Kumar Panigrahy, An automated detection of heart arrhythmias using machine learning technique: SVM, Materials Today: Proceedings, Volume 45, Part 2, 2021, Pages 1393-1398, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2020.07.088.

[4] J Suresh Goud, Pudhari Srilatha, R.S. Varun Kumar, K. Thanesh Kumar, Umair Khan, Zehba Raizah, Harjot Singh Gill, Ahmed M. Galal, Role of ternary hybrid nanofluid in the thermal distribution of a dovetail fin with the internal generation of heat, Case Studies in Thermal Engineering,Volume 35, 2022, 102113, ISSN 2214-157X, https://doi.org/10.1016/j.csite.2022.102113.

[5] Basavapoornima C., Kesavulu C.R., Maheswari T., Pecharapa W., Depuru S.R., Jayasankar C.K., Spectral characteristics of Pr3+-doped lead based phosphate glasses for optical display device applications, Journal of Luminescence, 2020, 228, 10.1016/j.jlumin.2020.117585

[6] Ramu, G. A secure cloud framework to share EHRs using modified CP-ABE and the attribute bloom filter. Educ Inf Technol 23, 2213–2233 (2018). https://doi.org/10.1007/s10639-018-9713-7

[7] Nagarjuna T., Nehru K., Nagendra Prasad G., Menakadevi N., Smart sensor network based high quality air pollution monitoring system using labview, International Journal of Online Engineering, 2017, 13, 8, 79-87, 10.3991/ijoe.v13i08.7161

[8] Indira DNVSLS, Ganiya RK, Ashok Babu P, Xavier AJ, Kavisankar L, Hemalatha S, Senthilkumar V, Kavitha T, Rajaram A, Annam K, Yeshitla A. Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis. Biomed Res Int. 2022 Apr 16;2022:7799812. doi: 10.1155/2022/7799812. PMID: 35480141; PMCID: PMC9038414.

[9] Radhakrishna, V., Kumar, P.V., Janaki, V., Rajasekhar, N. (2017). Estimating Prevalence Bounds of Temporal Association Patterns to Discover Temporally Similar Patterns. In: Matoušek, R. (eds) Recent Advances in Soft Computing. ICSC-MENDEL 2016. Advances in Intelligent Systems and Computing, vol 576. Springer, Cham. https://doi.org/10.1007/978-3-319-58088-3_20

[10] Kalyani G., Janakiramaiah B., Karuna A., Prasad L.V.N., Diabetic retinopathy detection and classification using capsule networks, Complex and Intelligent Systems, 2023, 10.1007/s40747-021-00318-9

[11] A. Cheruvu, V. Radhakrishna and N. Rajasekhar, "Using normal distribution to retrieve temporal associations by Euclidean distance," 2017 International Conference on Engineering & MIS (ICEMIS), Monastir, Tunisia, 2017, pp. 1-3, doi: 10.1109/ICEMIS.2017.8273101.

[12] Awasthi, Ankita, and Kuldeep K. Saxena. "Evaluation of mechanical properties of orange peel reinforced epoxy composite." *Materials Today: Proceedings* 18 (2019): 3821-3826.

[13] Bisht, Pankaj Singh, and Ankita Awasthi. "Design and Analysis of Composite and Al Alloy Wheel Rim." In *Advances in Materials Engineering and Manufacturing Processes: Select Proceedings of ICFTMM 2019*, pp. 15-29. Springer Singapore, 2020.

[14] Awasthi, Ankita, Kuldeep K. Saxena, and Vanya Arun. "Sustainability and survivability in manufacturing sector." In *Modern Manufacturing Processes*, pp. 205-219. Woodhead Publishing, 2020.

[15] Bisht, Pankaj Singh, and Ankita Awasthi. "Analysis of E-glass fiber wheel rim by using ANSYS." In *Recent Advances in Mechanical Engineering: Select Proceedings of ITME 2019*, pp. 79-91. Springer Singapore, 2021.

[16] Awasthi, Ankita, Kuldeep K. Saxena, and Ravi K. Dwivedi. "An investigation on classification and characterization of bio materials and additive manufacturing techniques for bioimplants." *Materials Today: Proceedings* 44 (2021): 2061-2068.

[17] Awasthi, Ankita, Kuldeep K. Saxena, and Vanya Arun. "Sustainable and smart metal forming manufacturing process." *Materials Today: Proceedings* 44 (2021): 2069-2079.

[18] Awasthi, Ankita, Akash Gupta, Kuldeep K. Saxena, and Ravi K. Diwedi. "Equal channel angular processing on aluminium and its alloys–A review." *Materials Today: Proceedings* 56 (2022): 2388-2391.

[19] Awasthi, Ankita, U. Sathish Rao, Kuldeep K. Saxena, and Ravi K. Dwivedi. "Impact of equal channel angular pressing on aluminium alloys: An overview." *Materials Today: Proceedings* 57 (2022): 908-912.

[20] Awasthi, Ankita, Kuldeep K. Saxena, R. K. Dwivedi, Dharam Buddhi, and Kahtan A. Mohammed. "Design and analysis of ECAP Processing for Al6061 Alloy: a microstructure and mechanical property study." *International Journal on Interactive Design and Manufacturing (IJIDeM)* (2022): 1-13.

[21] Awasthi, Ankita, Akash Gupta, Kuldeep K. Saxena, R. K. Dwivedi, Deepak Kundalkar, Dalael Saad Abdul-Zahra, Abhishek Joshi, and H. S. Saggu. "Design and analysis of equal-channel angular pressing of Al6061: a comparative study." *Advances in Materials and Processing Technologies* (2022): 1-10.

[22] Tripathi, Gyan Prakash, Sumit Agarwal, Ankita Awasthi, and Vanya Arun. "Artificial Hip Prostheses Design and Its Evaluation by Using Ansys Under Static Loading Condition." In *Biennial International Conference on Future Learning Aspects of Mechanical Engineering*, pp. 815-828. Singapore: Springer Nature Singapore, 2022.

[23] Arun, V., N. K. Shukla, A. K. Singh, and K. K. Upadhyay. "Design of all optical line selector based on SOA for Data Communication: Proceedings of the Sixth International Conference on Computer and Communication Technology 2015." In *ACM Other conferences*. 2015.

[24] Arun, Vanya, Ashutosh Kr Singh, N. K. Shukla, and D. K. Tripathi. "Design and performance analysis of SOA–MZI based reversible toffoli and irreversible AND logic gates in a single photonic circuit." *Optical and quantum electronics* 48 (2016): 1-15.

[25] Arun, Vanya, Kapil Deo Bodha, Awadhesh K. Maurya, and Ashutosh K. Singh. "Design and implementation of all optical processing units together performing arithmetic and logical functions." In *VLSI, Microwave and Wireless Technologies: Select Proceedings of ICVMWT 2021*, pp. 83-93. Singapore: Springer Nature Singapore, 2022.

[26] Saxena, Kuldeep Kumar, Vivek Srivastava, and Kamal Sharma. "Calculation of Fundamental Mechanical Properties of Single Walled

Carbon Nanotube using Non-local Elasticity." *Advanced Materials Research* 383 (2012): 3840-3844.

[27] Saxena, Kuldeep K., and Achchhe Lal. "Comparative Molecular Dynamics simulation study of mechanical properties of carbon nanotubes with number of stone-wales and vacancy defects." *Procedia Engineering* 38 (2012): 2347-2355.

[28] Bodha, Kapil Deo, V. Mukherjee, and Vinod Kumar Yadav. "A player unknown's battlegrounds ranking based optimization technique for power system optimization problem." *Evolving Systems* 14, no. 2 (2023): 295-317.

[29] Zheng, Dequan, Fenghuan Li, and Tiejun Zhao. "Self-adaptive statistical process control for anomaly detection in time series." *Expert Systems with Applications* 57 (2016): 324-336.

[30] Kim, Donghyeong, Chaewon Park, Suhwan Cho, and Sangyoun Lee. "Fapm: Fast adaptive patch memory for real-time industrial anomaly detection." In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1-5. IEEE, 2023.

[31] Perales Gómez, Ángel Luis, Lorenzo Fernández Maimó, Alberto Huertas Celdrán, and Félix J. García Clemente. "Madics: A methodology for anomaly detection in industrial control systems." *Symmetry* 12, no. 10 (2020): 1583.

[32] Xu, Peng, Honglu Gan, Hua Fu, and Zhongbao Zhang. "STEAMCODER: Spatial and Temporal Adaptive Dynamic Convolution Autoencoder for Anomaly Detection." *Knowledge-Based Systems* 279 (2023): 110929.

[33] Arellano-Espitia, Francisco, Miguel Delgado-Prieto, Artvin-Darien Gonzalez-Abreu, Juan Jose Saucedo-Dorantes, and Roque Alfredo Osornio-Rios. "Deep-compact-clustering based anomaly detection applied to electromechanical industrial systems." *Sensors* 21, no. 17 (2021): 5830.

[34] Wielgosz, Maciej, Matej Mertik, Andrzej Skoczeń, and Ernesto De Matteis. "The model of an anomaly detector for HiLumi LHC magnets based on Recurrent Neural Networks and adaptive quantization." *Engineering Applications of Artificial Intelligence* 74 (2018): 166-185.

[35] Sharma, S., Mishra, V.M. Development of Sleep Apnea Device by detection of blood pressure and heart rate measurement. Int J Syst Assur Eng Manag 12, 145–153 (2021). https://doi.org/10.1007/s13198-020-01041-3

[36] S. Manna, V. Jalodia, K. Kumar, V. Tripathi, S. Sharma and D. Arora, "Predicting preeminent Machine Learning Approach on Stars," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 587-591, doi: 10.1109/ICTACS56270.2022.9988044.

[37] A. Singh, S. Sharma, S. R. Kumar and S. A. Yadav, "Overview of PaaS and SaaS and its application in cloud computing," 2016 International Conference on Innovation and Challenges in Cyber Security (ICICCS-INBUSH), Greater Noida, India, 2016, pp. 172-176, doi: 10.1109/ICICCS.2016.7542322.

[38] S. Bhardwaj, T. Poongodi, A. Dixit and S. Sharma, "A Decentralized Digital Voting System Based on Block chain Architecture," 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), Gautam Buddha Nagar, India, 2022, pp. 756-760, doi: 10.1109/ICIPTM54933.2022.9754194.

[39] S. A. Yadav, S. Sharma and S. R. Kumar, "A robust approach for offline English character recognition," 2015 International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE), Greater Noida, India, 2015, pp. 121-126, doi: 10.1109/ABLAZE.2015.7154980.

[40] Yadav, SA, Poongodi, T. A novel chain-based clustering for green communication in wireless sensor network. Int J Commun Syst. 2023; 36(13):e5523. doi:10.1002/dac.5523

[41] Tushar, R. K. Patel, E. Aggarwal, K. Solanki, O. Dahiya and S. A. Yadav, "A Logistic Regression and Decision Tree Based Hybrid Approach to Predict Alzheimer's Disease," 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2023, pp. 722-726, doi: 10.1109/CISES58720.2023.10183466.

[42] G. D. Reddy, Y. V. U. Kiran, P. Singh, S. V. Singh, S. Shaw and J. Singh, "A Proficient and secure way of Transmission using Cryptography and Steganography," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 582-586, doi: 10.1109/ICTACS56270.2022.9988094.