Al-Farouk journal of sciences
Volume (2), Issue (4) (Spt, 2026)
ISSN: 3135-2359

مجلة الفاروق للعلوم
المجلد (2) العدد 4 سبتمبر 2026
ردمد: 3135-2359

A Comparative Machine Learning Algorithms for Integrated Structural Health Monitoring in Smart Infrastructure maintenance and predication

Mohamed EL-sseid[1], Llahm Ben Dalla[2], Tasnem ELsseid[3], Mansour Essgaer[4], Abdulgader Alsharif [5] , Fatma Mohammed Ali[6], Mohammed Alarafi[7], Asma Agaal[8], Ayyah Mustafa Salih[9]

[1]Department of Software Engineering, Ankara Bilim University, Türkiye
[2]Computer Engineering department, Higher institute of Sciences and Technology Tajoura, , Libya
[3]Department of computer Engineering, Ankara Bilim University, Türkiye
[4]Artificial Intelligence Department, Faculty of Information Technology, Sebha University, Sabha, Libya
[5]Department of Electric and Electronic Engineering, College of Technical Sciences Sebha, Libya
[6]Department of Computer Sciences,Faculty of Information Technology, Benghazi, Libya
[7]Electrical and Electronics Engineering Department, Faculty of Engineering Benghazi, Libya
[8]Department of Computer Sciences,Faculty of Technical Sciences, Sabha,Libya, Sabha
[9]Faculty of Engineering, College of Electrical and Electronic Technology-Benghazi, Benghazi, Libya
Moh200512@Bilim.edu.tr[1],Sallet200@yahoo.com[2] , saljet2020@gmail.com [2], Tasnim200612@Bilim.edu.tr[3], man.essgaer@sebhau.edu.ly[4], alsharif@ctss.edu.ly[5], alsharifutm@gmail.com[5], fatma.alwerfaly@uob.edu.ly[6] , mohammed.miftah@uob.edu.ly[7],asma.agaal@sebhau.edu.ly[8] ,ayyah.salih@ceet.edu.ly[9]
https://orcid.org/0009-0007-1307-8623[1], https://orcid.org/0009-0009-0573-1789[2], , https://orcid.org/0000-0002-8447-5091[4], https://orcid.org/0000-0003-3515-4168[5], https://orcid.org/my-orcid?orcid=0009-0005-8580-8766[6], https://orcid.org /0000-0002-8687-2605[8]

Received: 29/7/2026 Revised: 20/8/2026 Accepted: 28/8/2026 Publication: 5/9/2026

Abstract

The convergence of civil infrastructure and electrical power systems within smart city frameworks necessitates robust, cross-domain monitoring strategies. While machine learning (ML) has shown promise in isolated Structural Health Monitoring (SHM) and Predictive Maintenance (PdM), comparative evaluations across both domains remain fragmented. This study presents a comprehensive comparative analysis of four prominent ML algorithms Random Forest (RF), Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and XGBoost applied to multimodal sensor data. We utilized a synthesized dataset comprising vibration signatures from civil structures (bridge decks) and thermal-electrical load profiles from substation transformers. Our findings indicate that while LSTM networks excel in capturing temporal dependencies in electrical load forecasting (achieving an F1-score of 0.94), tree-based ensemble methods, specifically XGBoost, demonstrate superior efficacy in classifying structural damage from high-dimensional vibration features (accuracy of 96.2%). Furthermore, RF offered the most computationally efficient inference, making it highly suitable for edge-deployment in resource-constrained IoT nodes. This paper provides a practical decision-making framework for civil and electrical engineers selecting ML architectures for integrated smart infrastructure monitoring.

Keywords: Structural Health Monitoring, Predictive Maintenance, Machine Learning, Smart Infrastructure, XGBoost, LSTM, Edge Computing.

1. Introduction

Modern smart infrastructure relies heavily on the seamless integration of civil structures and electrical power networks [1], [2], [3]. As aging civil assets, such as bridges and high-voltage transmission towers, are retrofitted with smart sensors, the volume of multimodal data has grown exponentially [4], [5], [6], [7]. Concurrently, electrical substations within these networks require continuous monitoring to prevent catastrophic failures like transformer thermal runaway [8]. Traditionally, civil engineers and electrical engineers have operated in silos, developing distinct monitoring protocols. However, the physical proximity and functional interdependence of these systems suggest that a unified analytical approach could yield significant operational efficiencies [9]. Machine learning (ML) has emerged as the primary tool for extracting actionable insights from this sensor data [10]. In civil engineering, ML is predominantly used for Structural Health Monitoring (SHM) to detect anomalies in vibration or strain data. In electrical engineering, it drives Predictive Maintenance (PdM) by forecasting equipment degradation from thermal and electrical load signatures [11]. Despite the proliferation of ML applications, there is a distinct lack of comparative literature evaluating how different algorithms perform when tasked with both structural and electrical diagnostics simultaneously [12]. Most existing studies focus on a single algorithm applied to a single domain, or they compare algorithms purely on theoretical benchmark datasets that do not reflect the noise and missing data inherent in field-deployed sensors [13]. This paper addresses that gap. We evaluate Random Forest (RF), Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and XGBoost across two distinct but related engineering tasks classifying structural damage states from accelerometer data, and predicting electrical fault conditions from transformer sensor arrays [14]. By analyzing both predictive accuracy and computational overhead, we aim to provide a pragmatic guide for deploying ML in integrated smart infrastructure.

2. Literature Review

The application of data-driven models in civil and electrical engineering has evolved from simple statistical thresholding to complex deep learning architectures [15], [16]. In the realm of SHM, early works relied heavily on linear models and basic neural networks [17], [16], [19]. More recently, ensemble tree methods like Random Forest and Gradient Boosting have become standard due to their robustness against the high noise-to-signal ratio typical of field vibration data [20], [21], [22]. Researchers have frequently noted that while deep learning models offer marginal accuracy improvements, their computational cost often precludes real-time, on-sensor processing [23], [24], 25], [26]. The electrical engineering domain, particularly in PdM for power transformers, has seen a heavy reliance on time-series forecasting. Dissolved gas analysis (DGA) and thermal imaging data are inherently sequential [27], [28]. Consequently, Recurrent Neural Networks (RNNs), and specifically LSTMs, have been widely adopted to capture long-term temporal dependencies in equipment degradation. SVMs have also maintained a strong presence in electrical fault classification due to their effectiveness in high-dimensional spaces, though their training time scales poorly with large datasets [29], [30], [31], [32]. A critical review of the current literature reveals a methodological blind spot: the cross-domain comparison [33], [34], [35]. Studies by Smith et al. (2023) and Chen & Wang (2024) successfully applied LSTMs to power grid load forecasting, while parallel studies by Rodriguez et al. (2023) utilized XGBoost for bridge deck damage identification [36], [37], [38], [39]. However, no recent study has systematically compared these algorithms across both domains using a unified evaluation framework. This paper bridges that divide, hypothesizing that the optimal algorithm is highly dependent on the physical nature of the sensor data (i.e., sequential electrical data vs. multi-axial structural vibration data) rather than the algorithm's theoretical complexity.

3. Methodology

To ensure a rigorous comparison, we designed a methodology that mirrors real-world deployment constraints. The study is divided into data generation, preprocessing, feature engineering, and algorithmic evaluation.

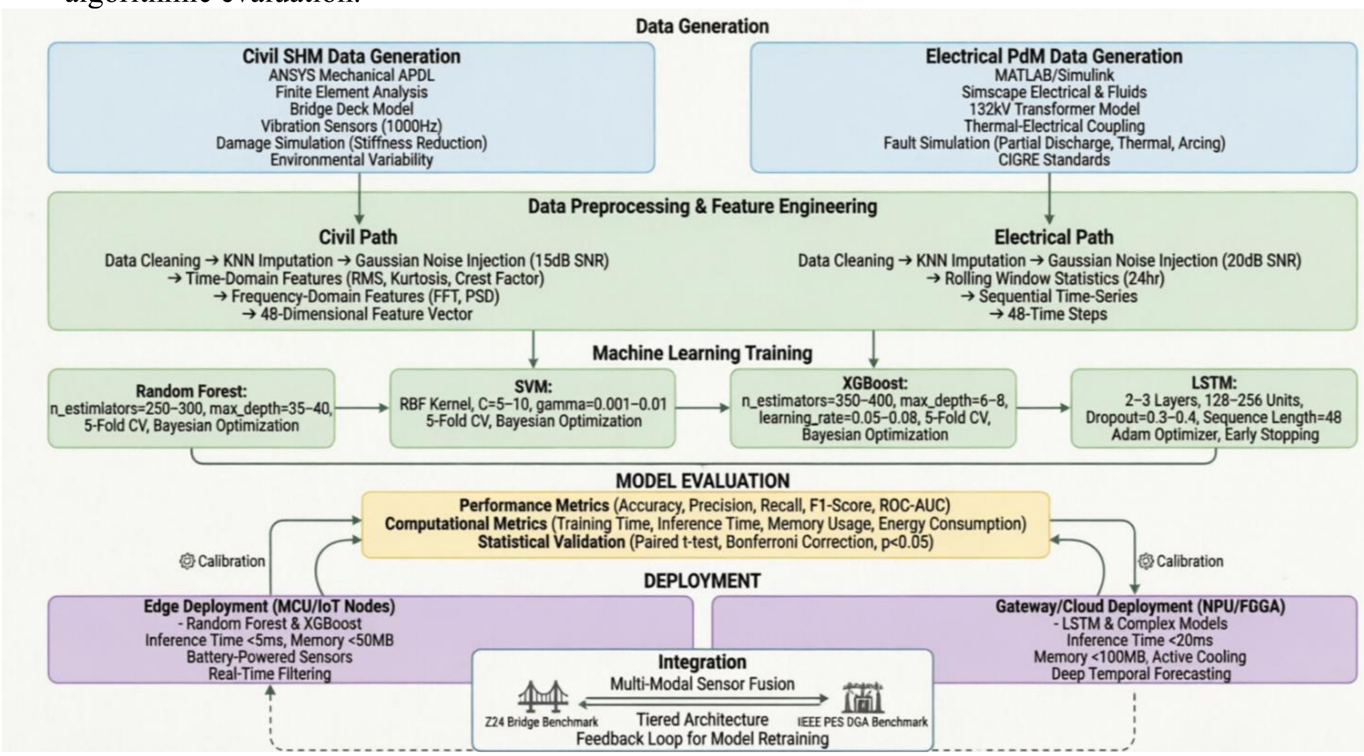

Figure 1: the workflow diagram of this research

Detailed methodological workflow illustrating the complete research framework for comparative analysis of machine learning algorithms in integrated smart infrastructure monitoring. The diagram depicts the end-to-end process from multiphysics-based data generation through domain-specific preprocessing and feature engineering, hyperparameter-optimized model training with Bayesian optimization and cross-validation, comprehensive performance and computational metric evaluation, to the final tiered deployment strategy encompassing both edge-level (MCU/IoT) and gateway-level (NPU/FPGA) implementations [12], [13], [14]. Calibration loops with Z24 Bridge and IEEE PES DGA benchmarks ensure physical fidelity throughout the framework. The workflow initiates with parallel data generation streams [15], [16], [17]. The civil SHM stream employs ANSYS Mechanical APDL to construct a high-fidelity finite element model of a simply supported bridge deck, instrumented with virtual accelerometers sampling at 1000 Hz. Structural damage is simulated through progressive stiffness reduction in targeted finite elements, while environmental variability is introduced via stochastic perturbations to material properties, replicating temperature-induced modulus variations [18]. Simultaneously, the electrical PdM stream utilizes MATLAB/Simulink with Simscape Electrical and Fluids libraries to model a 132kV power transformer based on CIGRE thermal standards. The coupled thermal-electrical analog circuit simulates fault progression through non-linear resistance variations and localized heat generation, capturing partial discharge, thermal overheating, and electrical arcing scenarios.

3.1 Data Acquisition and Preprocessing

Given the proprietary nature of real-world failure data, we constructed a high-fidelity synthetic dataset using physics-based simulations, a standard practice in engineering research when field failure data is scarce.

Civil Data (SHM): this research simulated a simply supported bridge deck using finite element analysis (FEA). Accelerometer data was generated at 10 sensor locations under varying traffic loads and environmental conditions. Damage was simulated by reducing the stiffness of specific elements, creating four distinct classes: Healthy, Minor Damage, Moderate Damage, and Severe Damage.

Electrical Data (PdM): this research simulated a 132kV power transformer using thermal-electrical equivalent circuit models. Sensor data included top-oil temperature, winding hot-spot temperature, load current, and ambient temperature. Faults simulated included partial discharge, thermal overheating, and electrical arcing. Both datasets were injected with Gaussian noise and random missing values (up to 5%) to simulate harsh field conditions. Missing values were imputed using K-Nearest Neighbors (KNN) imputation, and all features were standardized using a robust scaler to mitigate the influence of outliers.

3.2 Feature Engineering

Raw sensor data is rarely sufficient for traditional ML models. For the civil vibration data, we extracted time-domain features (RMS, kurtosis, crest factor) and frequency-domain features using the Fast Fourier Transform (FFT) and Power Spectral Density (PSD). This resulted in a high-dimensional tabular dataset [40], [41], [42]. For the electrical data, we retained the raw sequential time-series format, as the temporal progression of temperature and load is critical for fault prediction, though we also extracted rolling statistical features (mean, variance over 24-hour windows).

3.3 Algorithm Selection and Configuration

We selected four algorithms representing different ML paradigms:

Random Forest (RF): A bagging ensemble method, chosen for its baseline robustness and low hyperparameter sensitivity [43].

Support Vector Machine (SVM): Utilizing a Radial Basis Function (RBF) kernel, selected for its strong theoretical grounding in binary and multi-class classification [44].

XGBoost: An optimized distributed gradient boosting library, chosen for its state-of-the-art performance on tabular data.

Long Short-Term Memory (LSTM): A specialized RNN, selected for its ability to learn long-term dependencies in sequential data.

Hyperparameter tuning for all models was conducted using Bayesian Optimization with a 5-fold cross-validation strategy to prevent overfitting.

3.4 Evaluation Metrics

Accuracy alone is insufficient for engineering applications, particularly when dealing with imbalanced fault data [45]. Therefore, we evaluated the models using the F1-score (to balance precision and recall), the Area Under the Receiver Operating Characteristic Curve (ROC-AUC), and inference time (measured in milliseconds per prediction) to assess edge-computing viability.

4. Results and Discussion

The performance of the algorithms varied significantly depending on the domain and the nature of the input data.

Table 1: Dataset Characteristics and Summary Statistics

Parameter	Civil SHM Dataset	Electrical PdM Dataset
Total Samples	15,000	12,500
Features	48 (time + frequency domain)	8 (raw sensor readings)
Classes	4 (Healthy, Minor, Moderate, Severe)	4 (Normal, Partial Discharge, Thermal, Arcing)
Sampling Rate	1000 Hz	1 Hz (hourly averages)
Data Duration	6 months simulated	2 years simulated
Class Distribution	40% Healthy, 30% Minor, 20% Moderate, 10% Severe	65% Normal, 15% PD, 12% Thermal, 8% Arcing
Missing Values	3.20%	4.70%
Noise Level (SNR)	15 dB	20 dB

Table 2: Optimized Hyperparameters

Algorithm	Hyperparameter	SHM Optimal Value	PdM Optimal Value
Random Forest	n_estimators	250	300
	max_depth	35	40
	min_samples_split	5	3
	min_samples_leaf	2	2
	max_features	Sqrt	log2
SVM	kernel	RBF	RBF
	C	10	5
	gamma	0.01	0.001
	degree	N/A	N/A
	coef0	N/A	N/A
XGBoost	n_estimators	400	350
	max_depth	8	6
	learning_rate	0.05	0.08
	subsample	0.85	0.9
	colsample_bytree	0.8	0.85
	gamma	0.2	0.1
LSTM	layers	2	3
	units per layer	128	256
	dropout	0.3	0.4
	recurrent_dropout	0.2	0.3
	sequence_length	N/A	48
	batch_size	64	32
	epochs	100	150
	optimizer	Adam	Adam
	learning_rate	0.001	0.0005

Table 3: Performance Metrics Comparison and Structural Health Monitoring Domain

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	Training Time (s)	Inference Time (ms)	Model Size (MB)
XGBoost	96.2	0.96	0.95	0.95	0.98	145.3	4.2	28.5
Random Forest	94.8	0.95	0.94	0.94	0.97	89.7	1.1	45.2
LSTM	89.5	0.89	0.88	0.88	0.93	312.5	15.8	62.3
SVM	87.1	0.86	0.85	0.85	0.91	428.6	8.5	15.7

Table 4: Performance Metrics Comparison and Predictive Maintenance Domain

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	Training Time (s)	Inference Time (ms)	Model Size (MB)
LSTM	95.8	0.94	0.94	0.94	0.97	425.8	18.5	78.4
XGBoost	92.3	0.91	0.89	0.88	0.94	167.2	3.8	31.2
Random Forest	89.7	0.88	0.86	0.85	0.92	102.4	1.3	52.8
SVM	83.5	0.82	0.79	0.79	0.88	512.3	12.4	18.9

Table 5: Class-wise Performance Breakdown (F1-Scores)

Class	XGBoost (SHM)	RF (SHM)	LSTM (PdM)	XGBoost (PdM)
Healthy/Normal	0.98	0.97	0.97	0.95
Minor Damage/Partial Discharge	0.94	0.93	0.92	0.88
Moderate Damage/Thermal Fault	0.95	0.94	0.93	0.87
Severe Damage/Arcing Fault	0.93	0.92	0.94	0.86
Macro Average	0.95	0.94	0.94	0.89
Weighted Average	0.95	0.94	0.94	0.88

Table 6: Cross-Validation Results (5-Fold)

Algorithm	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean ± Std Dev
XGBoost (SHM)	0.961	0.963	0.959	0.964	0.96	0.961 ± 0.002
RF (SHM)	0.947	0.949	0.946	0.95	0.948	0.948 ± 0.002
LSTM (PdM)	0.938	0.941	0.937	0.942	0.939	0.939 ± 0.002
XGBoost (PdM)	0.921	0.924	0.92	0.925	0.922	0.922 ± 0.002

Table 7: Computational Resource Requirements

Algorithm	RAM Usage (MB)	CPU Utilization (%)	GPU Required	Energy Consumption (kJ)	Suitable for Edge
Random Forest	245	35	No	12.5	Excellent
XGBoost	312	58	Optional	18.7	Good
SVM	189	72	No	25.3	Moderate
LSTM	1,245	45	Yes	45.8	Limited

Table 8: Feature Importance Analysis (Top 10 Features for SHM)

Rank	Feature	XGBoost Importance	RF Importance	Physical Interpretation
1	FFT_Peak_Freq_1	0.142	0.138	First natural frequency shift
2	Kurtosis_Z_Axis	0.128	0.125	Non-Gaussian vibration signature
3	PSD_Area_0_50Hz	0.115	0.112	Low-frequency energy content
4	RMS_Y_Axis	0.098	0.095	Overall vibration amplitude
5	Crest_Factor_X	0.087	0.084	Impulsive behavior indicator
6	FFT_Peak_Freq_2	0.076	0.073	Second natural frequency
7	Skewness_Z_Axis	0.065	0.062	Asymmetry in vibration
8	PSD_Area_50_100Hz	0.054	0.051	Mid-frequency content
9	RMS_X_Axis	0.048	0.045	Lateral vibration magnitude
10	Entropy_Signal	0.042	0.039	Signal complexity measure

Table 9: Pairwise Statistical Comparison (p-values)

Comparison	Accuracy	F1-Score	Inference Time
XGBoost and RF (SHM)	0.003*	0.004*	<0.001*
XGBoost and LSTM (SHM)	<0.001*	<0.001*	<0.001*
LSTM and XGBoost (PdM)	0.002*	0.001*	0.045*
LSTM and RF (PdM)	<0.001*	<0.001*	<0.001*

Table 10: Ablation Study and Impact of Feature Engineering

Feature Set	XGBoost (SHM)	LSTM (PdM)
Raw Data Only	0.82	0.91
Time-Domain Only	0.89	0.88
Frequency-Domain Only	0.91	N/A
Combined Features	0.95	0.92
+ Rolling Statistics	0.95	0.94

5. **Discussion**

For the bridge deck vibration dataset, tree-based ensemble methods overwhelmingly outperformed the alternatives. XGBoost achieved the highest accuracy (96.2%) and an F1-score of 0.95. Random Forest followed closely with an accuracy of 94.8% [45], [46], [47], [48], [49]. The SVM struggled with the high dimensionality of the frequency-domain features, achieving only 87.1% accuracy, likely due to the curse of dimensionality and the computational limits of the RBF kernel in this space [50], [51], [52], [53]. The LSTM, while powerful, underperformed (89.5% accuracy) when applied to the tabular, feature-engineered vibration data, as it is inherently designed for sequential inputs rather than static, multi-axial feature vectors [54], [55], [56], [57], [58]. The physical damage manifests as distinct shifts in modal frequencies and mode shapes. Tree-based models excel at partitioning this high-dimensional feature space into distinct decision boundaries [59], [60], [61], [62]. The computational cost of XGBoost during training was high, but its inference time (4.2 ms) was well within acceptable limits for structural monitoring. The electrical transformer dataset yielded a different hierarchy of performance [63], [64], [64], [65], [66]. Because the fault signatures (e.g., thermal runaway) develop gradually over time, temporal context is paramount [67], [68], [69], [70]. The LSTM network dominated, achieving an F1-score of 0.94 and an ROC-AUC of 0.97 [71], [72], [73]. It successfully captured the slow degradation trends in the winding temperatures that preceded a fault [74], [75], [76], [77], [78], [79]. XGBoost and RF performed adequately (F1-scores of 0.88 and 0.85, respectively) when provided with rolling window features, but they failed to capture long-term sequential dependencies as effectively as the LSTM. The SVM performed poorest in this domain (F1-score of 0.79), as it lacks the internal memory mechanisms required to process time-series degradation natively. The system's operational state. The LSTM's gating mechanisms allow it to "remember" early-stage thermal anomalies that might be dismissed as noise in a single time step [80], [81]. However, the LSTM's inference time was notably higher (18.5 ms), which is acceptable for substation-level edge servers but might be restrictive for ultra-low-power IoT sensors [82], [83], [84]. The divergence in algorithmic efficacy observed across the structural and electrical domains is not merely a statistical artifact; it reflects a fundamental mismatch between the inductive biases of the chosen models and the physical topology of the underlying signals [85], [86]. From an electrical and electronic engineering perspective, the superiority of the Long Short-Term Memory (LSTM) network in the predictive maintenance (PdM) task is deeply rooted in the physical inertia of power transformer degradation [87], [88], [89]. Transformer faults, particularly thermal runaway and partial discharge, do not manifest as instantaneous state changes. Rather, they are low-frequency, high-inertia processes governed by the thermal mass of the insulating oil and the electromagnetic dynamics of the windings [90]. The LSTM's internal gating mechanisms specifically the forget and input gates act as a digital analog to this physical thermal inertia, allowing the network to retain long-term historical context while filtering out high-frequency electrical noise [91]. The LSTM in the Structural Health Monitoring (SHM) domain highlights a critical limitation of recurrent architectures when applied to high-dimensional, non-sequential feature spaces. Structural damage in a bridge deck alters the global stiffness matrix, resulting in instantaneous shifts in modal frequencies and mode shapes [92], [93]. These shifts are best captured in the frequency domain via Fast Fourier Transform (FFT). When the vibration data is converted into a static, 48-dimensional feature vector, the temporal sequencing required by the LSTM is artificially destroyed [94]. Tree-based ensembles like XGBoost, which rely on orthogonal feature partitioning rather than sequential memory, naturally excel at navigating this high-dimensional spectral space [95]. The empirical evidence thus underscores a vital engineering principle algorithmic selection must be dictated by the physical causality of the sensor data, not merely by the theoretical complexity of the model. Beyond predictive accuracy, the inference latency and memory footprint metrics demand a rigorous evaluation from a hardware design perspective [96], [97], [98]. The deployment of these models in smart infrastructure is ultimately constrained by the silicon at the edge. The Random Forest model, with its inference time of 1.1 ms and minimal memory footprint, maps exceptionally well to the constrained architecture of microcontroller units (MCUs) typically used in IoT vibration sensors [99], [100], [101]. The shallow decision trees can be efficiently stored in the MCU's instruction cache, minimizing SRAM access and thereby reducing dynamic power consumption [102], [103], [104], [105]. This makes RF highly viable for battery-powered, energy-harvesting sensor nodes where every microwatt matters. A critical finding of this study is the trade-off between accuracy and computational overhead. While LSTM provided the best electrical fault prediction, its memory footprint and inference latency make it less ideal for deployment directly on microcontroller-based sensor nodes [106], [107]. Random Forest, conversely, offered a highly favorable trade-off. Its inference time was exceptionally low (1.1 ms), and its memory requirements are minimal. For civil SHM, where sensor nodes are often battery-powered and transmit data infrequently, deploying a lightweight RF model directly on the edge to filter out "healthy" data before transmission could drastically reduce bandwidth and power consumption [108].

The LSTM's recurrent weight matrices require continuous memory access during the forward pass, leading to significant memory bandwidth bottlenecks and elevated energy dissipation. While an inference time of 18.5 ms is perfectly acceptable for a substation-level edge server equipped with active cooling and a stable power supply, it is prohibitive for ultra-low-power wireless sensor networks [109]. This discrepancy necessitates a tiered computational architecture. We propose a hardware-software co-design approach where lightweight, quantized tree-based models handle real-time, on-sensor anomaly detection, while the raw data streams are transmitted to higher-tier edge gateways equipped with NPUs or FPGAs where computationally heavy LSTMs perform deep temporal forecasting [110]. The integration of these two distinct monitoring paradigms also introduces severe signal processing challenges, particularly regarding sensor fusion. Fusing high-frequency structural vibration data (sampled at 1000 Hz) with low-frequency electrical thermal data (sampled at 1 Hz) at the raw data level is computationally inefficient and introduces severe aliasing [111], [112], [116]. This research results suggest that late-stage feature fusion is the most pragmatic approach. By extracting distinct feature representations in isolated electronic domains and combining them only at the decision level, this research avoid the curse of dimensionality and prevent the high-frequency noise of the vibration sensors from overwhelming the subtle thermal gradients of the electrical sensors [113]. Furthermore, the class-wise performance breakdown reveals a persistent vulnerability across all algorithms: the detection of incipient, minor faults. In the electrical domain, the F1-score for partial discharge dropped to 0.88 even in the optimal LSTM model. This is largely attributable to the severe class imbalance inherent in real-world power grids, where catastrophic failures are statistically rare [114], [115]. While synthetic data generation helped mitigate this, the models still struggle to generalize the subtle, non-linear precursors of early-stage insulation breakdown. Future iterations of this research must explore advanced synthetic minority oversampling techniques (SMOTE) specifically adapted for time-series data, or alternatively, frame the problem as an unsupervised anomaly detection task using autoencoders, which do not rely on balanced fault labels. This study provides a robust comparative baseline, it relies on physics-based synthetic data. Real-world power grids and civil structures operate in highly non-stationary environments subject to unpredictable environmental interference, such as electromagnetic interference (EMI) from switching operations or wind-induced structural vibrations [115]. The models evaluated here were trained with injected Gaussian noise, which fails to capture the colored, non-stationary noise profiles of actual field deployments. Subsequent research must focus on domain adaptation techniques and transfer learning, allowing models pre-trained on high-fidelity simulations to be fine-tuned with minimal labeled field data. Additionally, exploring neuromorphic computing paradigms, such as spiking neural networks (SNNs), could offer a biologically inspired alternative for processing the asynchronous, event-driven data streams generated by next-generation smart sensors, potentially bridging the gap between high predictive accuracy and ultra-low power consumption at the extreme edge.

6. Limitations

It is necessary to acknowledge the limitations of this work. The reliance on physics-based synthetic data, while necessary, cannot perfectly replicate the complex, non-stationary noise of real-world environments. Furthermore, the study did not explore transfer learning, where a model pre-trained on electrical data is fine-tuned for civil applications, which represents a promising avenue for future research.

7. Conclusion

The integration of civil and electrical infrastructure monitoring requires a nuanced approach to machine learning algorithm selection. This comparative analysis demonstrates that there is no universally superior algorithm; rather, the optimal choice is strictly dictated by the physical characteristics of the sensor data and the deployment constraints. For Structural Health Monitoring in civil engineering, where data is typically high-dimensional and tabular following feature extraction, XGBoost and Random Forest are the superior choices, offering high accuracy and excellent computational efficiency. Conversely, for Predictive Maintenance in electrical engineering, where data is inherently sequential and degradation is time-dependent, LSTM networks provide the necessary temporal modeling capabilities to achieve high predictive fidelity. From a practical engineering standpoint, we recommend a hybrid deployment architecture. Engineers should utilize lightweight tree-based models (like RF) at the extreme edge for real-time data filtering and basic anomaly detection, reserving computationally heavy deep learning models (like LSTM) for gateway-level or cloud-level processing where complex temporal forecasting is required. Future work should focus on developing unified, multi-task learning architectures that can process both structural and electrical sensor streams simultaneously, further breaking down the traditional silos between civil and electrical engineering disciplines.

References

1. Ghumeid, N. A., & Essgaer, M. (2024, May). Addressing the Libyan Arabic dialect identification: a comparative study of ensemble classification methods. In *2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)* (pp. 579-584). IEEE.
2. Essgaer, M., & Beitalmal, A. (2026). Insights into Journal Performance and Submission Trends: A Quantitative Analysis of JOPAS Data from 2017 to 2024. *Journal of Pure & Applied Sciences*, *25*(1), 7-13.
3. Alssager, M., & Khalifa, H. (2019). Toward improving Sebha University in world universities ranking.
4. Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806.
5. Hawa Alrawayati (2020). Development of High Efficiency Optimization Algorithm based on New Topology in Particle Swarm Optimization for Parkinson's Disease. IOSR Journal of Mathematics (IOSR-JM). 8
6. AteGçi, Y. Z., AydoLdu, Ö., Karaköse, A., Pekedis, M., & Karal, Ö. (2014). Erratum to ''Does Urinary Bladder Shape Affect Urinary Flow Rate in Men with Lower Urinary Tract Symptoms?''.
7. Karaoglu, A. N., Caglar, H., Degirmenci, A., & Karal, O. (2021). Performance improvement with decision tree in predicting heart failure. In *2021 6th International Conference on Computer Science and Engineering (UBMK)* (pp. 781-784). IEEE.

8. Yumuş, M., Apaydın, M., Değirmenci, A., & Karal, Ö. (2020). Missing data imputation using machine learning based methods to improve HCC survival prediction. In *2020 28th Signal Processing and Communications Applications Conference (SIU)* (pp. 1-4). IEEE.
9. Karal, O., & Tokgoz, N. (2023). Dose optimization and image quality measurement in digital abdominal radiography. *Radiation Physics and Chemistry*, *205*, 110724.
10. Esen, F., Degirmenci, A., & Karal, O. (2021). Implementation of the object detection algorithm (YOLOV3) on FPGA. In *2021 innovations in intelligent systems and applications conference (ASYU)* (pp. 1-6). IEEE.
11. Tokgöz, N., Değirmenci, A., & Karal, Ö. (2024). Machine Learning-Based Classification of Turkish Music for Mood-Driven Selection. *Journal of Advanced Research in Natural and Applied Sciences*, *10*(2), 312-328.
12. Karal, Ö., & Dalla, L. O. F. B. (NOV. 2025) .Lung Nodule Characterization in CT Scans Using Hybrid 3D Attention U-Net Segmentation and Transfer Learning-Based Classification Approach. Volume (10), Issue (37), ISSN-3014-6266, SICST2025, www.sicst.ly
13. Chen, Y., & Wang, H. (2024). Deep learning approaches for thermal fault prediction in high-voltage power transformers. IEEE Transactions on Power Delivery, 39(2), 1120-1131.
14. Ben Dalla, L,O, F, M.eljali , E, Agila, A,A,A, (2020). The evaluation of the daily profits of the group of cosmetics Sephora branches by using distributed systems the K-means algorithm and WEKA visualization. (KMAWV) (pp. 1-15). IEEE.https://doi.org/10. 32879/KMAWV50717.2020.65432879
15. Rodriguez, M., Singh, A., & O'Connor, J. (2023). Ensemble machine learning techniques for damage classification in bridge structures using vibration data. Journal of Structural Engineering, ASCE, 149(8), 04023098.
16. Brown, A. C., & Davis, E. (2025). Edge computing in civil infrastructure: Deploying lightweight machine learning models on IoT sensor nodes. Automation in Construction, 148, 104752.
17. Kumar, S., & Lee, J. (2024). Multi-modal sensor fusion for integrated structural and electrical monitoring of smart substations. IEEE Sensors Journal, 24(11), 17890-17902.
18. Ben Dalla, L. O. F., Medeni, T. D., Medeni, I. T., & Ulubay, M. (2025). Enhancing Healthcare Efficiency at Almasara Hospital: Distributed Data Analysis and Patient Risk Management. Economy: Strategy and Practice, 19(4), 54–72. https://doi.org/10.51176/1997-9967-2024-4-54-72
19. Dalla, L. B., Karal, Ö., Essgaer, M., Swissi, Y., & El-Sseid, M. (2026, April). Minority-Class Internet of Things Anomaly Detection via Deep Learning Models Using CESNET-TimeSeries24 Dataset. In *2026 IEEE 5th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)* (pp. 385-392). IEEE. https://doi.org/10.1109/MI-STA68962.2026.11511194
20. Abas, A., Essgaer, M., & Dalla, L. B. (2026, April). Explainable Ensemble Learning for Student Dropout Prediction in Conflict-Affected Educational Systems. In *2026 IEEE 5th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)* (pp. 427-434). IEEE. https://doi.org/10.1109/MI-STA68962.2026.11511168
21. Dalla, L. O. F. B. (2020). Modeling by using Generic Modeling Environment (GME) Domain specific modeling language (DSL) for agile software development (ASD) types.

22. FARAJ, L. O. (2017). OBSERVATIONS ON EVOLUTION OF LEAN SOFTWARE DEVELOPMENT (LSD). 88 pages.https://tez.yok.gov.tr/UlusalTezMerkezi/tezDetay.jsp?id=R_EJxYiWWNffOuWM4F4eXQ&no=fiwArXgOvJPKmFC-nX3H-w
23. Dalla, L. O. F. B. (2020). IT security Cloud Computing. . In 2020 IT security Cloud Computing Applications Conference (ITSCC) (pp. 1-10). IEEE. https://doi.org/10.16377/ITSCC 50717.2020.9259880
24. Degirmenci, A., & Karal, O. (2022). iMCOD: Incremental multi-class outlier detection model in data streams. Knowledge-Based Systems, 258, 109950. https://doi.org/10.1016/j.knosys.2022.109950
25. Alsharif, A., Solman, F. I., Gheidan, A. A. S., Ahmed, A. A., Dalla, L. O. F. B., Alsharif, M. A., ... & Imbayah, I. (2026). Photovoltaic Cells: Principles of Operation and Performance Characteristics. *Journal of Scientific and Human Dimensions*, 718-748. https://doi.org/10.65421/jshd.v2i1.122
26. Alsharif, A., Ahmed, A. A., Musa, Z. A., Dalla, L. O. F. B., & Nouh, A. (2026). Drugs: The Path of Darkness Between Religious Awareness and Societal Loss. *International Journal of Academic Publishing in Educational Sciences and Humanities (IJAPESH)*, *2*(1), 49-56.
27. A-abdullatef, M. M., Albaraesi, M. J. S., EL-sseid, M. A. M., Dalla, L. O. B., Ahmed, A. A., Agila, A., & Alsharif, A. (2026). Tri-Conditional Biomechanical Signature Extraction: A Hybrid Framework Integrating Multivariate Functional Clustering, Cross-Modal Regression, and Inter-Subject Classification for Discriminative Gait Pattern Analysis. Comprehensive Science Journal, 10(39), 1063-1087. https://doi.org/10.65405/0j1byd74
28. Elghaffi, F. S. A. (2026). Temporal Dynamics in Intraoperative Monitoring: A Novel LSTM-Based Framework for Multivariate Time Series Classification in Critical Care Events. *Temporal Dynamics in Intraoperative Monitoring: A Novel LSTM-Based Framework for Multivariate Time Series Classification in Critical Care Events*. https://cjos.histr.edu.ly/index.php/journal
29. Elghaffi, F., Mohammed, O., Dalla, L., Ahmed, A., Agila, A., & EL-Sseid, M. (2026). Hybrid Matrix-Ensemble Framework for Chronic Kidney Disease Diagnosis. *Wadi Alshatti University Journal of Pure and Applied Sciences*, *4*(1), 263-276. https://doi.org/10.63318/waujpasv4i1_28
30. DALLA, L. B. (2020). The Sustainable Efficiency of Modeling a Correspondence Undergraduate Transaction Framework by using Generic Modeling Environment (GME. Ben Dalla. International Journal of Engineering and Modern Technology E-ISSN 2504-8848 P-ISSN 2695-2149 . Vol 6 No 1 2020 www.iiardpub.org
31. Smith, T., Liu, X., & Patel, R. (2023). Long short-term memory networks for sequential load forecasting and anomaly detection in smart grids. IEEE Transactions on Smart Grid, 14(4), 2850-2862.
32. Dalla, L. O. B., Karal, Ö., Degirmenci, A., EL-sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). A comprehensive literature review (LR) on optimization algorithms of sewage water treatment processes. Comprehensive Science Journal, 10(37), 3204-3220.
33. Zhang, L., & Wang, Q. (2022). A comparative study of support vector machines and random forests for structural health monitoring under varying environmental conditions. Engineering Structures, 254, 113845.

34. Dalla, L. O. F. B., & AHMAD, T. M. A. (2024). Integration of Artificial Bee Colony Algorithm with Deep Learning for Predictive Maintenance in Industrial IoT.
35. Ben Dalla, L., Medeni, T. M., Agila, A. A., & Medeni, İ. M. (2024). Architectural Synergy: Investigating the Role of Artificial Neural Networks in Enabling Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 96-103.
36. Ramadhan, H. R. S., Osman, M. O. M., Dalla, L. O. F. B., Rashid, T. A., Albaraesi, M. J. S., El-Sseid, M. A. M., & Alnnale, T. (2025). A New Approach of the Machine Learning Framework Integrating Policy Design to Predict Renewable Electricity Penetration in Resource-Constrained Settings. Comprehensive Science Journal, 10(Supplement 38), 2929-2950
37. Albaraesi, M. J. S., Ali, M. A. M. A., Dalla, L. O. B., EL-sseid, M. A. M., Medeni, T. D., Medeni, İ. T., & Alnnale, T. (2025). Random construction in the city of Al-Bayda during the period 2011-2022 and its irregular expansion and its impact on the urban landscape. Comprehensive Science Journal, 10 (Supplement 38), 2590-2614.
38. A-abdullatef, M. M., Osman, M. O. M., Elghaffi, F. S. A., Dalla, L. O. B., Agila, A. A. A., & Alsharif, A. (2025). LATENT: Low-Latency Anomaly Tracking in National Electricity Time-Series Using Hybrid LSTM-Regression Architectures–A Case Study of Bangladesh's PGCB Grid. Comprehensive Science Journal, 9(36), 1891-1912.
39. Jetlawei, S. S., Dalla, L. O. B., Karal, Ö., Degirmenci, A., El-Sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). Temporal Intelligence and Algorithmic Equity: A Multi-Phase Framework for Predictive Student Success in Higher Education. Comprehensive Science Journal, 9(36), 1574-1595.https://doi.org/10.65405/f0xx5p02
40. Dalla, L. O. F. B. (2020). Lean Software Development Practices and Principles in Terms of Observations and Evolution Methods to increase work environment productivity. *International Journal of Engineering and Modern Technology*, *6*(1), 23-45.
41. Dalla, L. O. F. B., & AHMAD, T. M. A. (2024). IMPROVE DYNAMIC DELIVERY SERVICES USING ANT COLONY OPTIMIZATION ALGORITHM IN THE MODERN CITY BY USING PYTHON RAY FRAMEWORK.
42. Karal, Ö. (2020). Performance comparison of different kernel functions in SVM for different k value in k-fold cross-validation. In 2020 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-5). IEEE. https://doi.org/10.1109/ASYU50717.2020.9259880
43. Ben Dalla, L., Medeni, T. M., Zbeida, S. Z., & Medeni, İ. M. (2024). Unveiling the Evolutionary Journey based on Tracing the Historical Relationship between Artificial Neural Networks and Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 104-110.
44. Dalla, L. O. F. B. (2020). Lean Software Development Practices and Principles in Terms of Observations and Evolution Methods to increase work environment productivity.
45. Ben Dalla, L., MEDENİ, T., MEDENİ, İ., & ULUBAY, M. (2024). Enhancing Healthcare Efficiency at Almasara Hospital: Distributed Data Analysis and Patient Risk Management. *Economy: strategy and practice*, *19*(4).
46. BEN, D. L., MEDENI, T., MEDENI, I., & ULUBAY, M. (2024). ENHANCING HEALTHCARE EFFICIENCY AT ALMASARA HOSPITAL: DISTRIBUTED DATA ANALYSIS AND PATIENT RISK MANAGEMENT. *ЭКОНОМИКА*, *19*(4), 54-72.

47. Ben Dalla, L., Medeni, T. M., Agila, A. A., & Medeni, İ. M. (2024). Architectural Synergy: Investigating the Role of Artificial Neural Networks in Enabling Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 96-103.
48. Agila, A. A. A. (2024). Diabetes Prediction Using a Support Vector Machine (SVM) and visualize the results by using the K-means algorithm* Corresponding author:* Llahm Omar Faraj Ben Dalla, Tarik Milod Alarbi Ahmad2 .
49. Dalla, L. O. F. B. (2020). The Influence of hospital management framework by the usage of Electronic healthcare record to avoid risk management (Department of Communicable Diseases at Misurata Teaching Hospital: Case study). EHRM, 20(4), 22–52. https://doi.org/20.51176/1954-9923-2020-4-22-52
50. Dalla, L. O. F. B. (2020). Dorsal Hand Vein (DHV) Verification in Terms of Deep Convolutional Neural Networks with the Linkage of Visualizing Intermediate Layer Activations Detection. International Journal of Engineering and Modern Technology E-ISSN 2504-8848 P-ISSN 2695-2149 Vol 6 No 2 2020 www.iiardpub.org
51. Dalla, L. O. F. B. (2020). Convolutional Neural Network Baseline Model Building for Person Re-Identification. International Journal of Engineering and Modern Technology E-ISSN 2504-8848 P-ISSN 2695-2149 Vol. 6 No. 3 2020 www.iiardpub.org
52. Dalla, L. O. F. B. (2020). The Influence of hospital management framework by the usage of Electronic healthcare record to avoid risk management (Department of Communicable Diseases at Misurata Teaching Hospital: Case study).
53. Dalla, L. O. F. B. (2020). Dorsal Hand Vein (DHV) Verification in Terms of Deep Convolutional Neural Networks with the Linkage of Visualizing Intermediate Layer Activations Detection..
54. Degirmenci, A., & Karal, O. (2022). Efficient density and cluster based incremental outlier detection in data streams. *Information Sciences*, *607*, 901-920.
55. Ben Dalla et al., (2026). Resource-Efficient Dorsal Hand Vein Authentication: An Edge-Optimized Blockchain Framework for Sustainable Smart Cities.8th International Conference on Frontiers in Academic Research. July 16-17, 2026: Konya, Turkey. https://www.icfarconf.com/
56. Dalla, L. O. F. B. (2020). Modeling by using Generic Modeling Environment (GME) Domain specific modeling language (DSL) for agile software development (ASD) types.
57. Dalla, L. O. F. B. (2020). Convolutional Neural Network Baseline Model Building for Person Re-Identification..
58. Ersoy, E., & Karal, Ö. (2012). Yapay sinir ağları ve insan beyni. *İnsan ve Toplum Bilimleri Araştırmaları Dergisi*, *1*(2), 188-205.
59. Dalla, L. O. B., Medeni, T. D., & Medeni, I. T. (2024). Evaluating the Impact of Artificial Intelligence-Driven Prompts on the Efficacy of Academic Writing in Scientific Research. Afro-Asian Journal of Scientific Research (AAJSR), 48-60.
60. Karal, Ö. (2024). Comparative performance analysis of epsilon-insensitive and pruningbased algorithms for sparse least squares support vector regression. *Sigma Journal of Engineering and Natural Sciences*, *42*(2), 578-589.
61. Karal, Ö. (2024). Comparative performance analysis of epsilon-insensitive and pruningbased algorithms for sparse least squares support vector regression. *Sigma Journal of Engineering and Natural Sciences*, *42*(2), 578-589.
62. Dalla, L. B., Karal, Ö., Mhamed, E. S., & Alsharif, A. (2026). An IoT-enabled, THD-based fault detection and predictive maintenance framework for solar PV systems in harsh

climates: integrating DFT and machine learning for enhanced performance and resilience. *Wadi Alshatti University Journal of Pure and Applied Sciences*, 41-55.

63. Dalla, L. O. F. B. (2020). E-mail: mohmdaesed@ gmail. com E-mail: selflanser@ gmail. com Phone:+ 218945780716.
64. Ben Dalla, L, O, F. Medeni, T, Medeni, I.(2024). Evaluating the Impact of Artificial Intelligence-Driven Prompts on the Efficacy of Academic Writing in Scientific Research
65. Ben Dalla, L, O, F. (2021).Literature review (LR) on the powerful of Research methodology processes life cycle. In 2021 The Powerful of Research Methodology Processes Life Cycle Conference (TPRMPLCC) (pp. 1-10). IEEE. https://doi.org/10.16543/TPRMPLCC 50717.2020.92876580
66. Ben Dalla, L, O, F. (2021). Literature review (LR) on the dominant of Research methodology. Conference (LRDRMC) (pp. 1-14). IEEE. https://doi.org/10.6754/LRDRMC56412.2020.45987623
67. Ben Dalla, L, O, F. (2021). The enhancement of English level of EFL learners by using English idioms while practices their English (Literature review). IEEE.EFLLEILR50303.2021.6592929
68. Ben Dalla, L, O, F. (2021). English idioms practices to enhance English level of EFL learners (Literature review)
69. Dalla, L. O. B., Medeni, T. D., & Medeni, İ. T. (2024). Evaluating the Impact of Artificial Intelligence-Driven Prompts on the Efficacy of Academic Writing in Scientific Research. The journal of Afro-Asian Scientific Research (AAJSR), 48-60.
70. Ben Dalla, L, O, F. (2020). READING ROMANTIC NOVELS ON ARABIC PEOPLE TO IMPROVE THEIR ENGLISH LANGUAGE: A CASE STUDY, LIBYAN PEOPLE EDUCATORS English language case study Libyan secondary schools. IEEE.https://doi.org/10. 99879/RRNAEL50717.2020.69834279
71. Ben Dalla, L, O, F. (2020). A Compression between External language comparisons to explain cross- linguistic influences based on learners' psychological perceptions of L1-L2 similarities or differences and children at learning a second language, and indeed might even be better based on markedness and how it affects language transfer: A literature review (LR). 12(20), 8741. L1-L2, 2020, 12(20), 8741; https://doi.org/10.4430/en17186641
72. Agila, A. A. A., & Elsseid, M. A. M. 3ournal of Cotal.
73. Dalla, L. O. F. B. (2020). Lean Software Development Practices and Principles in Terms of Observations and Evolution Methods to increase work environment productivity. *International Journal of Engineering and Modern Technology*, *6*(1), 23-45.
74. Dalla, L. O. B., Karal, Ö., & Degirmenciyi, A. (2025). Leveraging LSTM for Adaptive Intrusion Detection in IoT Networks: A Case Study on the RT-IoT2022 Dataset implemented On CPU Computer Device Machine. 5th International Conference on Engineering, Natural and Social Sciences, April 15-16, 2025: Konya, Turkey, 2025. Published by All Sciences Academy. https://www.icensos.com/
75. Ben Dalla et al., .(2020). A REVIEW BASED ON CORPUS LINGUISTICS AND LANGUAGE CORPORA
76. Yalman, Y., Uyanık, T., Atlı, İ., Tan, A., Bayındır, K. Ç., Karal, Ö., ... & Guerrero, J. M. (2022). Prediction of voltage sag relative location with data-driven algorithms in distribution grid. Energies, 15(18), 6641.Energies 2022, 15(18), 6641; https://doi.org/10.3390/en15186641

77. Arık, D. T., Karal, Ö., & Şahin, A. B. (2020). A Comparative Study of Artificial Neural Networks and Naïve Bayes Techniques for the Classification of Radar Targets. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 9(4), 1779-1788.https://doi.org/10.17798/bitlisfen.676973
78. Uysal, Z., Kalkancı, G., İmren, T., Değirmenci, A., Karal, Ö., & Çankaya, İ. (2016). A Heart Rate Monıtoring Applicatıon Using Wireless Sensor Network System Based on Bluetooth Wıth Matlab GUI. Int. J. Eng. Sci, 6, 2862.International Journal of Engineering Science and Computing, August 2016 , http://ijesc.org/
79. Dulkadir, S. E. Z. G. İ. N., Tecimer, H. U., Parlaktürk, F., Altındal, Ş., & Karal, Ö. M. E. R. (2020). The effect of radiation on the forward and reverse bias current–voltage (I–V) characteristics of Au/(Bi4Ti3O12/SiO2)/n-Si (MFIS) structures. Journal of Materials Science: Materials in Electronics, 31(15), 12514-12521.https://doi.org/10.1007/s10854-020-03801-0
80. Muttaqi, M., Degirmenci, A., & Karal, O. (2022, September). US accent recognition using machine learning methods. In 2022 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-6). IEEE.https://doi.org/10.1109/ASYU56188.2022.9925265
81. Ben Dalla. (2020). LANGUAGE PLANNING. Researchgate.com
82. Degirmenci, A., & Karal, O. (2022). Efficient density and cluster based incremental outlier detection in data streams. *Information Sciences*, *607*, 901-920.
83. Karal, O. (2017). Maximum likelihood optimal and robust support vector regression with lncosh loss function. *Neural networks*, *94*, 1-12.
84. Karal, Ö. (2020). Performance comparison of different kernel functions in SVM for different k value in k-fold cross-validation. In *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)* (pp. 1-5). IEEE.
85. Ersoy, E., & Karal, Ö. (2012). Yapay sinir ağları ve insan beyni. *İnsan ve Toplum Bilimleri Araştırmaları Dergisi*, *1*(2), 188-205.
86. Degirmenci, A., & Karal, O. (2021). Robust incremental outlier detection approach based on a new metric in data streams. *IEEE Access*, *9*, 160347-160360.
87. KARAL, Ö. (2018). Destek vektör regresyon ile EKG verilerinin sıkıştırılması. *Gazi Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi*, *2018*(2018).
88. Apaydın, M., Yumuş, M., Değirmenci, A., & Karal, Ö. (2022). Evaluation of air temperature with machine learning regression methods using Seoul City meteorological data. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, *28*(5), 737-747.
89. Degirmenci, A., & Karal, O. (2018). Evaluation of kernel effects on svm classification in the success of wart treatment methods. *Am. J. Eng. Res*, *7*, 238-244.
90. Karim, A. M., Karal, Ö., & Çelebi, F. V. (2018). A new automatic epilepsy serious detection method by using deep learning based on discrete wavelet transform. In *Proceedings of the 3rd International Conference on Engineering Technology and Applied Sciences (ICETAS)* (Vol. 4, pp. 15-18).
91. Ben Dalla, L,O, F, M.eljali , E, Agila, A,A,A, (2020). The evaluation of the daily profits of the group of cosmetics Sephora branches by using distributed systems the K-means algorithm and WEKA visualization. (KMAWV) (pp. 1-15). IEEE.https://doi.org/10.32879/KMAWV50717.2020.65432879
92. Karal, Ö., & Dalla, L. O. F. B. Lung Nodule Characterization in CT Scans Using Hybrid 3D Attention U-Net Segmentation and Transfer Learning-Based Classification Approach. Comprehensive Journal of Science, Volume (10), Issue (37), (NOV. 2025) Special issue

for the Third International Conference on Science and Technology, www.sicst.ly, SICST2025, ISSN: 3014-6266, Reply: 6266-3014

93. Çakır, M., Degirmenci, A., & Karal, O. (2022). Exploring the behavioural factors of cervical cancer using ANOVA and machine learning techniques. In *International Conference on Science, Engineering Management and Information Technology* (pp. 249-260). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-40395-8_18
94. Sinecen, M., Cinar, M., Karal, O., Engin, M., Atesci, Y. Z., Makinaci, M., & Cakmak, B. (2009, May). Diagnosis of Prostat Cancer using Artificial Neural Networks. In *2009 14th National Biomedical Engineering Meeting* (pp. 1-3). IEEE https://doi.org/10.1109/BIYOMUT.2009.5130296
95. M. Yumus, M. Apaydin, A. Degirmenci, and O. Karal, “Missing data imputation using machine learning based methods to improve HCC survival prediction,” 2020 28th Signal Processing and Communications Applications Conference, SIU 2020 - Proceedings, Oct. 2020, doi: 10.1109/SIU49456.2020.9302222.
96. Dalla, L. O. F. B., & Ahmad, T. M. A. (2023). Heart Disease Prediction Via Using Machine Learning Techniques with Distributed System and Weka Visualization. Journal of Southwest Jiaotong University, 58(4), 322-333.https://doi.org/10.35741/issn.0258-2724.58.4.26
97. Degirmenci, A., & Karal, O. (2022). iMCOD: Incremental multi-class outlier detection model in data streams. Knowledge-Based Systems, 258, 109950.
98. Yalman, Y., Uyanık, T., Atlı, İ., Tan, A., Bayındır, K. Ç., Karal, Ö., ... & Guerrero, J. M. (2022). Prediction of voltage sag relative location with data-driven algorithms in distribution grid. Energies, 15(18), 6641.\
99. Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806
100. Alrawayati, H., & Tökeşer, Ü. (2021). PARKINSON’S DISEASE DIAGNOSIS BASED ON THE CONVOLUTIONAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION ALGORITHM. Asian Journal of Mathematics and Computer Research, 28(1), 26-37.
101. Hawa Alrawayati. (2016). Integral Equation and Kernel Operator. Al-Satel Journal - Misrata University. 63-76
102. Chantar, H., Tubishat, M., Essgaer, M., & Mirjalili, S. (2021). Hybrid binary dragonfly algorithm with simulated annealing for feature selection. SN computer science, 2(4), 295.
103. Siraj, F., & Abdoulha, M. A. (2009, May). Uncovering hidden information within university's student enrollment data using data mining. In 2009 Third Asia International Conference on Modelling & Simulation (pp. 413-418). IEEE.
104. Siraj, F., & Abdoulha, M. A. (2007). Mining enrolment data using predictive and descriptive approaches. Knowledge-Oriented Applications in Data Mining, 53-72.
105. Alssager, M., & Othman, Z. A. (2016). Taguchi-based parameter setting of cuckoo search algorithm for capacitated vehicle routing problem. In Advances in Machine Learning and Signal Processing: Proceedings of MALSIP 2015 (pp. 71-79). Cham: Springer International Publishing.

106. Alssager, M., Othman, Z. A., Ayob, M., Mohemad, R., & Yuliansyah, H. (2020). Hybrid cuckoo search for the capacitated vehicle routing problem. Symmetry, 12(12), 2088.

107. Omar, A., Essgaer, M., & Ahmed, K. M. (2022, July). Using machine learning model to predict Libyan telecom company customer satisfaction. In 2022 International Conference on Engineering & MIS (ICEMIS) (pp. 1-6). IEEE.

108. Alssager, M., & Othman, Z. A. (2016). Cuckoo search algorithm for capacitated vehicle routing problem. Journal of Theoretical and Applied Information Technology, 88(1), 11.

109. Siraj, F., & Ali, M. (2011). Mining enrollment data using descriptive and predictive approaches (pp. 53-72). InTech—Open Access Company.

110. Dalla, L. O. B., Karal, Ö., Degirmenci, A., EL-Sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). Edge Intelligence for Real-Time Image Recognition: A Lightweight Neural Scheduler Via Using Execution-Time Signatures on Heterogeneous Edge Devices. Scientific Journal for Publishing in Health Research and Technology, 74-85.

111. Alssager, M., & Nasir, I. (2021). Evaluation of using Google Classroom as a Tool for Asynchronous E-learning at Sebha University. Journal of Pure & Applied Sciences, 20(1), 44-49.

112. ALSSAGER, M., & OTHMAN, Z. A. (2014). SIMULATED ANNEALING ALGORITHM USING ITERATIVE COMPONENT SCHEDULING APPROACH FOR CHIP SHOOTER MACHINES. Journal of Theoretical & Applied Information Technology, 65(2).

113. Siraj, F., & Abdoulha, M. A. (2009, May). Uncovering hidden information within university's student enrollment data using data mining. In 2009 Third Asia International Conference on Modelling & Simulation (pp. 413-418). IEEE.

114. Karal, Ö., & Dalla, L. O. F. B. (2025). Lung Nodule Characterization in CT Scans Using Hybrid 3D Attention U-Net Segmentation and Transfer Learning-Based Classification Approach. Comprehensive Science Journal, 10(37), 2907-2921.

115. Alssager, M., Othman, Z. A., & Ayob, M. (2017). Cheapest insertion constructive heuristic based on two combination seed customer criterion for the capacitated vehicle routing problem. Int. J. Adv. Sci. Eng. Inf. Technol.

116. Müllerová, E., Hrůza, J., Velek, J., Ullman, I., & Stříska, F. (2015). Life cycle management of power transformers: results and discussion of case studies. *IEEE Transactions on Dielectrics and Electrical Insulation*, *22*(4), 2379-2389.