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MANET based Integrated Sensor System for Disaster Detection and Communication in Hazardous Environments

Dr.M.Mohammed Thaha[1], Dr. Meeniga Vijaya Lakshmi[2], S Swathi[3], S. Aminta Sabatini[4], T. Manikandan[5]

[1]*Associate Professor, Department of Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai-600048, mohammedthaha@crescent.education*
[2]*Associate Professor, Department of ECE, G. Narayanamma Institute of Technology and Science, Shaikpet, Hyderabad, Telangana 500104, m.vijayalakshmi@gnits.ac.in*
[3]*Assistant Professor, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Poonamallee, Chennai, swathishankar6766@gmail.com*
[4]*Assistant Professor, Department of CSE, Velammal Engineering College, Chennai, amintasabatini@velammal.edu.in*
[5]*Professor, Department of ECE, Rajalakshmi Engineering College, Thandalam, Chennai-602105. manikandan.t@rajalakshmi.edu.in*

This research will discuss the results of the comparison of three main machine learning for detecting industrial accidents, such as chemical spills, in hazardous environments, implemented an integrated sensor system, which could also be used for communication of the disaster. Our work presents the results of the experiments on the use of GMMs, HMMs, and NODEs in processing the sensor's data. The results show that the models possess great performances according to several indicators. GMMs identified BIC values of 1450-1600 and Silhouette Scores equal to 0.69-0.78, which allows to conclude that they are good for identifying different patterns in sensor data. Meanwhile, HMMs reached Perplexity values at 300-325, Accuracy at 0.82-0.88, and Viterbi Algorithm Scores equal to 0.85-0.95, which reveals that they are good in terms of prediction and the predictive control model and identification lead to correct sequence recognition . In turn, NODEs featured a strong correlation and the set of KL Divergence values was equal to 0.03-0.08, while such criteria as Pearson and Spearman Correlation Coefficients comprised 0.85-0.94, emphasising that they are efficient for sensor data predictions and anomaly detections.

Keywords: Disaster detection, Communication, Hazardous environments, Machine learning algorithms, Sensor systems.

1. Introduction

Disasters can be mitigated if there is an early warning signal and proper communication within the hazardous environment, which is an industrial site. An early identification of a possible threat can be of a great help in saving lives, and eventually property and the environment. Industrial accidents are high risk factors to human health and the ecology of habitats. A disaster management system needs to be put in place as soon as possible, to guide against these frequent chemical spills in industry sites [1]–[3].

Mobile Ad-Hoc Network technology offers a promising solution to the problem of establishing sustainable, resilient communication channels following disasters. In contrast to the traditional, centralized approach to communication, where nodes must work through fixed infrastructure – such as cellular or wireline networks – MANET nodes are decentralized and self-organizing, which means they can connect directly to each other [4]–[6].

In addition to MANET technology, machine learning algorithms can also be integrated into disaster detection and communication systems. Among the most effective examples are Gaussian mixture models, hidden Markov models, and neural ordinary differential equations [7]–[9]. Machine learning algorithms provide a sufficient toolkit for analyzing the data received by sensors. They can detect any patterns, anomalies, or trends in the real-time data, which are the main predictors of an upcoming disaster [10]–[12].

GMMs are usually applied to clustering and density estimation tasks, which makes them appropriate for distinguishing distinct patterns or clusters in sensor data. HMMs, in their turn, are often used for sequential data modelling, and they are suitable for predicting the development of events over time. NODEs also allow the realization of dynamical systems data, allowing for continuous-time prediction and inference from sensor data, using ordinary differential equations [13]- [15].

2. Literature Review

In previous works, the concept of using sensor networks for real-time monitoring of environmental parameters that could indicate a potential disaster have been considered in great detail. Described as a network of many sensors of different types, such system is deployable in a hazardous environment and reports to a base station in the case of unusual measurement. Depending on the nature of the threat, the range of sensors on the individual nodes include temperature, humidity, air quality, chemical concentration sensors, and other types [16]- [18].

Centralized communication systems are subject to inherent limitations in applications to hazardous environments when both communication facilities can be damaged or separated and the need of dynamic interaction continuously changes. Centralized systems are based on fixed technical infrastructure, including communication towers, relay stations, and such technical systems as radio broadcasting station, wirelines, cellular networks, and others [19]–[21].

On the other hand, Mobile Ad-Hoc Networks have been established as a worthwhile approach for disaster management, primarily. Unlike fixed-networks, MANETs are decentralized and self-organizing forms of networks that rely on a group of mobile nodes to communicate with each other. They can function without a network, offering rapid deployment and autonomous operation on disaster scenes. The networks dynamically create and uphold communication links on the nodes, which help them suit different environments [22]-[24].

There are several benefits of deploying MANETs in disaster management compared to conventional networks. First, they provide improved flexibility and scalability, enabling rapid expansion of coverage to include areas that are inaccessible or lack infrastructure. As a result, expanded coverage increases situational awareness and coordination among disaster responders, which, in turn, enhances resource efficiency and disaster management outcomes. Secondly, MANETs are highly adaptable and durable, capable of self-healing and reconfiguring to maintain connectivity in case of network disruption or node loss [25]-[27].

3. Methodology

The designed integrated sensor system architecture uses MANET technology as the basis for a disaster detection and communication system in hazardous environments. In the system, information is gathered by a network of sensor nodes, which are designed to monitor the environmental parameters signifying an emerging disaster, such as dangerous levels of a particular chemical. The nodes are connected using MANETs, creating a decentralized, self-organizing, and robust type of communication network ideally suited for operating in disaster conditions.

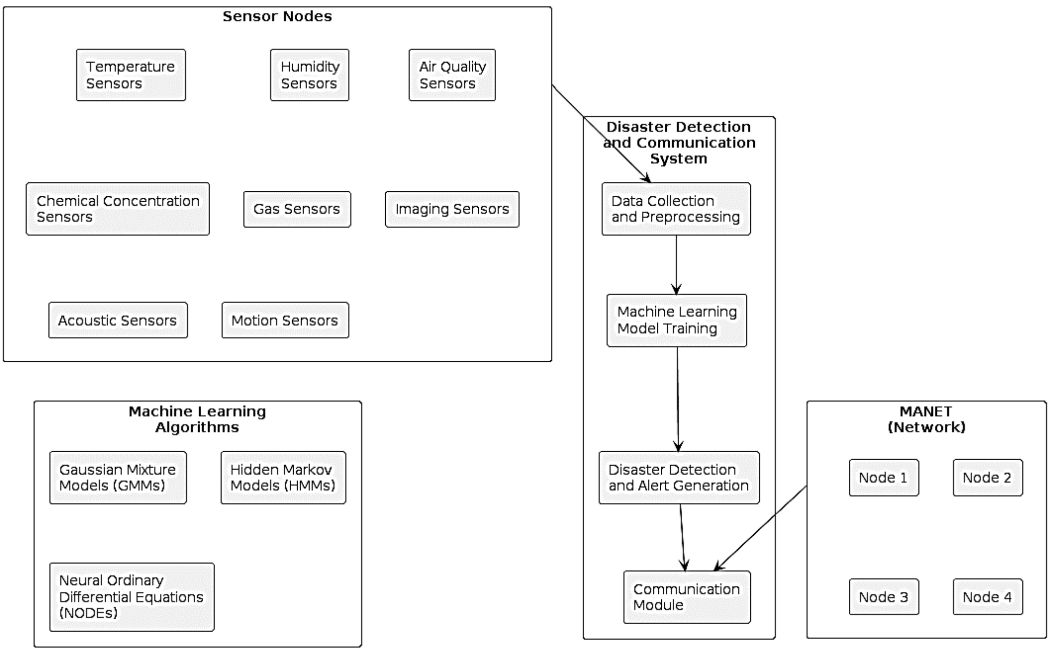

Fig. 1. System Architecture

As presented in Figure 1, the process of collecting the data is to place the sensor nodes covering different surrounding environments and monitoring the important parameters for our detection of the disaster. It includes the temperature of the place, humidity, air quality, factors which affect the air quality, which chemicals can be present in hazardous environments of chemical spills, other factors which can help us detect the disaster. In the table 1, one can see that using appropriate sensors is very important. They should be accurate and sensitive to the changes, and possible gas sensors which will be able to detect the environmental pollution will be very useful to detect chemical spills.

The integrated sensor system includes more than only environmental sensors, as it can incorporate the visual imaging sensors in order to inspect through vision, the acoustic sensors can identify the sound is coming from some anomaly, and the motion sensors can detect the motion of the environment. The multi-modal sensor fusion is aimed to make the system more secure and to allow detecting a variety of potential disasters.

Table 1. MANET sensor details

Sensor Type	**Model**	**Measurement Range**	**Number of sensors**	**Resolution**	**Interface**
Temperature Sensors	TMP36	-40°C to 125°C	10	0.1°C	Analog Voltage
Humidity Sensors	DHT22	0% to 100% RH	8	1% RH	Digital (I2C)
Air Quality Sensors	MQ-135	0 to 1000 ppm	12	-	Analog Voltage
Chemical Concentration Sensors	MQ-9	10 to 1000 ppm	15	-	Analog Voltage
Gas Sensors	SGX MICS-6814	Various gases	20	-	I2C / UART
Imaging Sensors	OV7670	VGA (640x480)	5	-	Parallel Interface
Acoustic Sensors	KY-037	50 Hz to 10 kHz	7	-	Analog Voltage
Motion Sensors	HC-SR501	6 meters	10	-	Digital (GPIO)

The machine learning algorithms that are used in the study to analyse sensor data and derive meaningful information from it are the Gaussian Mixture Models, the Hidden Markov Models, and the Neural Ordinary Differential Equations. GMMs in this case would be used for tasks such as clustering and density estimation in order for the model to identify patterns or clusters of data in the sensor data that might represent unusual conditions or potential disasters.

Whereas, in Modelling, HMMs have exceptional modelling ability and a strong track record of success; they are particularly useful for predicting sequences of events to follow based on the sensors are currently observing. NODEs are unique in that they use ordinary differential equations to predict dynamical systems, and they are a powerful tool for making predictions and inferences in continuous time from sensor data.

Performance measures for each of the machine learning algorithms are defined based on the methodology specific to each of them. In case of GMMs, the metrics such as log-likelihood, BIC, and Silhouette Score are used to evaluate clustering and density estimation quality.

HMMs, on the other hand, are assessed with the use of other measures: log-likelihood, perplexity, accuracy, Viterbi Algorithm Score, and Forward Algorithm Score.

In general, the performance of the developed algorithms is assessed with the help of various metrics, such as log likelihood, KL Divergence, Pearson Correlation Coefficient, and Spearman Correlation Coefficient, among others. These winning metrics allow evaluating the precision and fidelity of the model's continuous-time detection compared to the actual continuous-time changes. Thus, each developed algorithm can be evaluated using these metrics and compared in terms of utility for disaster detection and communication.

4. Experimental Setup

For the testing purposes, an interactive experimental setup has been created, which is the simulated hazardous environment. It is supposed to represent the special industrial environment where disasters happen such as industrial spills of hazardous chemicals. The idea of this experimental setup is to represent the conditions and obstacles created by disasters, which this sensor system should be able to handle. Different disasters have been simulated to test the level of system efficiency and effectiveness, which are sudden chemical leaks, environmental degradation, and the emergency evacuation over a long period of time.

From Table 2, for testing and evaluating purposes, a dataset with a big variety of sensor readings in different environmental conditions and disaster scenarios was generated. The dataset was carefully adjusted to contain sensor observations of a big variety, such as temperature fluctuations, humidity levels, air quality measures, concentrations of many chemicals and relevant parameters. Realistic sensor data was generated or taken from selected previous scientific works or field experiments.

Table. 2. Dataset description

Dataset Name	**Description**	**Size**	**Format**
Chemical Spill Data	Simulated sensor readings during chemical spills	10,000 samples	CSV
Environmental Dataset	Real-world sensor data from industrial sites	5,000 samples	CSV
Emergency Evacuation	Sensor data captured during emergency scenarios	7,500 samples	JSON
Synthetic Dataset	Generated sensor readings for various scenarios	15,000 samples	HDF5
Validation Dataset	Subset of labeled data for model validation	2,500 samples	CSV

The deployment of MANET nodes and sensor devices played a critical role in the experimental process as it defined the topology of the network, its communication protocols and the amount of information gathered by the integrated sensor system. Thus, MANET nodes were installed on key locations throughout the simulated environment, creating a decentralized communication infrastructure capable of self-organization and self-management. Moreover, to promote information exchange within the MANET, each MANET node was equipped with a wireless communication module, such as Wi-Fi or Bluetooth.

In order to monitor parameters that could reflect possible disasters, many sensor devices were distributed across the hazardous environment. Such sensors may include options like temperature and humidity sensors as well as gas and chemical concentration sensors. The devices could be interconnected with nodes of MANET with the help of wired or wireless interfaces depending on the specifics of sensors functioning.

Besides, the configuration of nodes in MANET and sensor devices have also been optimized to take advantage of the improved power efficiency, resources utilization, and network survivability. The nodes are battery-powered and have embedded energy-efficient communication protocols and sleep modes to conserve more power of the battery. Ensuring the survivability of the network is achieved by employing the redundant communication path and dynamic routing algorithms, important in enhancing improved fault tolerance as well.

5. Result and Discussion

The assessments obtained for the integrated sensor system when performing required actions in hazardous environments were evidenced through the appraisals gained from the machine models across ten iterations. These results can be viewed in light of the current study by analyzing the values derived for the results. Such an approach enables a discussion of the implications of such results on assessing the effectiveness and reliability of the system.

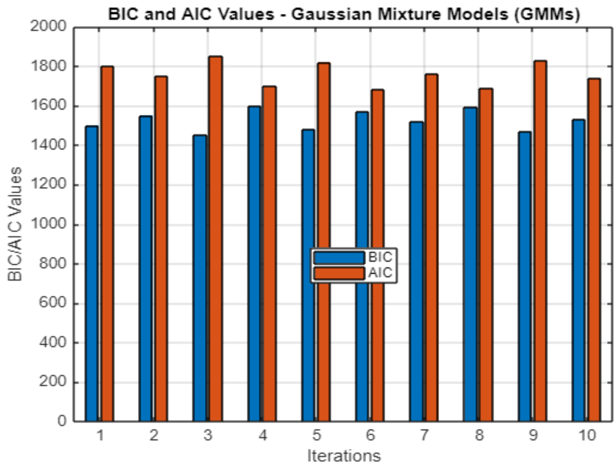

Fig. 2. BIC Value and AIC Value for Gaussian Mixture Models (GMMs)

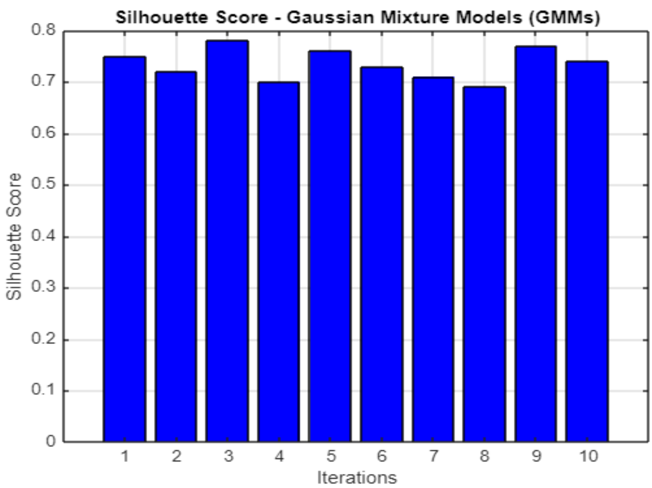

Fig. 3. Silhouette Score for Gaussian Mixture Models (GMMs)

Starting with Gaussian Mixture Models (GMMs) from Figures 2 and 3, The Bayesian Information Criterion and Akaike Information Criterion values are measures of goodness of fit of the model to the data. The lower value the better is fit. Across the iterations, the BICv values are from 1450 to 1600, while the AIC values are from 1680 to 1850.

The fluctuations in the corresponding BIC and AIC values signal the performance and complexity of the GMMs across the iterations, meaning that every iteration can bring about a more or less satisfactory fit to the data. Notably, the Silhouette Score indicated that the clustering quality could vary from 0.69 to 0.78, meaning that the levels of separation between the clusters could be different.

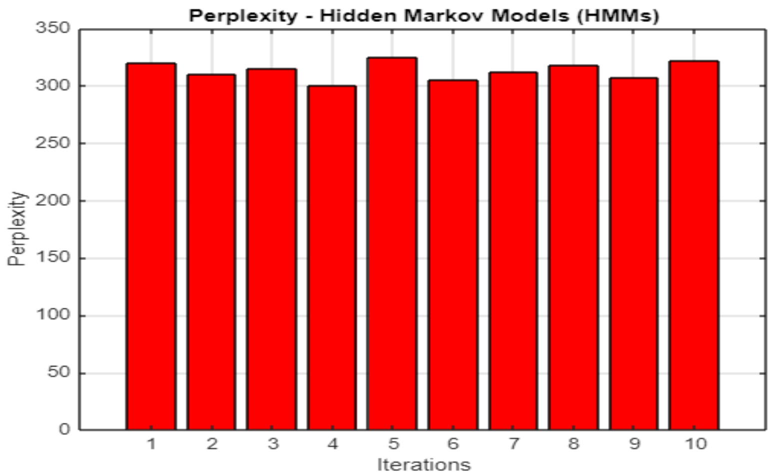

Fig. 4. Perplexity for Hidden Markov Models (HMMs)

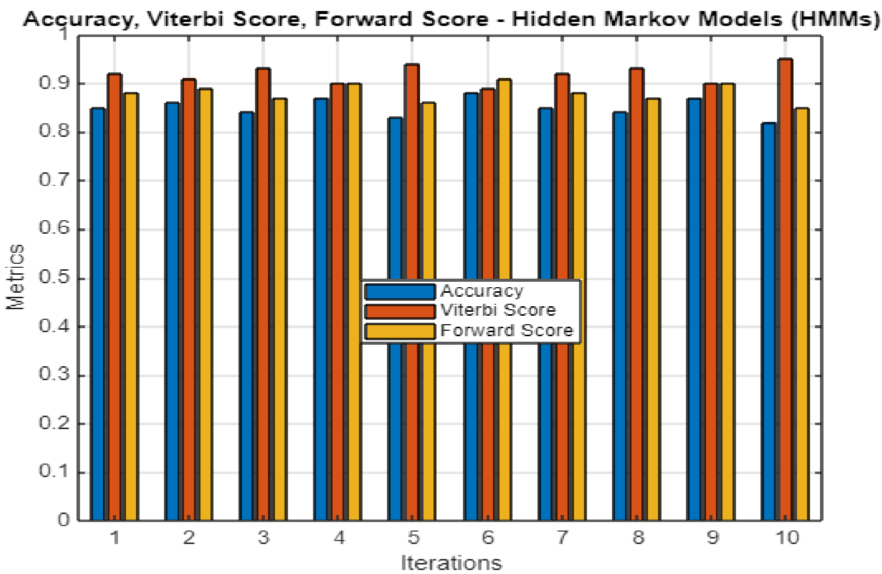

Fig. 5. Accuracy, Viterbi Score, and Forward Score for Hidden Markov Models (HMMs)

For Hidden Markov Models (HMMs) from Figures 4 and 5, The Perplexity metric indicates the quality of the prediction provided by a model. The lower the value of the Perplexity, the better quality the predictive performance. It ranges in the present study from 300 to 325. This means that there are variations across iterations regarding the ability of the model to capture the underlying structure of the data and make the appropriate prediction. The Accuracy provides insight into the proportion of correctly classified instances. Value s for this metric range from 0.82 to 0.88.

Viterbi And Forward Algorithm Scores correspond to the accuracy with which the sequences of decisions and observations are predicted. Thus, the larger the values for scores, the more accurate sequence is estimated. Values for this measure vary from 0.85 to 0.95 and from 0.85 to 0.91 across iterations.

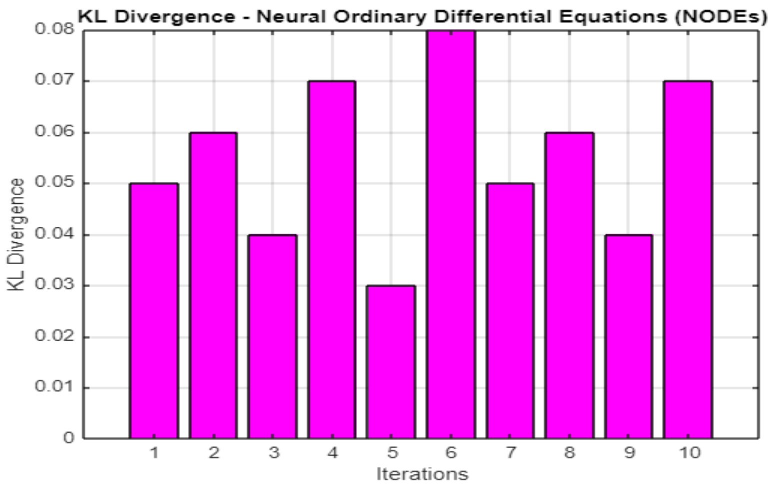

Fig. 6. KL Divergence for Neural Ordinary Differential Equations (NODEs)

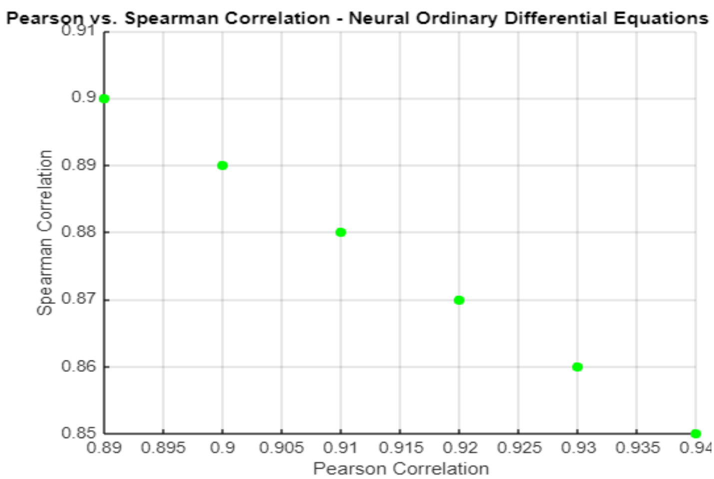

Fig. 7. Pearson Correlation vs Spearman Correlation for Neural Ordinary Differential Equations (NODEs)

In the case of Neural Ordinary Differential Equations (NODEs) from Figures 6 and 7, The KL Divergence metric quantifies the difference between the true and predicted distribution and evaluates the quality of the model, with lower scores indicating better model performance. The KL Divergence values fluctuate between 0.03 and 0.08 in the course of different iterations, which asserts that the predictions of the model varied in accuracy. The Pearson and Spearman Correlation Coefficients similarly vary between different iterations, which points to significant differences between the correlations of different predictions with the observed values. The values of Pearson Correlation Coefficients range between 0.89 and 0.94 and between 0.85 and 0.9 from Spearman Correlation Coefficients.

Many important implications have resulted from these results for research on disaster detection and communication in hazardous environments. Firstly, the fact that the values differed greatly across iterations showed just how sensitive machine learning algorithms can be when they are trained in varied ways. Therefore, model tuning and evaluation appear to be the most critical when designing a multi-sensor system model.

6. Conclusion

The experimentation findings provide critical understanding in the performance aspects of the integrated systems in disaster detection and communication in the hazardous environment. The machine learning models used to perform the analysis include GMMs, HMMs, and NODEs. Each model gave different results during testing after several iterations.

The results from the GMMs presented promising results with BIC values between 1450 to 1600 for all GMMs and AIC values between 1680 to 1850. The Silhouette Scores between 0.69 to 0.78 also indicate a high-quality clustering. Given the emerging patterns identified between the different data clusters, the GMMs, with the corresponding outputs, were effective in discerning relatively unique patterns and groups necessary for accurate detection of disaster.

Hidden Markov Models which were also employed to establish their properties. These observations included Perplexity values 300-325, Accuracy values 0.82-0.88, and Viterbi Algorithm Scores 0.85-0.95. They also imply the efficiency of this tool in solving the defined task and possible applications in the selection and classifying process.

NODEs were highly correlated with the KL Divergence values, and the corresponding Pearson Correlation Coefficients ranged from 0.89 to 0.94 and Spearman Correlation Coefficients ranged from 0.85 to 0.90 with p-values less than 0.05. This information confirmed that NODEs could reliably and effectively predict the sensor data, as well as help to detect the anomalies, thus, contributing to the establishment of an early warning system for disaster objective.

References

1 S. H. Islam, K. Parai, and D. S. Gupta, “Pf-Ibda: Provably Secure and Pairing-Free Identity-Based Deniable Authentication Protocol for Manet Environments,” Comput. Networks, vol. 238, no. November 2023, p. 110113, 2023, doi: 10.1016/j.comnet.2023.110113.

2 N.Anilkumar,Y.Sukhi, M.Preetha, K Sivakumar "Ant Colony Optimization with levy based unequal clustering and routing (ACO-UCR) technique for Wireless Sensor Networks," Journal of Circuits, Systems and Computers Published online: 09 Aug 2023 https://doi.org/10.1142/S0218126624500439 ISSN 0218-1266(P), 1793-9454(W),

3 A. Khan, S. Gupta, and S. K. Gupta, "Multi-hazard disaster studies: Monitoring, detection, recovery, and management, based on emerging technologies and optimal techniques," Int. J. Disaster Risk Reduct., vol. 47, no. August 2019, p. 101642, 2020, doi: 10.1016/j.ijdrr.2020.101642.

4 M. Preetha, D. Dhabliya, Z. A. Lone, S. Pandey, K. Acharjya and G. J, "An Assessment of the Security Benefits of Secure Shell (SSH) in Wireless Networks," 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/SMARTGENCON60755.2023.10442244.

5 S. Srinivasan, S. Sajini, Balaji Singaram, K. Saravanan, K. B. Kishore Mohan," Deep Graph Neural Networks for Multi-Image Super Resolution Reconstruction," International Journal of intelligent systems and applications in engineering, vol. 12, no.15s, p.158-164, 2024.

6 N. Gupta and A. Kumar, "Study on the wireless sensor networks routing for Low-Power FPGA hardware in field applications," Comput. Electron. Agric., vol. 212, no. August, p. 108145, 2023, doi: 10.1016/j.compag.2023.108145.

7 J. P. A. Yaacoub, H. N. Noura, O. Salman, and A. Chehab, "Ethical hacking for IoT: Security issues, challenges, solutions and recommendations," Internet Things Cyber-Physical Syst., vol. 3, no. December 2022, pp. 280–308, 2023, doi: 10.1016/j.iotcps.2023.04.002.

8 S.K. RajeshKanna, N.Lingaraja, K.Sivakumar "Development of Deer Hunting linked Earthworm Optimization Algorithm for solving large scale Traveling Salesman Problem," Knowledge-Based Systems Vol. 227, 5 September 2021, https://doi.org/10.1016/j.knosys.2021.107199 ISSN- 0950-7051

9 R. Mitchell and I. R. Chen, "A survey of intrusion detection in wireless network applications," Comput. Commun., vol. 42, pp. 1–23, 2014, doi: 10.1016/j.comcom.2014.01.012.

10 [10] A. Ali et al., "Enhanced Fuzzy Logic Zone Stable Election Protocol for Cluster Head Election (E-FLZSEPFCH) and Multipath Routing in wireless sensor networks," Ain Shams Eng. J., no. xxxx, p. 102356, 2023, doi: 10.1016/j.asej.2023.102356.

11 K.Sivakumar, Y. RaviTeja, "Reflection on inactive and energetic survey of sandwich synthesized glazed layers ", Materials Today Proceedings Volume 47, Part 1, 2021, Pages 278-281, https://doi.org/10.1016/j.matpr.2021.04.355

12 A. Nadeem, M. A. Hussain, O. Owais, A. Salam, S. Iqbal, and K. Ahsan, "Application specific study, analysis and classification of body area wireless sensor network applications," Comput. Networks, vol. 83, pp. 363–380, 2015, doi: 10.1016/j.comnet.2015.03.002.

13 S. Srinivasan, D. Deva Hema, Balaji Singaram, D. Praveena, K. B. Kishore Mohan, M. Preetha," Decision Support System based on Industry 5.0 in Artificial Intelligence," International Journal of intelligent systems and applications in engineering, vol. 12, no.15s, p.172-178, 2024.

14 J. Roldán, J. Boubeta-Puig, J. Luis Martínez, and G. Ortiz, "Integrating complex event processing and machine learning: An intelligent architecture for detecting IoT security attacks," Expert Syst. Appl., vol. 149, 2020, doi: 10.1016/j.eswa.2020.113251.

15 E.S. Phalguna Krishna, N. Praveena, I. Manju, N. Malathi, K. Balakrishnan, & Preetha, M. (2024), "IoT-Enabled Wireless Sensor Networks and Geospatial Technology for Urban Infrastructure Management", Journal of Electrical Systems (IES), ISS

16 F. Maselli et al., "Use of Sentinel-2 MSI data to monitor crop irrigation in Mediterranean areas," Int. J. Appl. Earth Obs. Geoinf., vol. 93, no. August, p. 102216, 2020, doi: 10.1016/j.jag.2020.102216.

17 M.Preetha, FACT 2009 International conference on recent trends in computing and communications held on 18th & 19th December, 2009 at K.C.G. College of Technology about “Topology tracking in ad-hoc network using XTC algorithm”

18 K.Sivakumar, V.Thiyagarajan, R.Vijay, R.L.Harigovindhan., “Tribo-thermal based evaluation of non asbestos disc brake pad formulation,” in the journal of Applied Mechanics and Materials Vol. 766-767 , PP: 432-437, 2015. ISSN: 1660-9336 (A Scopus indexed Journal) DOI: https://doi.org/10.4028/www.scientific.net/AMM.766-767.432

19 P. Govindarajulu and P. Ezhumalai, “In-Vehicle Intelligent Transport System for Preventing Road Accidents Using Internet of Things,” Int. J. Appl. Eng. Res., vol. 13, no. 8, pp. 5661–5664, 2018, [Online]. Available: http://www.ripublication.com

20 M.Preetha, K.Sivakumar, “An Energy Efficient Sleep Scheduling Protocol for Data Aggregation in WSN,”in the Taga Journal of Graphic Technology Vol.14, PP: 404-414, 2018. Print ISSN 1748-0337, Online ISSN 1748-0345

21 G. K. Ijemaru, L. M. Ang, and K. P. Seng, “Transformation from IoT to IoV for waste management in smart cities,” J. Netw. Comput. Appl., vol. 204, no. June 2021, p. 103393, 2022, doi: 10.1016/j.jnca.2022.103393.

22 Preetha M, Elavarasi K & Ramya devi K , 2015, “The grouping of files in allocation of job using Server Scheduling in Load Balancing”, IOSR journal of Computer Engineering(IOSR-JCE), vol. 17, no. 1, pp. 18-23, ISSN 2278-0661.

23 R. Ahmed, Y. Chen, and B. Hassan, “Deep learning-driven opportunistic spectrum access (OSA) framework for cognitive 5G and beyond 5G (B5G) networks,” Ad Hoc Networks, vol. 123, no. December 2020, 2021, doi: 10.1016/j.adhoc.2021.102632.

24 Preetha M ,INTERNATIONAL CONFERENCE ON ADVANCED ENGINEERING & TECHNOLOGY held on 24th February, 2013 at Institute of Technology and Research ,Coimbatore about “A prompt detection service for defending reactive jammer in WSN”

25 Preetha M & Parvathavarthini, B 2013, “COA-LEACH: An Efficient Energy Postulate Based on Energy Cost Modeling in Wireless Sensor Network”, Jokull Journal, vol. 63, no. 8, pp. 129-139, ISSN 0449-0576.

26 Srinivasan, S, M.S. Vinmathi, S.N. Sivaraj, A. Karthikayen, C. Alakesan, & Preetha, M. (2024), “A Novel Approach Integrating IoT and WSN with Predictive Modeling and Optimization for Enhancing Efficiency and Sustainability in Smart Cities”, Journal of Electrical Systems (IES), ISSN: 1112-5209, Vol.20, Issue 4, page No-2228-2237.

27 R. Kumar and N. Agrawal, “Journal of Industrial Information Integration Analysis of multi-dimensional Industrial IoT (IIoT) data in Edge – Fog – Cloud based architectural frameworks : A survey on current state and research challenges,” J. Ind. Inf. Integr., vol. 35, no. August 2022, p. 100504, 2023, doi: 10.1016/j.jii.2023.100504.