Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Analysis of Multiple Data Fusion Techniques for Performance Computation of Wireless Sensor Network

Naganna Shankar Sollapure[1*], Poornima G.[2], Maruthi H. C.[3]

[1]*Department of ECE, Government Engineering College Talakal, Koppal, India,*

[2]*Departmrnt of ECE, BMS College of Engineering Bengaluru, India,*

[3]*Department of ECE, Government Engineering College, Kushalnagar, India*

Abstract: - Wireless Sensor Networks (WSNs) have become more popular and common in today's technical era because it is simple to operate, affordable to set up, and convenient to administer. Any cluster of the multiple sensor nodes which have sensing as well as computation capabilities is to be deployed within the coverage network. The difficulty of such nodes having enough energy arises whenever they are placed in faraway locations. Since the sensing nodes run on batteries, power is indeed a valuable asset that needs to be used wisely. As a result, clustering the network while using datasets fusion methods to communicate information is the greatest effective way to address this problem. Dataset fusion is indeed a technology that allows for the collection of information from multiple sensing nodes to produce a unified picture and decrease redundant dataset that uses a significant amount of power. Designing applications, as well as methods for WSNs, must include handling mistakes and uncertainty in detecting datasets while optimizing network lifespan. In this article, the authors discussed and analysed multiple data fusion techniques for the performance computation of wireless sensor networks. Furthermore, recent trends and major future challenges of data fusion schemes implementation in the WSNs have indeed been explored and discussed for the future research direction in this domain for the researcher.

Keywords*: Data Fusion, Performance Computation, Network Power, Security, Sensor Network, WSN.*

1. Introduction

There are several implementations for WSNs, including defence purposes (including army intelligence) as well as domestic ones (for instance, industrial control as well as wildlife surveillance). To gather a dataset for a particular purpose, a lot of sensor clusters that can gather information, analyse it, as well as communicate with something like a BS (Base-Station) are often put inside the detecting area. The sensors readings or sensors values refer to the sensing observations [1], [2]. Every actual amount of an occurrence in the surroundings is indeed the matching right amount. This sensing measurement is thought to be inaccurate if it differs from the genuine number. What different operations, such as incident recognition, and path planning, including the decision-making process, could utilize the sensory data with higher certainty but with the least amount of power, and usage is a basic problem within WSNs. There are many causes for inaccurate sensor measurements [3], [4].

For instance, significant fluctuations inside the examined region's humidity, heat, irradiation, as well as electrical interference may interact with the sensor node's values and thus result in inaccurate sensing measurements. Additionally, any sensing cluster itself may sometimes gather inaccurate datasets as a result of dropout, issues with geographical as well as temporally covering, as well as other factors. Additionally, the nearby instruments inside the detecting area frequently produce redundant and strongly associated datasets, which might potentially lower the QoS (Quality-of-Service) [5], [6]. The dataset fusion process may be utilized to eliminate inaccurate as well as the redundant dataset from the sensor readings to solve such issues. Dataset fusion processes combine the datasets from several detectors to provide useful additional datasets which isn't possible with only one. Another major goal of dataset fusion methods with WSNs would be to increase QoS such that choices regarding the occurrences of concern can be made with better certainty as well as accuracy [7].

Therefore, the term QoS might refer to the transmission of trustworthy data that is precise, comprehensive, as well as trustworthy. In reality, dataset fusion assures that the entire WSN's dataset quality is improved while simultaneously reducing power usage by eliminating duplicate datasets. Numerous dataset fusion techniques exist to lower WSN power usage. Several processes utilize a variety of methods, including fuzzy sets, as well as the Dempster-Shafer evidences-theory, as well as neural networks, including the probabilistic concept. The majority of such methods are effective in removing redundant datasets from the fusion procedure [8]. Such methods, meanwhile, do not take into account particular sensing gadget restrictions. For instance, users take for granted that the sensing networks are consistently reliable as well as provide the correct dataset. Because the surroundings seem unpredictable, such expectations are not reasonable. For example, the reliability of the sensing node's functionality might be influenced by climate. Additionally, the current techniques convey both important as well as irrelevant detected datasets to the computing centre, which uses an inordinate amount of power [9]–[11]. One such research presents a fuzzy-rooted dataset fusion method for WSNs which improves QoS while improving channel lifespan and using the least amount of power possible. This suggested technique seems to be able to decrease the transfer as well as handling of all received datasets by identifying and combining just the genuine elements of the detected dataset. Additionally, it can remove duplicated datasets, which in turn lowers power usage as well as lengthens the networking lifespan [12]–[14].

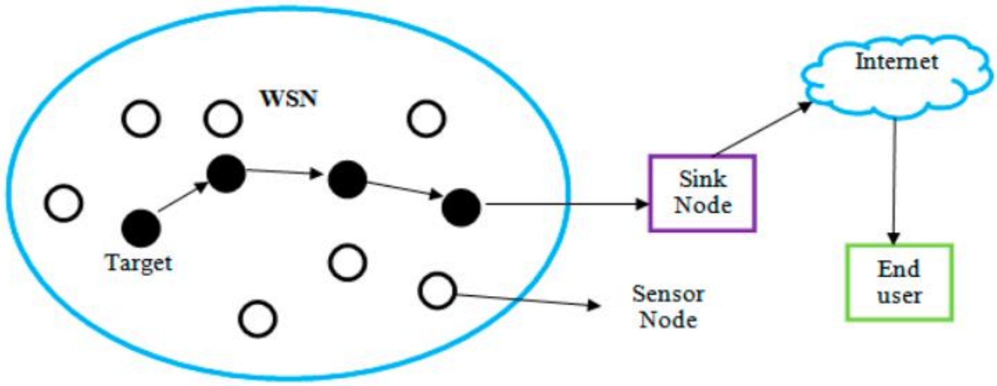

Figure 1: Illustrates the WSN architecture [15].

The WSN is represented as a collection of sensing nodes that can perceive an occurrence-driven environment as well as keep track of its surroundings. Defence, medicinal, surveillance, traffic surveillance, environmental studies, building intelligent cities, item tracing, and many more are some of the different disciplines. Heat, moisture, as well as altitude, are all sensed by the sensing clusters. The sensing clusters communicate with one another through transmitting data; thus, they respond when a certain occurrence takes place. Such networks contain computational power, memory space, and speed for communications, including power. Such networks both collect as well as distribute datasets. Data are disseminated by broadcasting them, while data are gathered by collecting them through sensing nodes. Both static, as well as dynamic WSNs, are possible. Stationary WSN refers to a connection where the endpoints remain fixed in place. This is referred to as a dynamical WSN if the endpoints really aren't permanent but migrate periodically from one area to the next. Increasing nodes' power becomes a significant problem in dynamical networks [16].

When data packages are being sent and retransmitted, a node's power begins to decrease. To increase the lifespan of the networking, it is crucial to use node power effectively in transmission networks. For sensing networks, power utilization may be maintained while networking performance could be increased by using task scheduling as well as traffic pattern management methods. Numerous restrictions, including those related to power, and resources, especially congestion, are faced by sensing devices. Whenever a network sends out more messages than just the recipient can handle. Some packages might be lost along the route. As a result, lost frames must be retransmitted. Overload is the term used to describe this kind of high volume of networking activity that causes data degradation, a drop in operation performance including transmission delays. WSN congestion may harm the effectiveness of the whole connection. To cope with traffic, there are numerous approaches. The first involves bottleneck prevention, in which the networks should operate in some kind of a balanced manner to prevent a scenario that resembles overcrowding [17]. Figure 1 illustrates the WSN architecture.

Before overcrowding occurs, the entire network has to take account of every one of the aspects. Latency may be prevented if indeed the data or demand is distributed evenly over this same entire infrastructure. The next step is bottleneck monitoring, which involves determining whether a node or connection is congested after it has happened. Network stage bottleneck often happens whenever a station receives additional dataset packages than it can handle. This overuse of networking capabilities leads to linked-level overload. Link stage traffic may be addressed by reconfiguring data to lesser crowded links, while nodes layer latency could be reduced by using a waiting approach. Bottleneck management, which comes following locating the traffic, is indeed the following step. It's indeed necessary to keep the system functioning as well as performing well. During varying phases of overcrowding, several investigations have previously been conducted [18].

Along with removing overcrowding, this paper will also provide some new and easier ways to keep track of them. These three methods can help balance and reduce channel traffic. Examples include cluster-routed networks and dataset fusion. These must be installed in the same WSN cluster, and the datasets inside the cluster must be fused using the techniques specified earlier. The recommended method helps reduce network capacity usage while reducing congestion. Dataset fusion is seen as a way to calculate total dataset transmission and dataset spread, which minimizes transaction volume and power consumption while increasing the lifetime of the network. As a result, fewer datasets are often collected from the source sensing network. Members of a group interact more often because they know each other, which minimizes the use of networking throughput [19]. The clustering networks have several benefits since it reuses bandwidth and allocates resources effectively. For a variety of reasons, including power saving, resource balanced, including traffic stream management, the entire infrastructure is separated into groups. Every endpoint inside a clustering network is regarded as clustering participants and therefore believed to share an identical level of power. One of such networks is chosen to serve as the clustering heads that function as the cluster's administrator. Every component within the clusters has an identical chance of becoming a clustering head. Each base station, which may be a single hop or numerous hops distant, receives the dataset packets from the cluster member and then the cluster head transmits the dataset collected. Inter-clustering communication refers to interaction amongst cluster members as well as cluster heads, while intra-clustering communication refers to communication amongst cluster heads as well as sink. The choice to choose a network as the clustering head is entirely based on the amount of power left, the location of the ground station, as well as the likelihood of congestion throughout the coming years [20].

2. Literature Review

This section provides an evaluation of a few popular methodologies that have recently been suggested to assemble datasets. The major applications for WSNs that include monitoring as well as reconnaissance produce a lot of duplicate datasets. The use of dataset aggregation methods to remove duplicate sensor datasets has been done in some kind of a variety of ways. Such methods could indeed be divided into four categories: cluster-rooted, tree-rooted, grid-rooted, as well as structure-independent methods. In [21], the authors discuss a hybrid clustering-rooted dataset aggregation mechanism that simultaneously applies stationary as well as dynamic cluster-rooted techniques. Depending on the state of the connection, the program selects an appropriate grouping method. The researchers, nevertheless, presuppose that the total amount of dataset gathered from every sensory cluster represents the actual amount. This assertion lowers the entire WSN's dataset packet ratio. In [22], A. Yazici discusses a different cluster-data aggregation method. Dataset is aggregated predicated on one's geographic areas throughout their groupings because the method uses a geographic location-rooted multicast procedure. Moreover, because a GPS framework is utilized throughout each detector base station, the power utilization effectiveness also isn't completely discussed. Additionally, the dataset is simply sent as-is by the detector endpoints to the ground terminal [23].

In their discussion of a tree-rooted protocol, C. Elkin et al. in [24], describe how the parent junction gathers dataset packets from tree endpoints as well as adds individuals to the datasets coming from the neighbouring endpoints. The fresh sequence of datasets packets is then sent on by the parental networks to respective master networks eventually they approach the base station. Any 2-D (2-Dimensional) logical pattern of cells is used throughout GBDAS [25], a grid-rooted-dataset-aggregation scheme, to divide the detector ground into molecules. This same cell leader, or component in every cell with the greatest amount of remaining power, is in charge of compiling the information gathered through the cell's various sensing networks. The compiled dataset is transferred from head-to-head together across the sequence formed by the cells chiefs until it attains the base station. Because all sensing networks must combine the acquired dataset, it is impossible to disregard the latency, particularly inside the edge devices. Additionally, it could indeed be an attractive remedy for big channels or sometimes for drains that are extremely far away.

There are numerous WSN datasets fusion algorithms available right now. Energy-balanced datasets fusion, tree-rooted datasets fusion, performance-rooted datasets fusion, as well as security-rooted dataset fusion, are the main topics of this research. The growth of WSNs has been fueled by such dataset fusion technologies. Such conventional dataset fusion processes, nevertheless, did not typically have higher dataset fusion efficiency. This same Nyquist sample selection principle, upon which the experiments mentioned above have been premised, stated that the previous transmitter would only be recovered from the analysed transmitter whenever the bandwidth had been greater than twice the initial transmitter resonant speed [26]. Nevertheless, this approach would significantly raise study costs as well as wastage in several emerging sectors that could be unable to meet the sample rate because of equipment constraints. The combined sparsity endorsed healing issue with 1-bit quantizing-compressive assessments inside a dispersed detector system was investigated throughout the study in reference [27].

C. M. de Farias et al. illustrated that have constructed two computational time amenable centralized methodologies (for instance, Modern language association) as well as suggested an innovative incremental vocabulary training method for sparseness trend recovering to 1-bit resampled assessments. Without knowing the sparsely scope beforehand, it could indeed be utilized to recreate the sound sparsely notification inside a 1-bit approach. The empirical findings demonstrated that it approach proved successful for a situation without vocabulary acquisition when used to develop the convolution (for example, the measuring matrix as well as dense field column) [28]. These same aforementioned techniques address the issue of an unfair internet backbone load by progressively adding the details of every base station to the dataset being broadcasted by encrypting during the procedure of dataset transfer. Nevertheless, the network may be able to communicate the obtained dataset straight to the sinking network without raising the power usage owing to the many networks as well as widespread dispersion inside the entire WSNs; this represents an important issue that requires to be resolved. There has indeed been a lot of discussion about dataset fusion rooted in clustering routing. F. Alshahrany et al. introduced a “Lower Energy Adaptable Clustered Hierarchy” (LE-ACH) method inside the research of [29], which is a traditional clustered methodology and the initial hierarchy transportation mechanism for dataset fusion. This offers bigger size networks as well as fixes the issue with the triangular navigation method's restricted networking scalability. Because WSNs have constrained power resources, it's indeed crucial to pick an efficient dataset fusion method. During the WSNs dataset fusion study, the concept of integrating grouping algorithms with CS technologies to analyze the dataset has emerged as a novel movement. Another energy-efficient dataset aggregation method was examined during the study in citation [30], for just a cluster-rooted Underwater Acoustic Sensor Network (UACN) that was motivated by the notion of decentralized compression sense.

3. Classification of Data fusion Techniques

Owing to their capacity for highly accurate training, artificial neural networks, one of the foremost Machine Learning (ML) based algorithms, have assumed a prominent stance throughout the previous decade. The Neural Network (NN) is indeed the brain of the Human that is inspired by the deep learning (DL) technique. The excellent effectiveness of DL relative to alternative ML architecture has made it a popular study topic in both academics as well as business. It has proven effective to use DL on a particular application sample. Currently conducted studies use input from several nodes. Multimodality is defined by G. Jesus et al. [31] as just a process that is seen by several detectors. The purpose of employing multimodality would be to gather crucial data from several detectors, combine them, as well as utilize the resulting characteristic to address a specific issue. As a result, the projected outcome would execute as well as communicate data more effectively than those separate modalities. A realistic answer to multiple fields of study, including commerce, autonomous technologies, healthcare, including entertainment, includes multimodal datasets analysis. Typical distant detecting equipment, such as cameras, LIDAR (Light Detection and Ranging), as well as radar are often combined. There seem to be three methods for fusing multimodal-datasets. Figure 2 illustrates the multimodality techniques.

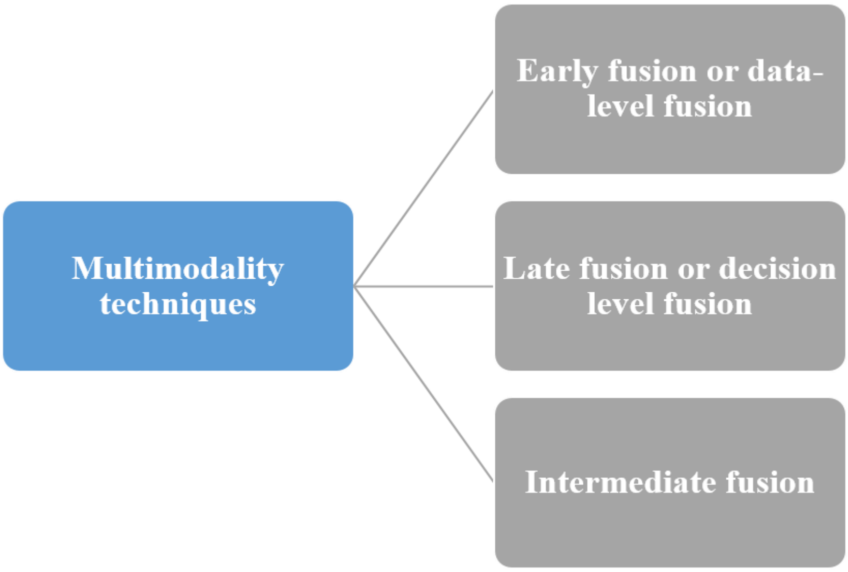

Figure 2: Illustrates the multimodality techniques.

3.1 Early fusion or dataset -level fusion

A common method of combining various datasets before completing the investigation is called dataset level fusion. This process is known as intake levels fusion. Two viable strategies for fast fusing procedures are suggested by researchers [32]. Datasets are combined using the initial method, which eliminates correlation between two detectors. Dataset is combined using its smaller dimensions shared area in the subsequent method. The Principal-Components-analysis (PCA), Canonical-Correlations-Analysis (CCA), as well as autonomous element assessment, are just a few analytical techniques that may be utilized to implement one or multiple methodologies. Initial fusing may be used with unprocessed or already-processed sensor datasets. The method would be difficult if dataset characteristics are not retrieved from the data before fusing, particularly if the dataset sources have varying sample rates across the modality. Whenever one dataset source is discontinuous while the other is constant, synchronizing the dataset sources might be difficult as well. Therefore, one of the biggest challenges in early dataset fusion is combining dataset sources into a unified characteristic vector. Figure 3 illustrates the dataset-level fusion or early fusion.

According to the figure it describes the dataset level fusion and firstly is consist of multiple sensors with virtually connected. In the next step all the sensors send the data in data fusion box, here data fusion use for generate the more accurate, consistence data, which is provided by both individual sensors. After that it create a model for the execute the process and at last the output is generated.

The conditioned freedom amongst several dataset sources is indeed the underlying premise of early dataset fusion. That premise is indeed not necessarily accurate, as per F. Alcaraz Velasco et al. [33], since various modalities might contain properties that are strongly associated, such as video as well as distance signals.

Separate senses may include data that is more highly connected to one some other, according to a distinct article [34]. Therefore, it may be presumed that every modality's data is evaluated separately from the others. Utilizing initial phase dataset fusion has two drawbacks. The same fact that a significant quantity of datasets would be removed from the modality to create a shared platform before fusing is among the key drawbacks of this technology. When the datasets have similar patterns, an ML method is used to evaluate them. The synchronization of the timestamps of the various modes would be the theory's additional drawback.

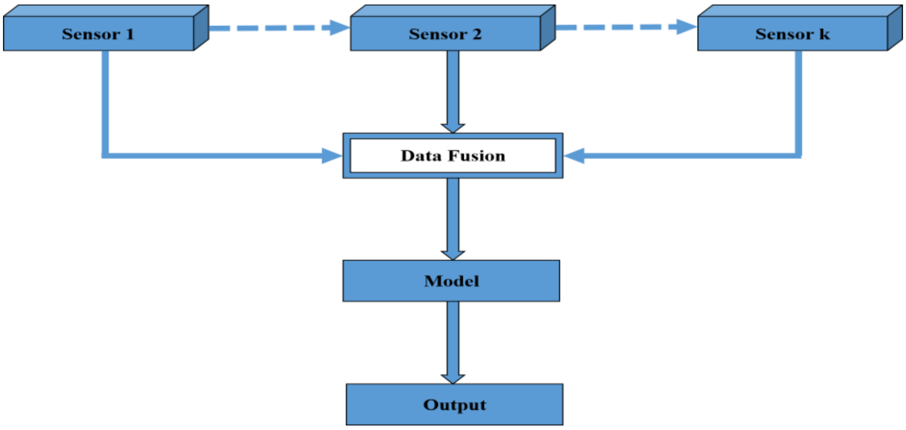

Figure 3: Illustrates the dataset-level fusion or early fusion [Medium].

Collecting the dataset or signals at a standard sample frequency is indeed a frequent strategy for overcoming this drawback. H. Xie et al. [35] also suggest retraining, filtering, and including convolutional fusing as further mitigation measures.

3.2 Late fusion or decision level fusion

After fusing at the choice-making phase, late fusing utilizes dataset sources separately. The prominence of ensemble classifications served as the impetus for late dataset fusion.

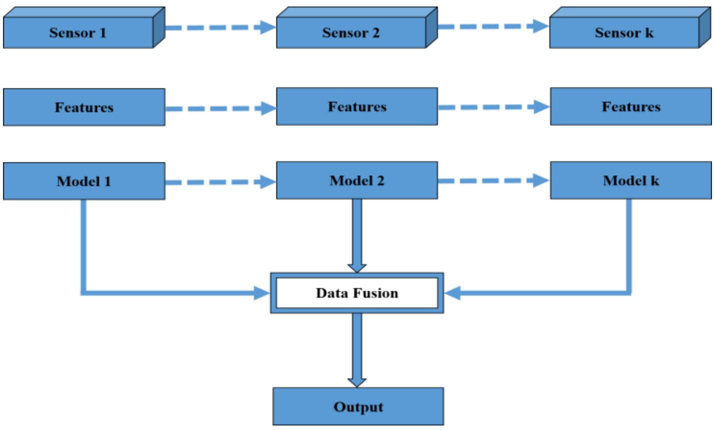

Figure 4: Illustrates the decision fusion approach or late fusion [Medium].

Whenever the dataset sources considerably differ from one another in regards to sample frequency, information complexity, as well as unit of measuring, such methodology is considerably easier than the earlier fusing procedure. Even though mistakes from various systems are handled individually, resulting in statistically independent mistakes, delayed convergence frequently produces remarkable throughput. There are several criteria for selecting how to merge every one of the individually generated algorithms inside the best possible method. Several of the often-used late fusing procedures include Bayes-rules, as well as the max-fusion, but also averagefusion. Employing late fusing is indeed a cheaper but more adaptable solution whenever the incoming dataset streams have a wide range of complexity as well as sampled rates. Figure 4 illustrates the decision fusion approach or late fusion.

3.3 Intermediate Fusion

The widely used DNN serves as the foundation for the design of intermediary fusing. Such an approach represents the most adaptable since it permits dataset fusion at various model-training phases. Accuracy has significantly increased using multimodal datasets fusion using neural networks. With the use of numerous levels, intermediary fusing transforms incoming datasets into a higher degree of description. Every level acts on linear as well as nonlinear variables that change the size, skewed, as well as swinging of the incoming dataset to produce a unique depiction of the identical source information. In a DL-multimodal setting, intermediary fusing is indeed the merging of abstractions from many modalities into unified hidden-layers such that the prototype generates a combined description of all of the senses. Various types of layers, such as 2D (2-Dimensional) convolution, and 3D (3-Dimensional) convolution, as well as completely linked, may be used to acquire characteristics. The fusing layers or sharing depiction layer is indeed the layer in which the fusing of several modalities' characteristics has occurred.

4. Discussion

The duplicated dataset within WSNs is substantial. The channel's entire lifespan would be impacted if such duplicated datasets are processed as well as delivered since node power usage would be excessive. The dataset fusing method significantly reduces the quantity of dataset supplied through the nodes that lengthens the lifespan of the networks by compressing the sampled dataset to remove duplication. WSNs are dynamic systems, therefore classic dataset fusion methods continue to face a lot of issues. To address such issues for WSNs, additional concepts have been presented by Compressed-Sensing (CS) concept. Several sensor endpoints with detecting, processing, as well as transmission capabilities make up a WSN, which is a multi-hopping self-organizing networking architecture. Ecological tracking, agriculture productivity, defending army observation, industrial automated management, healthcare shrivelling, intelligence robotics, as well as intelligent municipalities all make extensive utilization of this sort of networking. Endpoints often have minimal energy as well as battery-powered functions, which makes it impractical to repair or recharge the batteries after it has run out of energy. As a result, existing investigation continues to be focused on finding efficient ways to lower WSNs' power usage.

Through collaborative monitoring, and data gathering, including dataset fusion, the WSNs analyze a particular dataset inside the network covering region before transmitting it to BS (base stations) using multiple-hop relaying. To increase the effectiveness of dataset collecting, dataset fusion is employed to analyze duplicate datasets or information as well as integrate more precise as well as energy-effective data. Dataset fusion is indeed a crucial component of WSNs development as well as a successful way to lower the power requirements of WSNs. Significantly reducing dataset transfer plus energy use is possible with dataset fusion. The issue of real-time correctness, as well as dependability of dataset fusion, has, nevertheless, become a scientific focus owing to the intense dynamism of WSNs. Novel solutions to such issues have been offered by compression (or CS (compressive-sensing), a recent data technology study field. So it has been considered crucial to do an investigation on ways to integrate WSNs dataset using the notion of the CS approach. Figure 5 illustrates the major application of the WSNs.

Table 1 illustrates the improved performance percentage of the WSNs and IRST in existing models using diverse data fusion approaches. The data fusion techniques play a very noteworthy role in the diverse model's development for the WSNs environment and contribute to performance improvement of the models in real-time. We have presented the performance improvement in percentage for the existing models. In [36], the authors used the early fusion technique and the proposed WSN-based model offered 95.19% improvement in performance.

Table 1: Illustrates the improved performance percentage of the WSNs in existing models using diverse data fusion approaches.

S. NO.	Technique of fusion	Performance improvement in %
		WSNs Models
1	Early fusion or dataset-level fusion [36]	95.19
2	Late fusion or decision level fusion [37]	94.33
3	Intermediate fusion [38]	92.56

In this article, we have discussed three diverse data fusion techniques namely early fusion or dataset-level fusion, late fusion or decision-level fusion as well as intermediate fusion. In this work, we analyzed multiple research articles in which these data fusion approaches have indeed been utilized for diverse model developments for the WSNs models.

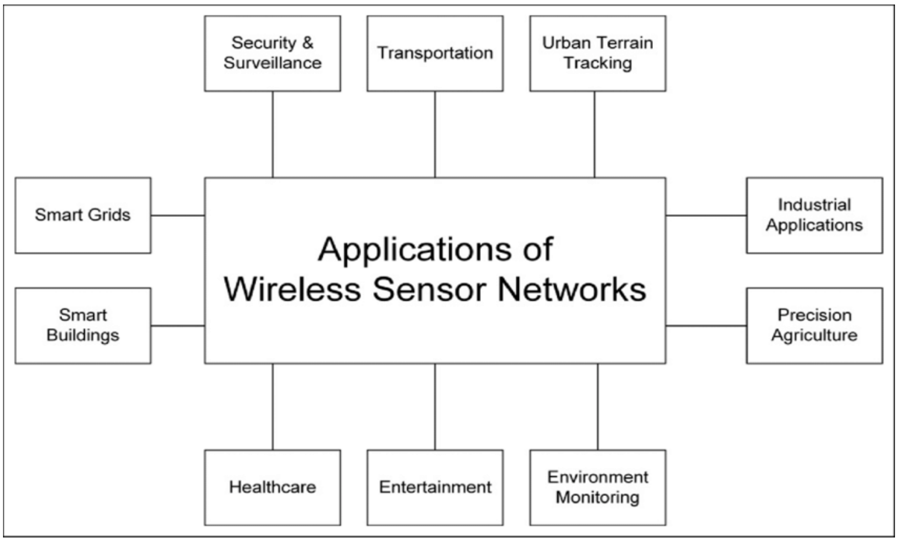

Figure 5: Illustrates the major application of the WSNs [15].

In [37], the researcher's utilized the late fusion technique, and the proposed WSN-based model offered 94.33% improvement in performance. Furthermore, in [39], the investigators utilized the intermediate fusion technique and the proposed WSN-based model offered 92.56% improvement in the performance of the model.

The data fusion approaches have been proven inevitable to enhance the accuracy as well as reliability of the WSNs environment. In this section, three diverse data fusion methods namely early, as well as intermediate, and late fusion techniques have indeed been described. Each of the three approaches executes the fusion procedure in real-time within the spherical coordinates. This is indeed easy for utilization of the Cartesian coordinate's approaches because the linear movement along with the zero acceleration could be discussed via mere 1st-order differential formula. Besides the such benefit, the spherical coordinate arrangement was selected owing to jointly uncorrelated errors within polar extent (namely the entire range along with the elevation as well as azimuth) becoming mutually correlated whenever altered in the mutual Cartesian coordinate arrangement. It could not enhance the noise variance evaluation complexness within the Cartesian coordinate arrangement, however, incorporates a bias within noise constraint.

The fusion approach, rooted in the minimal mean square error measure, receives a fusing track through the weight of the combined identification as described.

$$LT_f = [LS_R^{-1} + LS_I^{-1}]^{-1}[LS_R^{-1}LT_R + LS_I^{-1}LT_I] \quad (1)$$

Herein, SR as well as SI describes the covariance error matrices.

$$\rho_F = \frac{\rho_{LR}}{\rho_{LR}+\rho_I} \quad (2)$$

The linear group of combined identification along with diverse weights may be evaluated via the ρ_F produces as fused tracks.

$$LT_f = [LT_R LT_I]\begin{bmatrix}\rho_F \\ 1-\rho_f\end{bmatrix} \quad (3)$$

The optimal fused estimation could be received through the following expression.

$$LT_f = LB_R LT_R + LB_I LT_I \quad (4)$$

As per the level of the fusion inside diverse activity pipelining, the separate three families of methods can be described i.e. early fusion as well as intermediate along with late fusion. In the early fusion procedure entire selected raw modality is to be joined onward of the features extraction. Another approach is the intermediate fusion, in which the entire chosen features of all modalities have to be associated prior to categorization. Lastly, in the late fusion procedure, the diverse modalities-wise categorization outcomes are joined. Prior to joining a recognizing network, the early fusion method has been used. This converts the unprocessed dataset into a shorter intermediary version. One kind of fusing which occurs within the identification paradigm is called the intermediate fusions approach. These same qualities that set every sort of dataset apart are combined throughout this manner to create a novel depiction that is greater descriptive than the individual expressions from where it evolved. As an illustration, combining characteristics using skeletal sequences as well as RGB (Red, Green, and Blue) photos enables researchers to concurrently benefit from each depiction's advantages. A combining technique called late fusion takes place irrespective of monomodal categorization frameworks. This aggregates every classifier's judgment to create additional judgments which are highly accurate as well as trustworthy.

5.Conclusion

Datasets fusion is the method of combining many dataset sources to offer information that is more constant, reliable, as well as practical than what is offered via any one dataset source alone. Relying on the step of computing at some fusing occurs, dataset fusion procedures are often characterized as lower, middle, or higher. Lower-level dataset fusion integrates datasets from multiple sources to create novel datasets. It is anticipated that the combined dataset would be more insightful as well as artificial than that of the unique sources. This study analyzes the greatest well approaches to fusing datasets as well as information. Researchers must assess the computing expense of the procedure as well as the transmission latency caused to decide if the implementation of datasets/information fusion techniques is practical. Whenever there is no transmit price and just enough processing power, a centralized dataset fusion solution is ideal conceptually. In this article, the authors discussed several methodologies and existing work done in the field of WSNs based on diverse datasets fusion approaches. Furthermore, the researchers presented the major challenges and realistic solutions in the real-time implementations of the WSNs in diverse application based on the diverse dataset fusion techniques. At last, a thorough discussion is given for the future research directions in the field of the WSNs using the diverse data fusion methods for higher network security and many more.

Refrences

[1] M. Koupaee and M. Reza, “Data Fusion Techniques in Wireless Sensor Networks: Structured Vs. Structure-Free Approaches,” J. Netw. Technol., vol. 9, no. 2, p. 41, Jun. 2018, doi: 10.6025/jnt/2018/9/2/41-47.

[2] Q. Chen, Y. Hu, J. Xia, Z. Chen, and H.-W. Tseng, “Data fusion of wireless sensor network for prognosis and diagnosis of mechanical systems,” Microsyst. Technol., vol. 27, no. 4, pp. 1187–1199, Apr. 2021, doi: 10.1007/s00542-018-4144-3.

[3] A. R. Pinto, C. Montez, G. Araújo, F. Vasques, and P. Portugal, “An approach to implement data fusion techniques in wireless sensor networks using genetic machine learning algorithms,” Inf. Fusion, vol. 15, pp. 90–101, Jan. 2014, doi: 10.1016/j.inffus.2013.05.003.

[4] D. Izadi, J. Abawajy, S. Ghanavati, and T. Herawan, “A Data Fusion Method in Wireless Sensor Networks,” Sensors, vol. 15, no. 2, pp. 2964–2979, Jan. 2015, doi: 10.3390/s150202964.

[5] Ritika, N. A. Farooqui, and A. Tyagi, “Data Mining and Fusion Techniques for Wireless Intelligent Sensor Networks,” in Advances in Intelligent Systems and Computing, 2020, pp. 592–615. doi: 10.1007/978-3-030-40305-8_28.

[6] X. Bai, Z. Wang, L. Sheng, and Z. Wang, “Reliable Data Fusion of Hierarchical Wireless Sensor Networks With Asynchronous Measurement for Greenhouse Monitoring,” IEEE Trans. Control Syst. Technol., vol. 27, no. 3, pp. 1036–1046, May 2019, doi: 10.1109/TCST.2018.2797920.

[7] S. Gavel, R. Charitha, P. Biswas, and A. S. Raghuvanshi, “A data fusion based data aggregation and sensing technique for fault detection in wireless sensor networks,” Computing, vol. 103, no. 11, pp. 2597–2618, Nov. 2021, doi: 10.1007/s00607-021-01011-y.

[8] Y. Liu, Q.-A. Zeng, and Y.-H. Wang, “Energy-Efficient Data Fusion Technique and Applications in Wireless Sensor Networks,” J. Sensors, vol. 2015, pp. 1–2, 2015, doi: 10.1155/2015/903981.

[9] Z. Wang, A. Li, C. Ao, D. Wu, W. Zhou, and X. Yu, “Multi-level data fusion algorithm towards privacy protection in wireless sensor networks,” Int. J. Commun. Networks Distrib. Syst., vol. 25, no. 3, p. 265, 2020, doi: 10.1504/IJCNDS.2020.109568.

[10] L. Liu, G. Luo, K. Qin, and X. Zhang, “An algorithm based on logistic regression with data fusion in wireless sensor networks,” EURASIP J. Wirel. Commun. Netw., vol. 2017, no. 1, p.10, Dec.2017, doi: 10.1186/s13638-016-0793-z.

[11] L. Cao, Y. Cai, Y. Yue, S. Cai, and B. Hang, “A Novel Data Fusion Strategy Based on Extreme Learning Machine Optimized by Bat Algorithm for Mobile Heterogeneous Wireless Sensor Networks,” IEEE Access, vol. 8, pp. 16057–16072, 2020, doi: 10.1109/ACCESS.2020.2967118.

[12] A. Reyana and P. Vijayalakshmi, “Multisensor data fusion technique for energy conservation in the wireless sensor network application ‘condition-based environment monitoring,’” J. Ambient Intell. Humaniz. Comput., Jan. 2021, doi: 10.1007/s12652-020-02687-4.

[13] L. Ma, J. Liu, and J. Luo, “Method of Wireless Sensor Network Data Fusion,” Int. J. Online Eng., vol. 13, no. 09, p. 114, Sep. 2017, doi: 10.3991/ijoe.v13i09.7589.

[14] J. Wang, Y. Gao, W. Liu, A. K. Sangaiah, and H.-J. Kim, “An intelligent data gathering schema with data fusion supported for mobile sink in wireless sensor networks,” Int. J. Distrib. Sens. Networks, vol. 15, no. 3, p. 155014771983958, Mar. 2019, doi: 10.1177/1550147719839581.

[15] R. A. Khan and A.-S. K. Pathan, “The state-of-the-art wireless body area sensor networks: A survey,” Int. J. Distrib. Sens. Networks, vol. 14, no. 4, p. 155014771876899, Apr. 2018, doi: 10.1177/1550147718768994.

[16] S. DAS, S. BARANI, S. WAGH, and S. S. SONAVANE, “Extending lifetime of wireless sensor networks using multi-sensor data fusion,” Sādhanā, vol. 42, no. 7, pp. 1083–1090, Jul. 2017, doi: 10.1007/s12046-017-0669-x.

[17] J. J. Jijesh, Shivashankar, and Keshavamurthy, “A Supervised Learning Based Decision Support System for Multi-Sensor Healthcare Data from Wireless Body Sensor Networks,” Wirel. Pers. Commun., vol. 116, no. 3, pp. 1795–1813, Feb. 2021, doi: 10.1007/s11277-020-07762-9.

[18] S. A. Jesudurai and A. Senthilkumar, “An improved energy efficient cluster head selection protocol using

the double cluster heads and data fusion methods for IoT applications," Cogn. Syst. Res., vol. 57, pp. 101–106, Oct. 2019, doi: 10.1016/j.cogsys.2018.10.021.

[19] H. H. Bosman, G. Iacca, A. Tejada, H. J. Wörtche, and A. Liotta, "Spatial anomaly detection in sensor networks using neighborhood information," Inf. Fusion, vol. 33, pp. 41–56, Jan. 2017, doi: 10.1016/j.inffus.2016.04.007.

[20] Y. Zhou, M. Zhang, P. Xie, J. Zhu, R. Zheng, and Q. Wu, "Sparse long short-term memory for information fusion in wireless sensor networks," Int. J. Distrib. Sens. Networks, vol. 15, no. 4, p. 155014771984215, Apr. 2019, doi: 10.1177/1550147719842153.

[21] Z. Baloch, F. K. Shaikh, and M. A. Unar, "A context-aware data fusion approach for health-IoT," Int. J. Inf. Technol., vol. 10, no. 3, pp. 241–245, Sep. 2018, doi: 10.1007/s41870-018-0116-1.

[22] A. Yazici, M. Koyuncu, S. A. Sert, and T. Yilmaz, "A Fusion-Based Framework for Wireless Multimedia Sensor Networks in Surveillance Applications," IEEE Access, vol. 7, pp. 88418–88434, 2019, doi: 10.1109/ACCESS.2019.2926206.

[23] G. Martins, S. G. de Souza, I. L. dos Santos, L. Pirmez, and C. M. de Farias, "On a multisensor knowledge fusion heuristic for the Internet of Things," Comput. Commun., vol. 176, pp. 190–206, Aug. 2021, doi: 10.1016/j.comcom.2021.04.025.

[24] C. Elkin, R. Kumarasiri, D. B. Rawat, and V. Devabhaktuni, "Localization in wireless sensor networks: A Dempster-Shafer evidence theoretical approach," Ad Hoc Networks, vol. 54, pp. 30–41, Jan. 2017, doi: 10.1016/j.adhoc.2016.09.020.

[25] K. Zhu, Z. Wang, Q.-L. Han, and G. Wei, "Distributed Set-Membership Fusion Filtering for Nonlinear 2-D Systems Over Sensor Networks: An Encoding-Decoding Scheme," IEEE Trans. Cybern., pp. 1–12, 2021, doi: 10.1109/TCYB.2021.3110587.

[26] S. Ananda Kumar and P. Ilango, "Data Funnelling in Wireless Sensor Networks: A Comparative Study," Indian J. Sci. Technol., vol. 8, no. 5, p. 472, Mar. 2015, doi: 10.17485/ijst/2015/v8i5/61705.

[27] S. G. Shivaprasad Yadav and A. Chitra, "MZDF: An energy aware framework for multiple-zone data fusion technique in WSN," Int. J. Appl. Eng. Res., 2016.

[28] C. M. de Farias, L. Pirmez, G. Fortino, and A. Guerrieri, "A multi-sensor data fusion technique using data correlations among multiple applications," Futur. Gener. Comput. Syst., vol. 92, pp. 109–118, Mar. 2019, doi: 10.1016/j.future.2018.09.034.

[29] F. Alshahrany, M. Abbod, J. Alshahrani, and A. Alshahrani, "Intelligent networks data fusion web-based services for ad-hoc integrated WSNs-RFID," Int. J. Eng. Technol. Innov., 2016.

[30] W. Fang, W. Zhang, Q. Zhao, X. Ji, W. Chen, and B. Assefa, "Comprehensive Analysis of Secure Data Aggregation Scheme for Industrial Wireless Sensor Network," Comput. Mater. Contin., vol. 61, no. 2, pp. 583–599, 2019, doi: 10.32604/cmc.2019.05237.

[31] G. Jesus, A. Casimiro, and A. Oliveira, "A Survey on Data Quality for Dependable Monitoring in Wireless Sensor Networks," Sensors, vol. 17, no. 9, p. 2010, Sep. 2017, doi: 10.3390/s17092010.

[32] N. Verma and D. Singh, "Data Redundancy Implications in Wireless Sensor Networks," Procedia Comput. Sci., vol. 132, pp. 1210–1217, 2018, doi: 10.1016/j.procs.2018.05.036.

[33] F. Alcaraz Velasco, J. M. Palomares, and J. Olivares, "Lightweight method of shuffling overlapped data-blocks for data integrity and security in WSNs," Comput. Networks, vol. 199, p. 108470, Nov. 2021, doi: 10.1016/j.comnet.2021.108470.

[34] H. Marzi and A. Marzi, "A security model for wireless sensor networks," in 2014 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and

Applications (CIVEMSA), May 2014, pp. 64–69. doi: 10.1109/CIVEMSA.2014.6841440.

[35] H. Xie, Z. Yan, Z. Yao, and M. Atiquzzaman, “Data Collection for Security Measurement in Wireless Sensor Networks: A Survey,” IEEE Internet Things J., vol. 6, no. 2, pp. 2205–2224, Apr. 2019, doi: 10.1109/JIOT.2018.2883403.

[36] S. L. Yadav and R. L. Ujjwal, “Sensor data fusion and clustering : A congestion detection and avoidance approach in wireless sensor networks,” J. Inf. Optim. Sci., vol. 41, no. 7, pp. 1673–1688, Oct. 2020, doi: 10.1080/02522667.2020.1799512.

[37] F. Wang and H. Hu, “Multi-path data fusion method based on routing algorithm for wireless sensor networks,” Int. J. Comput. Appl., vol. 43, no. 9, pp. 916–923, Oct. 2021, doi: 10.1080/1206212X.2019.1652786.

[38] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, “Multisensor data fusion: A review of the state-of-the-art,” Inf. Fusion, vol. 14, no. 1, pp. 28–44, Jan. 2013, doi: 10.1016/j.inffus.2011.08.001.

[39] J. Li, X. Jia, X. Lv, Z. Han, J. Liu, and J. Hao, “Opportunistic routing with data fusion for multi-source wireless sensor networks,” Wirel. Networks, vol. 25, no. 6, pp. 3103–3113, Aug. 2019, doi: 10.1007/s11276-018-1705-4.