Journal of Biostatistics and Epidemiology

J Biostat Epidemiol. 2021;7(2): 189-216

Review Article

Advantages and Challenges of Information Fusion Technique for Big Data Analysis: Proposed Framework

Elham Nazari[1], Rizwana Biviji[2], Amir Hossein Farzin[3], Parnian Asgari[4], Hamed Tabesh[1,*],

[1]Department of Medical Informatics, Mashhad University of Medical Sciences, Mashhad, Iran.
[2]Science of Healthcare Delivery, College of Health Solutions, Arizona State University, Phoenix, AZ, USA.
[3]Department of Computer Engineering, Ferdowsi University, Mashhad, Iran.
[4]Department of Health and Information Technology, Mashhad University of Medical Sciences, Mashhad, Iran.

ARTICLE INFO

Received 13.04.2021
Revised 03.05.2021
Accepted 29.05.2021
Published 19.06.2021

Key words:
Information fusion;
Symbol fusion;
Decision fusion;
Big data;
Data mining

ABSTRACT

Introduction: Recently, with the surge in the availability of relevant data in various industries, the use of Information Fusion technique for data analysis is increasing. This method has several advantages, such as increased accuracy, and the use of meaningful information. In addition, there are certain challenges, including the impact of data type and analytical method on results. The goal of this study is to propose a framework for introducing the advantages and classifying the challenges of this technique.

Method: We conducted a review of articles published between January 1960 and December 2017 for the design stage and from January 2018 to December 2018 for the evaluation stage. Articles were identified from various databases such as Science Direct, IEEE, Scopus, Web of Science, and Google Scholar, using the keywords decision fusion, information fusion, and symbolic fusion. We report the advantages and challenges of the methodologies described in these articles. Analysis was conducted in accordance with PRISMA guidelines.

Results: A total of 132 articles were identified in the design stage and 90 articles were identified in the evaluation stage. Categories within the framework for challenges include "hardware and software requirements for processing and maintaining the process", "data" and "data analysis method". The categories for advantages include "value modeling", "preferable management of uncertainty and variability", "excellent decision making", "comprehensive interpretation and representation", "data management" and "simplicity of infrastructure". Our results indicate using these two frameworks with 95% Confidence interval.

Conclusion: An overall understanding of the advantages and challenges of the information fusion technique could act as a guide for the researcher for the correct usage of this technique.

Introduction

Today, the amount of data that is digitally collected and stored in large volumes is increasing exponentially due to the advent of technology. It is predicted that the collective sum of world's data will be as high as 175 ZB by the year 2025 (1-3). Such massive data

* .Corresponding Author Email: Tabeshh@mums.ac.ir

sets are termed as 'Big Data', which has become a topic of interest in all industries. However, this huge amount of data is largely unstructured (4, 5). This unstructured data can be translated into meaningful information using data management techniques such as the information fusion technique (6-8). Analyzing such data to identify hidden patterns within the data is called Big Data analysis. The data that is generated from online transactions, (emails, videos, audio, images, click streams, logs, posts, search queries, health records, social networking interactions, science data, sensors, mobile phones and applications) have characteristics such as diversity, scalability, uncertainty, speed in production and complexity, where analysis using conventional data mining methods is not possible (2, 9, 10). In such cases, information fusion technique offers a potential solution to derive valuable outcomes from complex systems (11). In fact, this technique is a method associated with data mining, which uses the concepts of knowledge representation, arithmetic and mathematics that can be used in constructing a model, extracting information, pre-processing and increasing the quality of data for better understanding of information (12, 13). This can play an important role for decision-making in a variety of domains, such as sensor and image processing (13, 14).

Classical data mining techniques frequently do not work when problems get increasingly complicated (15). To solve complex problems, a classifier cannot be used on its own to categorize data. Simple data mining techniques prove ineffective since they do not offer the needed performance. In such instances, more robust techniques such as the fusion techniques are used where classifiers are combined and often use selected sets of appropriate and useful features to perform tasks. The use and application of these techniques is increasing in various fields including healthcare and medicine. For example, the fusion techniques are used to analyze a variety of data such as diverse and high-volume gene data, image segmentation and signal analysis (11).

The overarching goal of the information fusion technique is to reduce complexity to a manageable level for a human analyst or operator and is used to optimize and summarize the information (16). Further, it utilizes multiple information sources to achieve objectivity and increased awareness of the goal (17). It is an effective method for the automatic or semi-automatic conversion of information from various sources and different time points. However, there are certain advantages and challenges presented with this technique. Some of the advantages are noise reduction, increased accuracy and delivering high quality unbiased results (11) The key challenges of this technique are associated with system processing, data storage, data representation and the type of method to be used (18).

A general understanding of the advantages of this technique will help capitalize its full potential and recognizing the challenges may assist in designing and delivering robust solutions. However, at present the advantages, challenges and functions of the technique are discussed separately in various studies. To our knowledge, there is only one framework that categorizes the challenges of this technique (16), while a framework that classifies the advantages of this technique currently does not exist in the literature. Availability of a framework serves as a useful guide for researchers by summarizing complicated information all in one place. The framework can be reused for similar fields of

study, thereby reducing the efforts of the researchers. Therefore, the objective of this study is twofold (i) to introduce a framework that describe the advantages of the technique and (ii) update the framework of challenges by comparing it with a previously proposed framework.

Method

Source of Data

To design the framework a comprehensive search was conducted on five bibliographic electronic databases (Science Direct, IEEE, Web of Science, Scopus and Google Scholar) using the keywords decision fusion, information fusion and symbolic fusion. We included articles published in the English language between January 1960 and December 2017 for the design stage and from January 2018 to December 2018 for the evaluation stage in accordance with the PRISMA guidelines (19).

Search Strategy

We followed a 2-stage process to identify a list of comprehensive literature for the study-stage 1, design and stage 2, evaluation (20, 21). We included all relevant literature (i.e., books, surveys, review papers and original research papers) for the design stage and only original research papers for the evaluation stage. We included literature (i) written in English language, (ii) discusses the advantages and/or challenges of the information fusion technique. The electronic search resulted in a total of 18,889 articles in the design stage (see Figure 1) and 2,429 articles in the evaluation stage (see Figure 2). After removing duplicates, the titles of 9,993 articles (design) and 1,482 articles (evaluation) were screened for relevance. Next, we reviewed the abstracts of 4,653 articles (design) and 150 articles (evaluation) and this process resulted in 166 articles (design) and 118 articles (evaluation) for full-text review. From this a total of 34 articles and 28 articles were excluded from the design and evaluation stages respectively, since the full text of these articles were not available, or they did not meet the inclusion criteria. This resulted in 132 articles and 90 articles in the design and evaluation stages that were included in the final analysis. Overall, two reviewers (EN and HT) independently evaluated the records for inclusion.

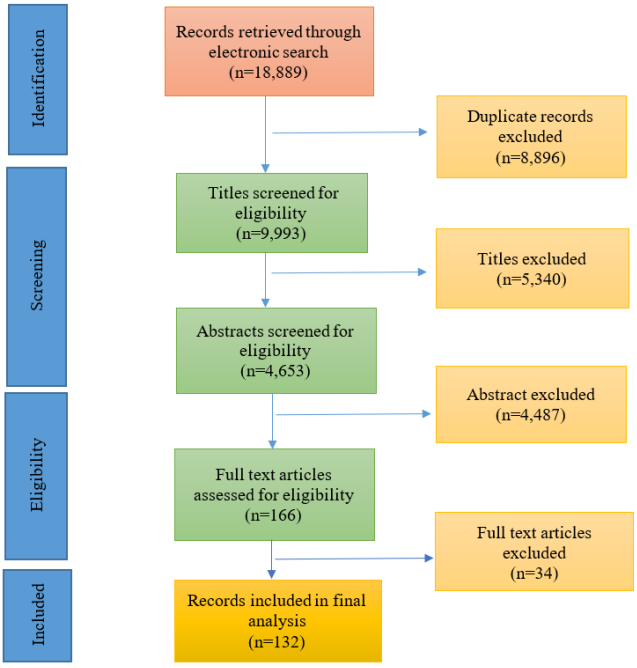

Figure1: Summary of the research process in the design step

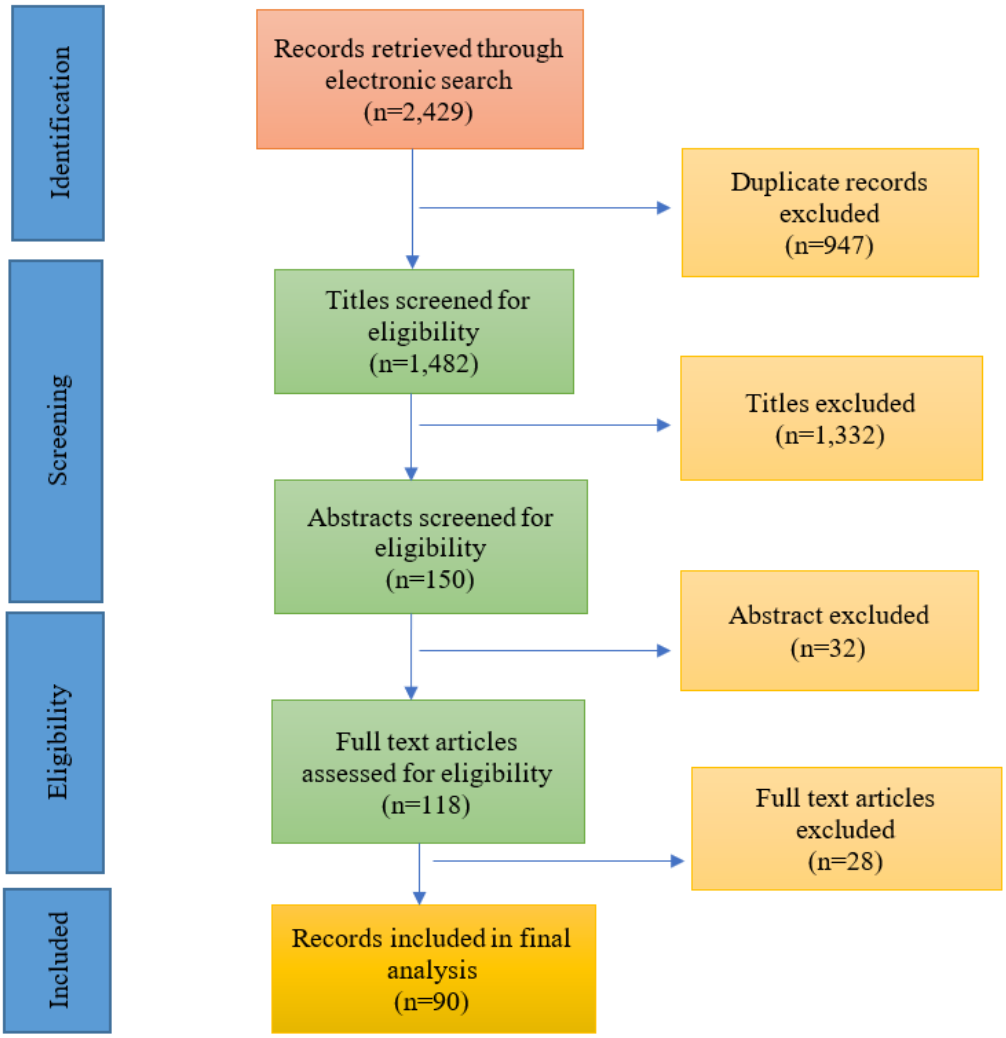

Figure 2: Summary of the research process in the evaluation step

Framework Development

We categorized the data based on the frequency of occurrence within the text to create the intended framework. Next, we tested the proposed framework by evaluating the challenges and advantages against 2018 papers by their confidence interval (evaluation stage). To check the compliance rate of the categories in the evaluation stage with that in the design stage, we used a confidence interval of 95%.

Results

Designing the Framework

After an extensive review of the texts and extracting the advantages and challenges, the related texts were categorized. The classification of the advantages and challenges are presented in Table1, Figure 3 and Table 2, Figure 4 respectively.

Table 1. Classification of advantages of Information Fusion technique in the design stage

Category	Subcategory	Description	Reference
Value modeling	Classification	It is used to categorize information and provides results with high accuracy, sensitivity, specificity, precision and consistency. It leads to improved modeling metrics such as the MCC (Matthews correlation coefficient), that is reliable, robust and effective. Also, the rating error rate is reduced.	(17, 22-79)
	Extract and display of best information	It extracts better, more important, useful, rich, valuable, relevant and meaningful information, and improves the signal-to-noise ratio (relative to unrelated information) and provides promising, better and reasonable results and consequently, makes a better decision.	(6, 30, 37, 51, 80-96)
	Segmentation	It provides partitioning, especially in high-performance images and low error rates and also allows automatic segmentation.	(37, 56, 88, 97-100)
	Disclose detail and summarized information	It summarizes the information and acts as a filter. In this way, it focuses on more important information by reducing information overload and occasionally provides relevant details for better discovery, for example, the discovery of tumor location.	(87, 101, 102)
	Tracking	It improves the tracking device or apps effectively and manages their changes. For this purpose, it uses indicators such as accuracy, latency, and robustness.	(103-105)
	Estimate	It provides the possibility of estimation with less error and high accuracy.	(51, 81, 106-108)
	Better understanding of complexity	It performs complex tasks by dividing them into components and discovering their relationships. In this way, it simplifies system perception and provides useful information about the underlying system.	(58, 91, 101, 109, 110)
	Detection	It identifies the region of interest with high accuracy for feature extraction, particularly in abnormality detection, it is useful for delivering reliable and robust results. It helps in discovering the boundaries/borders and identifying lesions in images, for example, in mammographic images, which can reduce false positive. It can also help in identifying surgical instruments and predicting protein subcellular location.	(14, 17, 26, 27, 34, 49, 50, 52, 57, 68, 79, 84, 85, 88, 92-94, 102, 110-124)

Preferable management of uncertainty and variability	----	It can handle the technique of disturbing the data analysis process. For example, it reduces uncertainty, eliminates noise in data, manipulates nonuniformities, reduces ambiguity, eliminates outliers, and is robust against variability by overcoming it.	(22-24, 28, 36, 42, 80, 91, 103, 125-130)
Excellent decision making	----	Where it is necessary to make a final decision from various decisions, it manages nonuniformity in individual decisions. The most informative benefits are extracted from individual decisions and duplicates are eliminated. Some individual decision challenges are resolved, and decisions are made more accurate, reliable, robust and relevant; and real-time decision making is provided.	(23, 80, 81, 131, 132)
Comprehensive interpretation and representation	Representation	It is capable to display important features and it provides the obtained knowledge especially on the basis of illustrating polymer emergence, which helps the protein feature representation.	(29, 49, 133, 134)
	Interpretation	It helps on the basis of results' interpretation. It helps the provider to interpret medical images and reduce misdiagnosis.	(29, 135)
Data management	Quality	It improves data quality in the fused environment. For example, it improves the accuracy of information or provides access to high-availability information.	(23, 51, 56, 86, 136)
	Retrieval	It improves the recovery function, which means it displays related items by improving indicators such as accuracy, precision and recall.	(68, 71, 90, 137)
	Conflict management	It automatically manages the coincidence of events, manages evidence interference in a data-driven approach and is able to clean up similar objects. It improves overlaps and minimizes duplication.	(28, 56, 80, 120)
Simplicity of infrastructure	System	It minimizes the amount of data transmission between resources and reduces the communication load. It is capable of performing parallel processing that saves time and memory.	(29, 93, 128, 138)
	Security	This method improves security in the biometric system by employing multimodal fusion and can effectively reduce the spoof attack.	(22)

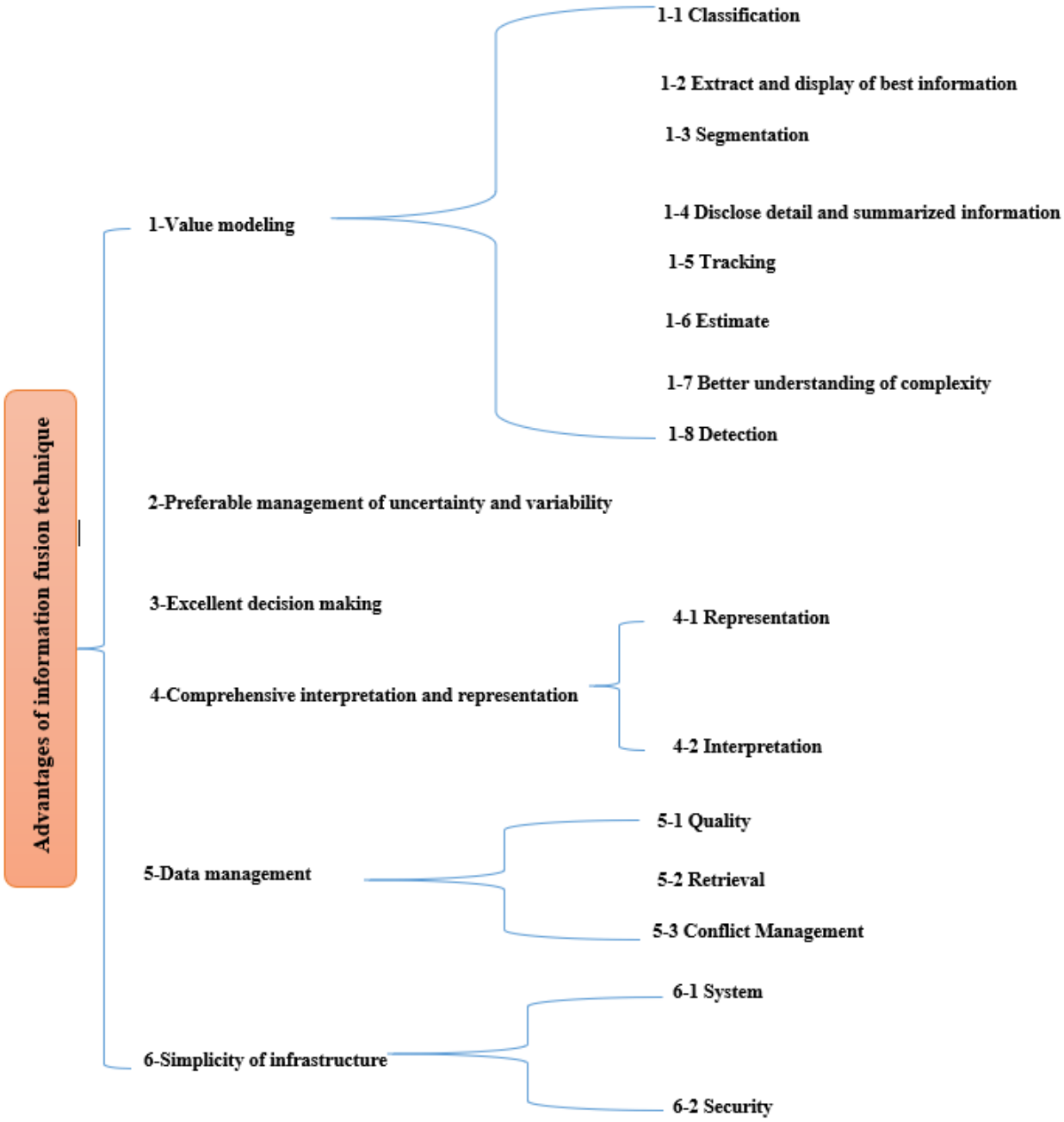

Figure 3: Advantages and applications of information fusion technique

Table 2. Classification of challenges of Information Fusion technique in the design stage

Category	Subcategory	Description	Reference
Hardware and software requirements for processing and maintaining the process	Hardware and software	For using this technique, system memory, CPU system and other requirements are needed to carry out heavy calculations and to process large volumes of data.	(18, 22, 23, 103, 139)
	Security	In social networks, security is a challenge that makes it difficult to process the technique and should be considered. Also, privacy and ownership are challenges in the field.	(18, 22)
	Visualization	To display fused information, the appropriate method should be considered such as the use of charts, or graphs, which is a challenge, especially in different fields.	(18, 24, 136)
Data	Lack of data quality	Data quality is an important factor that, if not considered, will cause difficulty in the result of the analysis. Data quality involves the use of appropriate information for demand (goal), complete and comprehensive information, transparency and consistency.	(25, 26, 80, 111, 133, 136, 140-142)
	Data with unclear and varied structures	The structure and type of data are important in the analysis process. For example, non-structured data will affect the results of the analysis. Also, dynamicity, uncertainty, noise, missing data, and complexity create problems. Additionally, different data formats and heterogeneity or diversity will affect the result of the analysis. Sometimes data measurements are faced with errors, which will not be effective.	(12, 17, 18, 22, 27-30, 106, 109, 140, 143-149)
	Streaming data	A quick change in the amount of data over time or in producing high-speed data is another challenge.	(18, 81, 140, 145)
	Unstructured correlated data	Data dependencies and multiple correlations of variables sometimes increase the effect of an error and influence the results.	(109, 125, 142, 143, 145)
Data analysis method	-----	The type of method used to process and analyze data with the goal of obtaining valuable information is very important, that includes: Choosing the right sources of data, choosing appropriate methods of extraction, and choosing the appropriate classifying method- especially in rare cases or in a high dimensional area, with a low sample size and selecting the appropriate analysis method.	(18, 31-34, 112, 145, 150)

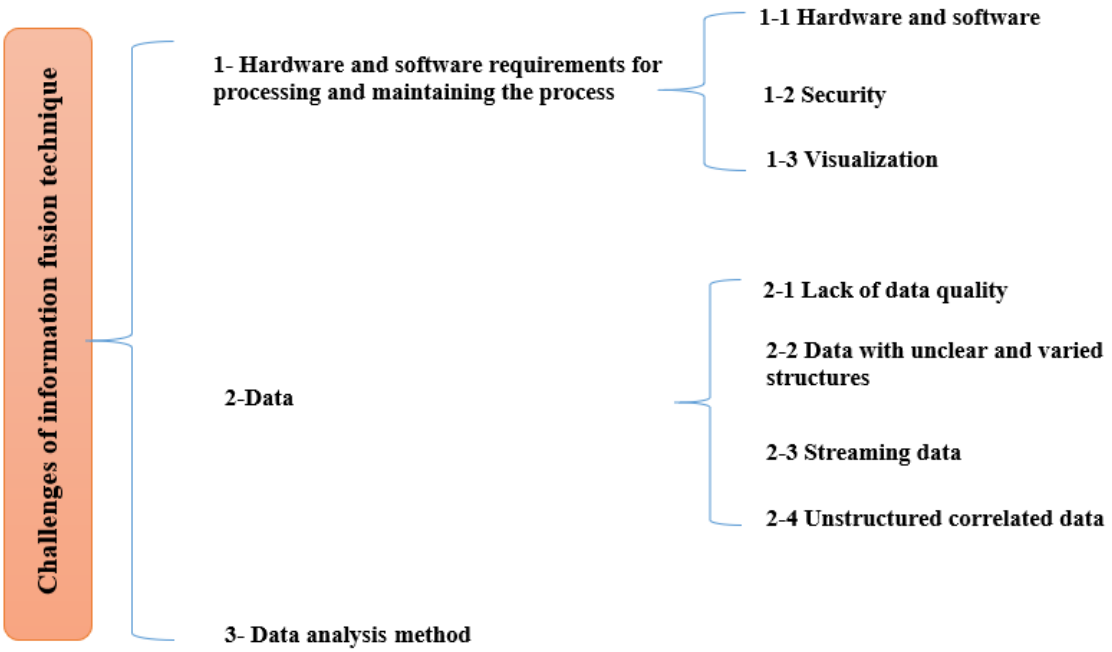

Figure 4: Challenges of information Fusion technique

Evaluating the Framework

In this step, we reviewed the papers from January 2018 to December 2018 that described the advantages and challenges of the information fusion technique within the text. Two reviewers (EN and HT) independently screened the articles and upon mutual consensus decided on the categories for the evaluation stage, which are presented in tables 3 and 4. Further, the prototype of the framework for advantages and challenges were calculated with 95% confidence interval, and the results are shown in Tables 5 and 6 respectively.

Table 3: Classification of advantages of Information Fusion technique in the evaluation stage

Category	Subcategory	Reference
Value modeling	Classification	(151-171)
	Extract and display of best information	(161, 172-177)
	Segmentation	--
	Disclose detail and summarized information	(174)
	Tracking	(178, 179)
	Estimate	(180-186)
	Better understanding of complexity	(187, 188)

	Detection	(154, 155, 165, 168, 178, 185, 188-212)
Preferable management of uncertainty and variability	----	(169, 180, 192, 213-227)
Excellent decision making	----	(225, 228)
Comprehensive interpretation and representation	Representation	(154, 193, 229)
	Interpretation	(168, 189, 224, 230-232)
Data management	Quality	(177, 184, 214, 228)
	Retrieval	(170, 176, 233)
	Conflict management	(188)
Simplicity of infrastructure	System	--
	Security	----

Table 4: Classification of challenges of Information Fusion technique in the evaluation stage

Category	Subcategory	Reference
Hardware and software requirements for processing and maintaining the process	Hardware and software	---
	Security	----
	Visualization	(193, 208)
Data	Lack of data quality	(151, 178, 194, 216)
	Data with unclear and varied structures	(151, 167, 189, 194, 216, 217, 222, 229)
	Streaming data	(178)
	Unstructured correlated data	(208, 232)
Data analysis method	-----	(189, 193, 194, 208, 216, 222, 229)

Table 5: Evaluation of proposed framework for advantages

Category	Subcategory	Design		Evaluation
Value modeling		n(%)	95% CI	n(%)
	Classification	58(43.94)	35.32-52.84	31(34.44)
	Extract and display of best information	21(15.91)	10.13-23.29	8(8.89)
	Segmentation	7(5.30)	2.16-10.62	0(0)
	Disclose detail and summarized information	3(2.27)	0.47-6.50	54(60.00)
	Tracking	3(2.27)	0.47-6.50	2(2.22)
	Estimate	5(3.79)	1.24-8.62	7(7.78)
	Better understanding of complexity	5(3.79)	1.24-8.62	2(2.22)
	Detection	33(25.00)	17.88-33.28	33(36.67)
Preferable management of uncertainty and variability	----	15(11.36)	6.50-18.05	20(22.22)
Excellent decision making	----	5(3.79)	1.24-8.62	2(2.22)
Comprehensive interpretation and representation	Representation	3(2.27)	0.47-6.50	3(3.33)
	Interpretation	2(1.52)	0.18-5.37	6(6.67)
Data management	Quality	5(3.79)	1.24-8.62	4(4.44)
	Retrieval	4(3.03)	0.83-7.58	3(3.33)
	Conflict management	4(3.03)	0.83-7.58	1(1.11)
Simplicity of infrastructure	System	4(3.03)	0.83-7.58	0(0)
	Security	1(0.76)	0.02-4.15	0(0)

Table 6: Evaluation of proposed framework for challenges

Category	**Subcategory**	**Design**		**Evaluation**
Hardware and software requirements for processing and maintaining the process		n(%)	95%CI	n(%)
	Hardware and software	5(3.79)	1.24-8.62	0(0)
	Security	2(1.52)	0.18-5.37	0(0)
	Visualization	3(2.27)	0.47-6.50	2(2.22)
Data	Lack of data quality	7(5.30)	2.16-10.62	5(5.55)
	Data with unclear and varied structures	37(28.03)	20.57-36.51	9(10.00)
	Streaming data	4(3.03)	0.83-7.58	1(1.11)
	Unstructured correlated data	5(3.79)	1.24-8.62	2(2.22)
Data analysis method	-----	8(6.06)	2.65-11.59	7(7.77)

As shown in tables 5 and 6, the categories of the proposed framework were verified in the evaluation stage with a high confidence interval.

Comparing the proposed framework with existing framework

In this field, a framework for challenges has been previously introduced that has identified a number of disadvantages associated with the use of the Information Fusion technique in the UDF / JDL framework(11).These challenges include:

Semantic: what symbols should be used and how are they meaningful?

Epistemic: what information should be presented and how it should be displayed and processed in the machine?

Paradigm: How does paradigm manage the interdependency between the sensor fusion and Information Fusion paradigm?

Interface: How to interface ourselves with people with sophisticated information stored in a machine?

System: How should the system manage the data-fusion system that is formed from the human-machine combination?

After comparing our proposed framework of challenges to the prior framework (11), we added the 'data analysis method' as an additional category. This is an important challenge of the information fusion technique, which needs to be addressed. Figure 5 maps each category from the proposed framework in comparison to the existing framework.

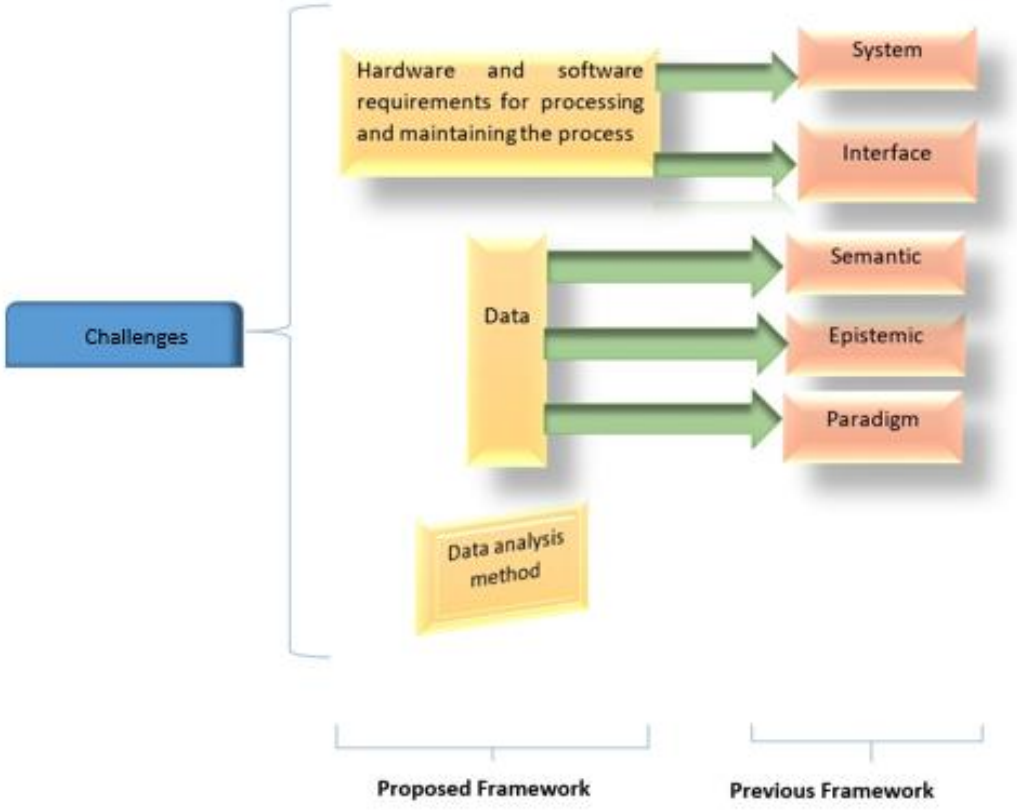

Figure 5: Mapping the proposed framework against existing framework

Table7: Resultant percentages of each category of the framework for challenges

Challenges	Design	Evaluation
Hardware and software requirements for processing and maintaining the process	0.14	0.08
Data	0.75	0.65
Data analysis method	0.11	0.27

As shown in table 7, the category 'data analysis method' was identified as 11% in the design stage and 27% in the evaluation stage. Thus, we conclude that this category should be studied further in future studies.

Discussion and Conclusion

Given the importance of the use of the information fusion technique in big data analysis, we introduced a proposed framework that classifies the advantages and challenges of this technique within this study. The categories identified for the challenges of this technique include "hardware and software requirements to process", "data", and "data analysis method". The categories for the advantages of this technique include "value modeling", "preferable management of uncertainty and variability", "excellent decision making", "comprehensive interpretation and representation", "data management" and "simplicity of infrastructure". We verified the proposed framework during the evaluation stage for its effectiveness. After comparing the proposed framework with the existing framework for challenges, we introduced "data analysis method" as an additional category. This category is deemed important, given that it has been identified as a potential challenge by a number of studies as identified above. Considering these challenges while selecting this technique for data analysis is crucial, as it will affect the nature of the results.

Overall, presenting information within a framework acts as a guide for researchers, thereby, making it possible to understand research goals. A proper understanding of the technique will help utilize the true potential of this technique, while, addressing the challenges will help offer meaningful solutions. Like any other methodology, this novel technique has a number of advantages and challenges for its use, and while we present the most representative categories within our framework, future studies may focus on developing a new framework or modifying this framework to include new categories that we may not have captured here.

To our knowledge, this a first study that introduces a framework for both the advantages and challenges of this technique, compares the proposed framework with the existing framework for challenges, and evaluates the proposed framework for effectiveness. These results serve as a general overview of the technique for researchers to make informed decisions pertaining to its use.

There are few possible limitations that need to be discussed here. First, our review of

literature was restricted to articles published in English, which limited our ability to identify relevant literature published in other languages. Second, our review was restricted to primarily peer-reviewed articles indexed in five electronic databases (Science Direct, IEEE, Web of Science, Scopus and Google Scholar), which limited our ability to identify articles published in other databases, or newer journals which are not indexed in these five databases. Third, we only included peer-reviewed journal article during the evaluation stage, which limited our ability to review other types of scientific literature. Fourth, we were not able to evaluate the framework for advantages with an existing framework, since it is presently unavailable.

Acknowledgements:

The authors would like to thank the anonymous reviewers who provided critical feedback and guidance on revising the manuscript before publication.

Reference

1. Zhang Q, Yang LT, Chen Z, Li P. A survey on deep learning for big data. Information Fusion. 2018;42:146-57.
2. Sagiroglu S, Sinanc D, editors. Big data: A review. 2013 international conference on collaboration technologies and systems (CTS); 2013: IEEE.
3. Chen M, Mao S, Liu Y. Big data: A survey. Mobile networks and applications. 2014;19(2):171-209.
4. Nazari E, Afkanpour M, Tabesh H. Big Data from A to Z. Frontiers in Health Informatics. 2019;8(1):20.
5. Nazari E, Tabesh H. Big Data In healthcare: A to Z. Journal of Biostatistics and Epidemiology. 2019;5(3):194-203.
6. Nazari E, Chang H-CH, Deldar K, Pour R, Avan A, Tara M, et al. A Comprehensive Overview of Decision Fusion Technique in Healthcare: A Systematic Scoping Review. Iranian Red Crescent Medical Journal. 2020;22(10).
7. Murdoch TB, Detsky AS. The inevitable application of big data to health care. Jama. 2013;309(13):1351-2.
8. Jin X, Wah BW, Cheng X, Wang Y. Significance and challenges of big data research. Big Data Research. 2015;2(2):59-64.
9. Jagadish HV, Gehrke J, Labrinidis A, Papakonstantinou Y, Patel JM, Ramakrishnan R, et al. Big data and its technical challenges. Communications of the ACM. 2014;57(7):86-94.
10. Nazari E, Aghemiri M, Zeinali N, Delaram Z, Mehrabian A, Tabesh H. Application of Big Data analysis in healthcare based on 'The 6 building blocks of health systems' Framework: A survey. Dokkyo Journal of Medical Sciences. 2021;48:01.
11. Bossé É, Solaiman B. Information fusion and analytics for big data and IoT: Artech House; 2016.
12. Zhong H, Xiao J. Enhancing health risk prediction with deep learning on big data and revised fusion node paradigm. Scientific Programming. 2017;2017.
13. Torra V. Information fusion-methods and aggregation operators. Data Mining and Knowledge Discovery Handbook: Springer; 2009. p. 999-1008.
14. Solaiman B, Debon R, Pipelier F, Cauvin J-M, Roux C. Information fusion, application to data and model fusion for ultrasound image segmentation. IEEE Transactions on Biomedical Engineering. 1999;46(10):1171-5.
15. Nazari E, Farzin AH, Aghemiri M, Avan A, Tara M, Tabesh H. Deep Learning for Acute Myeloid Leukemia Diagnosis.

Journal of Medicine and Life. 2020;13(3):382.
16.Bossé É, Roy J, Wark S, Rousseau R, Breton R, Lambert D, et al. Concepts, Models, and Tools for Information Fusion, Artech House Intelligence and Information Operations Library, Artech House. Inc; 2007.
17. Wang Y-q, Yan H-x, Guo R, Li F-f, Xia C-m, Yan J-j, et al. Study on intelligent syndrome differentiation in Traditional Chinese Medicine based on multiple information fusion methods. International Journal of Data Mining and Bioinformatics. 2011;5(4):369-82.
18. Bello-Orgaz G, Jung JJ, Camacho D. Social big data: Recent achievements and new challenges. Information Fusion. 2016;28:45-59.
19. Moher D, Liberati A. A., Tetzlaff, J., & Altman, DG (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. BMJ.339:b2535.
20. Nazari E, Shahriari MH, Tabesh H. Applications of Framework In Health Care: A Survey. Frontiers in Health Informatics. 2019;8(1):16.
21. Nazari E, Khodabandeh ME. Create Frameworks From Software Engineering To Health Care: A survey. Journal of Biostatistics and Epidemiology. 2019;5(3):216-25.
22. Paul PP, Gavrilova ML, Alhajj R. Decision fusion for multimodal biometrics using social network analysis. IEEE transactions on systems, man, and cybernetics: systems. 2014;44(11):1522-33.
23. Liu Y-T, Pal NR, Marathe AR, Wang Y-K, Lin C-T. Fuzzy decision-making fuser (fdmf) for integrating human-machine autonomous (hma) systems with adaptive evidence sources. Frontiers in neuroscience. 2017;11:332.
24. Tiwari P, Viswanath S, Kurhanewicz J, Sridhar A, Madabhushi A. Multimodal wavelet embedding representation for data combination (MaWERiC): integrating magnetic resonance imaging and spectroscopy for prostate cancer detection. NMR in Biomedicine. 2012;25(4):607-19.
25. Niemeijer M, Abramoff MD, Van Ginneken B. Information fusion for diabetic retinopathy CAD in digital color fundus photographs. IEEE transactions on medical imaging. 2009;28(5):775-85.
26. Fan X-N, Zhang S-W. lncRNA-MFDL: identification of human long non-coding RNAs by fusing multiple features and using deep learning. Molecular BioSystems. 2015;11(3):892-7.
27. Liang F, Xie W, Yu Y. Beating heart motion accurate prediction method based on interactive multiple model: An information fusion approach. BioMed research international. 2017;2017.
28. Terrades OR, Valveny E, Tabbone S. Optimal classifier fusion in a non-bayesian probabilistic framework. IEEE transactions on pattern analysis and machine intelligence. 2008;31(9):1630-44.
29. Velikova M, Lucas PJ, Samulski M, Karssemeijer N. A probabilistic framework for image information fusion with an application to mammographic analysis. Medical Image Analysis. 2012;16(4):865-75.
30. Anderson F, Birch DW, Boulanger P, Bischof WF. Sensor fusion for laparoscopic surgery skill acquisition. Computer Aided Surgery. 2012;17(6):269-83.
31. Zhang S, Han J, Liu J, Zheng J, Liu R. An improved poly (A) motifs recognition method based on decision level fusion. Computational biology and chemistry. 2015;54:49-56.
32. Yang P, Xu L, Zhou BB, Zhang Z, Zomaya AY, editors. A particle swarm based

hybrid system for imbalanced medical data sampling. BMC genomics; 2009: Springer.
33. Bosch M, Zhu F, Khanna N, Boushey CJ, Delp EJ, editors. Combining global and local features for food identification in dietary assessment. 2011 18th IEEE International Conference on Image Processing; 2011: IEEE.
34. Prasad S, Bruce LM, Ball JE, editors. A multi-classifier and decision fusion framework for robust classification of mammographic masses. 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2008: IEEE.
35. Mou Q, Xu Z, Liao H. An intuitionistic fuzzy multiplicative best-worst method for multi-criteria group decision making. Information Sciences. 2016;374:224-39.
36. Lelandais B, Ruan S, Denœux T, Vera P, Gardin I. Fusion of multi-tracer PET images for dose painting. Medical image analysis. 2014;18(7):1247-59.
37. Zanaty E. An approach based on fusion concepts for improving brain Magnetic Resonance Images (MRIs) segmentation. Journal of Medical Imaging and Health Informatics. 2013;3(1):30-7.
38. Tahir BA, Swift AJ, Marshall H, Parra-Robles J, Hatton MQ, Hartley R, et al. A method for quantitative analysis of regional lung ventilation using deformable image registration of CT and hybrid hyperpolarized gas/1H MRI. Physics in Medicine & Biology. 2014;59(23):7267.
39. Richard N, Dojat M, Garbay C. Automated segmentation of human brain MR images using a multi-agent approach. Artificial Intelligence in Medicine. 2004;30(2):153-76.
40. Kamali T, Boostani R, Parsaei H. A multi-classifier approach to MUAP classification for diagnosis of neuromuscular disorders. IEEE transactions on neural systems and rehabilitation engineering. 2013;22(1):191-200.
41. Guo P, Banerjee K, Stanley RJ, Long R, Antani S, Thoma G, et al. Nuclei-based features for uterine cervical cancer histology image analysis with fusion-based classification. IEEE journal of biomedical and health informatics. 2015;20(6):1595-607.
42. Jiang H, Liang Z, Gao J, Dang C. Classification of weld defect based on information fusion technology for radiographic testing system. Review of Scientific Instruments. 2016;87(3):035110.
43. Kook H, Gupta L, Kota S, Molfese D, editors. A dynamic multi-channel decision-fusion strategy to classify differential brain activity. 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2007: IEEE.
44. Gupta L, Chung B, Srinath MD, Molfese DL, Kook H. Multichannel fusion models for the parametric classification of differential brain activity. IEEE Transactions on Biomedical Engineering. 2005;52(11):1869-81.
45. Sung W-T, Chang K-Y. Evidence-based multi-sensor information fusion for remote health care systems. Sensors and Actuators A: Physical. 2013;204:1-19.
46. Zhang Z, Luo X. Heartbeat classification using decision level fusion. Biomedical Engineering Letters. 2014;4(4):388-95.
47. Li G-Z, Yan S-X, You M, Sun S, Ou A. Intelligent ZHENG classification of hypertension depending on ML-kNN and information fusion. Evidence-Based Complementary and Alternative Medicine. 2012;2012.

48. Stroud J, Enverga I, Silverstein T, Song B, Rogers T. Ensemble learning and the heritage health prize. California: University of California. 2012.
49. Chen J, Xu H, He P-a, Dai Q, Yao Y. A multiple information fusion method for predicting subcellular locations of two different types of bacterial protein simultaneously. Biosystems. 2016;139:37-45.
50. Malarvili M, Mesbah M, editors. Combining newborn EEG and HRV information for automatic seizure detection. 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2008: IEEE.
51. Barua S. Multi-sensor information fusion for classification of driver's physiological sensor data. 2013.
52. O'Regan S, Marnane W. Multimodal detection of head-movement artefacts in EEG. Journal of Neuroscience Methods. 2013;218(1):110-20.
53. Liu C, Zhao L, Tang H, Li Q, Wei S, Li J. Life-threatening false alarm rejection in ICU: Using the rule-based and multi-channel information fusion method. Physiological measurement. 2016;37(8):1298.
54. Santana R, Bielza C, Larrañaga P. Regularized logistic regression and multiobjective variable selection for classifying MEG data. Biological cybernetics. 2012;106(6):389-405.
55. Moslem B, Diab MO, Marque C, Khalil M, editors. Classification of multichannel uterine EMG signals. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
56. Heckemann RA, Hajnal JV, Aljabar P, Rueckert D, Hammers A. Automatic anatomical brain MRI segmentation combining label propagation and decision fusion. NeuroImage. 2006;33(1):115-26.
57. Zhang Y-C, Zhang S-W, Liu L, Liu H, Zhang L, Cui X, et al. Spatially enhanced differential RNA methylation analysis from affinity-based sequencing data with hidden Markov model. BioMed research international. 2015;2015.
58. Kasturi J, Acharya R. Clustering of diverse genomic data using information fusion. Bioinformatics. 2005;21(4):423-9.
59. Re M, Valentini G. Integration of heterogeneous data sources for gene function prediction using decision templates and ensembles of learning machines. Neurocomputing. 2010;73(7-9):1533-7.
60. Zhang S-W, Hao L-Y, Zhang T-H. Prediction of protein–protein interaction with pairwise kernel Support Vector Machine. International journal of molecular sciences. 2014;15(2):3220-33.
61. Chen Y, Xu J, Yang B, Zhao Y, He W. A novel method for prediction of protein interaction sites based on integrated RBF neural networks. Computers in biology and medicine. 2012;42(4):402-7.
62. Mnatsakanyan ZR, Burkom HS, Hashemian MR, Coletta MA. Distributed information fusion models for regional public health surveillance. Information Fusion. 2012;13(2):129-36.
63. Liu H, Shi X, Guo D, Zhao Z. Feature selection combined with neural network structure optimization for HIV-1 protease cleavage site prediction. BioMed research international. 2015;2015.
64. Moghadam H, Rahgozar M, Gharaghani S. Scoring multiple features to predict drug disease associations using information fusion and aggregation. SAR and QSAR in Environmental Research. 2016;27(8):609-28.

65. Xiong F, Hipszer BR, Joseph J, Kam M, editors. Improved blood glucose estimation through multi-sensor fusion. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
66. Depeursinge A, Racoceanu D, Iavindrasana J, Cohen G, Platon A, Poletti P-A, et al. Fusing visual and clinical information for lung tissue classification in high-resolution computed tomography. Artificial intelligence in medicine. 2010;50(1):13-21.
67. Ballanger B, Tremblay L, Sgambato-Faure V, Beaudoin-Gobert M, Lavenne F, Le Bars D, et al. A multi-atlas based method for automated anatomical Macaca fascicularis brain MRI segmentation and PET kinetic extraction. Neuroimage. 2013;77:26-43.
68. Rahman MM, Bhattacharya P. An integrated and interactive decision support system for automated melanoma recognition of dermoscopic images. Computerized Medical Imaging and Graphics. 2010;34(6):479-86.
69. Qian M, Aguilar M, Zachery KN, Privitera C, Klein S, Carney T, et al. Decision-level fusion of EEG and pupil features for single-trial visual detection analysis. IEEE Transactions on Biomedical Engineering. 2009;56(7):1929-37.
70. Daunizeau J, Grova C, Marrelec G, Mattout J, Jbabdi S, Pélégrini-Issac M, et al. Symmetrical event-related EEG/fMRI information fusion in a variational Bayesian framework. Neuroimage. 2007;36(1):69-87.
71. Quellec G, Lamard M, Cazuguel G, Roux C, Cochener B. Case retrieval in medical databases by fusing heterogeneous information. IEEE Transactions on Medical Imaging. 2010;30(1):108-18.
72. Ooi KEB, Lech M, Allen NB. Multichannel weighted speech classification system for prediction of major depression in adolescents. IEEE Transactions on Biomedical Engineering. 2012;60(2):497-506.
73. Jesneck JL, Nolte LW, Baker JA, Floyd CE, Lo JY. Optimized approach to decision fusion of heterogeneous data for breast cancer diagnosis. Medical physics. 2006;33(8):2945-54.
74. Leinwoll S. The future of high frequency broadcasting. IEEE transactions on broadcasting. 1988;34(2):94-101.
75. Zhang SW, Zhang TH, Zhang JN, Huang Y. Prediction of signal peptide cleavage sites with subsite-coupled and template matching fusion algorithm. Molecular informatics. 2014;33(3):230-9.
76. Nath A, Subbiah K. Maximizing lipocalin prediction through balanced and diversified training set and decision fusion. Computational biology and chemistry. 2015;59:101-10.
77. Acharya S, Rajasekar A, Shender BS, Hrebien L, Kam M. Real-time hypoxia prediction using decision fusion. IEEE journal of biomedical and health informatics. 2016;21(3):696-707.
78. Kochi N, Helikar T, Allen L, Rogers JA, Wang Z, Matache MT. Sensitivity analysis of biological Boolean networks using information fusion based on nonadditive set functions. BMC systems biology. 2014;8(1):1-14.
79. Neumuth T, Meißner C. Online recognition of surgical instruments by information fusion. International journal of computer assisted radiology and surgery. 2012;7(2):297-304.
80. Mirian MS, Ahmadabadi MN, Araabi BN, Siegwart RR. Learning active fusion of multiple experts' decisions: an attention-based approach. Neural Computation. 2011;23(2):558-91.

81. Jiang W, Cao Y, Yang L, He Z. A Time-Space Domain Information Fusion Method for Specific Emitter Identification Based on Dempster–Shafer Evidence Theory. Sensors. 2017;17(9):1972.
82. Wang Y, Zhang C, Luo J, editors. Study on information fusion algorithm and application based on improved SVM. 13th International IEEE Conference on Intelligent Transportation Systems; 2010: IEEE.
83. Abirami T, Taghavi E, Tharmarasa R, Kirubarajan T, Boury-Brisset A-C, editors. Fusing social network data with hard data. 2015 18th International Conference on Information Fusion (Fusion); 2015: IEEE.
84. Xuming Y, Yijun Y, Yong X, Xuanzhong W, Zheyu W, Hongmei N, et al. A precise and accurate acupoint location obtained on the face using consistency matrix pointwise fusion method. Journal of Traditional Chinese Medicine. 2015;35(1):110-6.
85. Comaniciu D, Zhou XS, Krishnan S. Robust real-time myocardial border tracking for echocardiography: an information fusion approach. IEEE transactions on medical imaging. 2004;23(7):849-60.
86. Köhler T, Haase S, Bauer S, Wasza J, Kilgus T, Maier-Hein L, et al. Multi-sensor super-resolution for hybrid range imaging with application to 3-D endoscopy and open surgery. Medical image analysis. 2015;24(1):220-34.
87. Kubinyi M, Kreibich O, Neuzil J, Smid R. EMAT noise suppression using information fusion in stationary wavelet packets. IEEE transactions on ultrasonics, ferroelectrics, and frequency control. 2011;58(5):1027-36.
88. Mahdavi SS, Moradi M, Morris WJ, Goldenberg SL, Salcudean SE. Fusion of ultrasound B-mode and vibro-elastography images for automatic 3-D segmentation of the prostate. IEEE transactions on medical imaging. 2012;31(11):2073-82.
89. Fan Y, Yin Y. Active and progressive exoskeleton rehabilitation using multisource information fusion from EMG and force-position EPP. IEEE Transactions on biomedical engineering. 2013;60(12):3314-21.
90. Lecornu L, Le Guillou C, Le Saux F, Hubert M, Puentes J, Montagner J, et al., editors. Information fusion for diagnosis coding support. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
91. Suárez-Araujo CP, Báez PG, Rodríguez ÁS, Santana-Rodrríguez JJ. Supervised neural computing solutions for fluorescence identification of benzimidazole fungicides. Data and decision fusion strategies. Environmental Science and Pollution Research. 2016;23(24):24547-59.
92. Chowdhury RA, Zerouali Y, Hedrich T, Heers M, Kobayashi E, Lina J-M, et al. MEG–EEG information fusion and electromagnetic source imaging: from theory to clinical application in epilepsy. Brain topography. 2015;28(6):785-812.
93. Antink CH, Brüser C, Leonhardt S. Detection of heart beats in multimodal data: a robust beat-to-beat interval estimation approach. Physiological measurement. 2015;36(8):1679.
94. Lelandais B, Gardin I, Mouchard L, Vera P, Ruan S, editors. Segmentation of biological target volumes on multi-tracer PET images based on information fusion for achieving dose painting in radiotherapy. International Conference on Medical Image Computing and Computer-Assisted Intervention; 2012: Springer.
95. Hassan SG, Hasan M. Information fusion in aquaculture: A state-of the art

review. Frontiers of Agricultural Science and Engineering. 2016;3(3):206-21.
96. Mei J, Liu H, Li X, Xie GT, Yu Y, editors. A Decision Fusion Framework for Treatment Recommendation Systems. MedInfo; 2015.
97. Akhondi-Asl A, Hoyte L, Lockhart ME, Warfield SK. A logarithmic opinion pool based STAPLE algorithm for the fusion of segmentations with associated reliability weights. IEEE transactions on medical imaging. 2014;33(10):1997-2009.
98. Isgum I, Staring M, Rutten A, Prokop M, Viergever MA, Van Ginneken B. Multi-atlas-based segmentation with local decision fusion—application to cardiac and aortic segmentation in CT scans. IEEE transactions on medical imaging. 2009;28(7):1000-10.
99. Zhu C, Jiang T. Multicontext fuzzy clustering for separation of brain tissues in magnetic resonance images. NeuroImage. 2003;18(3):685-96.
100. Barra V, Boire J-Y. Automatic segmentation of subcortical brain structures in MR images using information fusion. IEEE transactions on medical imaging. 2001;20(7):549-58.
101. Yang K, Koo H-W, Park W, Kim JS, Choi CG, Park JC, et al. Fusion 3-dimensional angiography of both internal carotid arteries in the evaluation of anterior communicating artery aneurysms. World neurosurgery. 2017;98:484-91.
102. Chen J, Yu H. Unsupervised ensemble ranking of terms in electronic health record notes based on their importance to patients. Journal of biomedical informatics. 2017;68:121-31.
103. Qi J, Yang P, Hanneghan M, Tang S. Multiple density maps information fusion for effectively assessing intensity pattern of lifelogging physical activity. Neurocomputing. 2017;220:199-209.
104. Ren H, Kazanzides P, editors. Hybrid attitude estimation for laparoscopic surgical tools: A preliminary study. 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2009: IEEE.
105. Ren H, Rank D, Merdes M, Stallkamp J, Kazanzides P, editors. Development of a wireless hybrid navigation system for laparoscopic surgery. MMVR; 2011.
106. Yang P, Dumont GA, Ansermino JM. Sensor fusion using a hybrid median filter for artifact removal in intraoperative heart rate monitoring. Journal of clinical monitoring and computing. 2009;23(2):75-83.
107. Tannous H, Istrate D, Benlarbi-Delai A, Sarrazin J, Gamet D, Ho Ba Tho MC, et al. A new multi-sensor fusion scheme to improve the accuracy of knee flexion kinematics for functional rehabilitation movements. Sensors. 2016;16(11):1914.
108. Antink CH, Gao H, Brüser C, Leonhardt S. Beat-to-beat heart rate estimation fusing multimodal video and sensor data. Biomedical optics express. 2015;6(8):2895-907.
109. Synnergren J, Olsson B, Gamalielsson J. Classification of information fusion methods in systems biology. In silico biology. 2009;9(3):65-76.
110. Monwar MM, Gavrilova ML. Multimodal biometric system using rank-level fusion approach. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). 2009;39(4):867-78.
111. Luo X, Wan Y, He X. Robust electromagnetically guided endoscopic procedure using enhanced particle swarm optimization for multimodal information fusion. Medical physics. 2015;42(4):1808-17.
112. Chowdhury AK, Tjondronegoro D, Chandran V, Trost SG. Physical activity

recognition using posterior-adapted class-based fusion of multiaccelerometer data. IEEE journal of biomedical and health informatics. 2017;22(3):678-85.
113. Haase S, Forman C, Kilgus T, Bammer R, Maier-Hein L, Hornegger J. ToF/RGB sensor fusion for 3-D endoscopy. Current Medical Imaging. 2013;9(2):113-9.
114. Fontana JM, Farooq M, Sazonov E. Automatic ingestion monitor: a novel wearable device for monitoring of ingestive behavior. IEEE Transactions on Biomedical Engineering. 2014;61(6):1772-9.
115. Zheng M, Krishnan S, Tjoa MP. A fusion-based clinical decision support for disease diagnosis from endoscopic images. Computers in Biology and Medicine. 2005;35(3):259-74.
116. Li Y, Porter E, Santorelli A, Popović M, Coates M. Microwave breast cancer detection via cost-sensitive ensemble classifiers: Phantom and patient investigation. Biomedical Signal Processing and Control. 2017;31:366-76.
117. Kirshin E, Oreshkin B, Zhu GK, Popovic M, Coates M. Microwave radar and microwave-induced thermoacoustics: Dual-modality approach for breast cancer detection. IEEE Transactions on Biomedical Engineering. 2012;60(2):354-60.
118. Freedman DD, editor Overview of decision level fusion techniques for identification and their application. Proceedings of 1994 American Control Conference-ACC'94; 1994: IEEE.
119. Chowdhury AK, Tjondronegoro D, Chandran V, Trost S. Ensemble methods for classification of physical activities from wrist accelerometry. Medicine and science in sports and exercise. 2017;49(9):1965-73.
120. Singh R, Murad W, editors. Protein disulfide topology determination through the fusion of mass spectrometric analysis and sequence-based prediction using Dempster-Shafer theory. BMC bioinformatics; 2013: Springer.
121. Liu F, Zhang S-W, Guo W-F, Wei Z-G, Chen L. Inference of gene regulatory network based on local Bayesian networks. PLoS computational biology. 2016;12(8):e1005024.
122. PRAKASH SM, BETTY P, SIVANARULSELVAN K. SURVEY ON FUSION OF MULTIMODAL BIOMETRICS USING SCORE LEVEL FUSION.
123. Lee MW. Fusion imaging of real-time ultrasonography with CT or MRI for hepatic intervention. Ultrasonography. 2014;33(4):227.
124. Wei J, Chan HP, Zhou C, Wu YT, Sahiner B, Hadjiiski LM, et al. Computer-aided detection of breast masses: four-view strategy for screening mammography. Medical physics. 2011;38(4):1867-76.
125. Castanedo F. A review of data fusion techniques. The scientific world journal. 2013;2013.
126. Wang J, Hu Y, Xiao F, Deng X, Deng Y. A novel method to use fuzzy soft sets in decision making based on ambiguity measure and Dempster–Shafer theory of evidence: an application in medical diagnosis. Artificial intelligence in medicine. 2016;69:1-11.
127. Hu W, Hu R, Xie N, Ling H, Maybank S. Image classification using multiscale information fusion based on saliency driven nonlinear diffusion filtering. IEEE transactions on image processing. 2014;23(4):1513-26.
128. Nakamura EF, Loureiro AA, editors. Information fusion in wireless sensor networks. Proceedings of the 2008 ACM SIGMOD international conference on Management of data; 2008.

129. Balazs JA, Velásquez JD. Opinion mining and information fusion: a survey. Information Fusion. 2016;27:95-110.
130. Liu S, Gao RX, John D, Staudenmayer J, Freedson PS, editors. SVM-based multi-sensor fusion for free-living physical activity assessment. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
131. Ehrenfeld S, Butz MV. The modular modality frame model: continuous body state estimation and plausibility-weighted information fusion. Biological cybernetics. 2013;107(1):61-82.
132. Sokolova MV, Fernández-Caballero A. Modeling and implementing an agent-based environmental health impact decision support system. Expert Systems with Applications. 2009;36(2):2603-14.
133. Kolesar I, Parulek J, Viola I, Bruckner S, Stavrum A-K, Hauser H. Interactively illustrating polymerization using three-level model fusion. BMC bioinformatics. 2014;15(1):1-16.
134. Li X, Dick A, Shen C, Zhang Z, van den Hengel A, Wang H. Visual tracking with spatio-temporal Dempster–Shafer information fusion. IEEE Transactions on Image Processing. 2013;22(8):3028-40.
135. Meng J, Li R, Luan Y. Classification by integrating plant stress response gene expression data with biological knowledge. Mathematical biosciences. 2015;266:65-72.
136. Waldron SM, Patrick J, Duggan GB, Banbury S, Howes A. Designing information fusion for the encoding of visual–spatial information. Ergonomics. 2008;51(6):775-97.
137. Kushki A, Androutsos P, Plataniotis KN, Venetsanopoulos AN. Retrieval of images from artistic repositories using a decision fusion framework. IEEE Transactions on Image Processing. 2004;13(3):277-92.
138. Promyarut I, Choksuriwong A, editors. A Review Perceptual Information Fusion. 2014 Fourth International Conference on Digital Information and Communication Technology and its Applications (DICTAP); 2014: IEEE.
139. Su K-L, Jau Y-M, Jeng J-T. Modeling of nonlinear aggregation for information fusion systems with outliers based on the Choquet integral. Sensors. 2011;11(3):2426-46.
140. Yao J, Raghavan VV, Wu Z. Web information fusion: a review of the state of the art. Information Fusion. 2008;9(4):446-9.
141. Fouad MM, Oweis NE, Gaber T, Ahmed M, Snasel V. Data mining and fusion techniques for WSNs as a source of the big data. Procedia Computer Science. 2015;65:778-86.
142. Sakkalis V, Zervakis M, Micheloyannis S, editors. Biopattern initiative: towards the development and integration of next-generation information fusion approaches. The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2004: IEEE.
143. Li H, Jeremic A, editors. Neonatal seizure detection using blind distributed detection with correlated decisions. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
144. Li Y. Research on efficiency evaluation model of integrated energy system based on hybrid multi-attribute decision-making. Environmental Science and Pollution Research. 2019;26(18):17866-74.
145. Zhang Y, Ji Q. Active and dynamic information fusion for multisensor systems with dynamic Bayesian networks. IEEE

Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). 2006;36(2):467-72.
146. Antink CH, Leonhardt S, Walter M. A synthesizer framework for multimodal cardiorespiratory signals. Biomedical Physics & Engineering Express. 2017;3(3):035028.
147. Rao NS, Reister DB, Barhen J. Information fusion methods based on physical laws. IEEE transactions on pattern analysis and machine intelligence. 2005;27(1):66-77.
148. Lee D, Kim S, Kim Y, editors. BioCAD: an information fusion platform for bio-network inference and analysis. Proceedings of the 1st international workshop on Text mining in bioinformatics; 2006.
149. Woźniak M, Grana M, Corchado E. A survey of multiple classifier systems as hybrid systems. Information Fusion. 2014;16:3-17.
150. White JR, Levy T, Bishop W, Beaty JD. Real-time decision fusion for multimodal neural prosthetic devices. PloS one. 2010;5(3):e9493.
151. Zhou Y, Chang L, Qian B. A belief-rule-based model for information fusion with insufficient multi-sensor data and domain knowledge using evolutionary algorithms with operator recommendations. Soft Computing. 2019;23(13):5129-42.
152. Zhou D, Wei T, Zhang H, Ma S, Wei F. An Information Fusion Model Based on Dempster–Shafer Evidence Theory for Equipment Diagnosis. ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg. 2018;4(2).
153. Zheng L, Ji R, Liao W, Li M. A Positioning Method for Apple Fruits Based on Image Processing and Information Fusion. IFAC-PapersOnLine. 2018;51(17):764-9.
154. Xiong S, Fu Y, Ray A. Bayesian nonparametric modeling of categorical data for information fusion and causal inference. Entropy. 2018;20(6):396.
155. Xinhua J, Heru X, Lina Z, Xiaojing G, Guodong W, Jie B. Nondestructive detection of chilled mutton freshness based on multi-label information fusion and adaptive bp neural network. Computers and Electronics in Agriculture. 2018;155:371-7.
156. Wang Y, Duan H. Spectral–spatial classification of hyperspectral images by algebraic multigrid based multiscale information fusion. International Journal of Remote Sensing. 2019;40(4):1301-30.
157. Wang J, Feng Z, Lu N, Sun L, Luo J. An information fusion scheme based common spatial pattern method for classification of motor imagery tasks. Biomedical Signal Processing and Control. 2018;46:10-7.
158. Surathong S AS, Theera-Umpon N. Incorporating fuzzy sets into dempster-Shafer theory for decision fusion. 2018.
159. Shang S, Li H, Lu M, editors. Research of GNSS spoofer localization using information fusion based on particle filter. China Satellite Navigation Conference; 2018: Springer.
160. Guan L, Gao L, Elmadany NED, Liang C, editors. Statistical machine learning vs deep learning in information fusion: Competition or collaboration? 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR); 2018: IEEE.
161. Dong L, Li Q, Xu T, Sun X, Wang D, Yin Q, editors. Multi-information Fusion Based Mobile Attendance Scheme with Face Recognition. International Conference on Intelligent Computing; 2018: Springer.
162. MOHAMMAD NB. AUTOMATED DETECTION OF AORTIC ANNULUS

SIZING BASED ON DECISION LEVEL FUSION. 2018.
163. Mosalanejad M, Arefi MM. UKF-based soft sensor design for joint estimation of chemical processes with multi-sensor information fusion and infrequent measurements. IET Science, Measurement & Technology. 2018;12(6):755-63.
164. Luo L-x. Information fusion for wireless sensor network based on mass deep auto-encoder learning and adaptive weighted D–S evidence synthesis. Journal of Ambient Intelligence and Humanized Computing. 2020;11(2):519-26.
165. Luo J, He X. A soft–hard combination decision fusion scheme for a clustered distributed detection system with multiple sensors. Sensors. 2018;18(12):4370.
166. Li S, Yao Y, Hu J, Liu G, Yao X, Hu J. An ensemble stacked convolutional neural network model for environmental event sound recognition. Applied Sciences. 2018;8(7):1152.
167. Lahmiri S. A technical analysis information fusion approach for stock price analysis and modeling. Fluctuation and Noise Letters. 2018;17(01):1850007.
168. Kanjo E, Younis EM, Sherkat N. Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach. Information Fusion. 2018;40:18-31.
169. Jin Z, Hu Y, Sun C. Event-triggered information fusion for networked systems with missing measurements and correlated noises. Neurocomputing. 2019;332:15-28.
170. Guo Y, Yin C, Li M, Ren X, Liu P. Mobile e-commerce recommendation system based on multi-source information fusion for sustainable e-business. Sustainability. 2018;10(1):147.
171. Berger D, Zaiß M, Lanza G, Summa J, Schwarz M, Herrmann H-G, et al. Predictive quality control of hybrid metal-CFRP components using information fusion. Production Engineering. 2018;12(2):161-72.
172. Wang J-Q, Zhang Z-G, Wang C-H, Wang L. A Maximum Entropy Multisource Information Fusion Method to Evaluate the MTBF of Low-Voltage Switchgear. Discrete Dynamics in Nature and Society. 2018;2018.
173. Seo D, Yoo B, Ko H. Information fusion of heterogeneous sensors for enriched personal healthcare activity logging. International Journal of Ad Hoc and Ubiquitous Computing. 2018;27(4):256-69.
174. Mohammad FR, Ciuonzo D, Mohammed ZAK. Mean-based blind hard decision fusion rules. IEEE Signal Processing Letters. 2018;25(5):630-4.
175. He Z, Lu D, Yang Y, Gao M. An elderly care system based on multiple information fusion. Journal of healthcare engineering. 2018;2018.
176. Liu X, Xu Y, Cheng Y, Li Y, Zhao L, Zhang X. A heterogeneous information fusion deep reinforcement learning for intelligent frequency selection of HF communication. China Communications. 2018;15(9):73-84.
177. Aiswarya K, Thomas AB, Motti AS, Kuriakose A, Jacob J. Decision fusion in cognitive radio using improved fuzzy approach. Procedia computer science. 2018;143:219-25.
178. Xu J, Luo N, Fu B, Li S, An T. Checking unscented information fusion algorithm for autonomous navigation vehicles. Optik. 2019;179:1140-51.
179. Benzerrouk H, Nebylov A, Li M. Multi-UAV Doppler information fusion for target tracking based on distributed high degrees information filters. Aerospace. 2018;5(1):28.

180. Cai W, Guo S, Zhang S, Lin J. Unified Framework of Modeling and Simulations for Multi-platforms Multi-sensors Multi-objects Source Information Fusion (M3SIF) System.
181. Liu G-X, Shi L-F, Xun J-H, Chen S, Zhao L, Shi Y-F. An orientation estimation algorithm based on multi-source information fusion. Measurement Science and Technology. 2018;29(11):115101.
182. Li W, Fu Z. Unmanned aerial vehicle positioning based on multi-sensor information fusion. Geo-Spatial Information Science. 2018;21(4):302-10.
183. Li R, Lu C, Liu J, Lei T. Air data estimation algorithm under unknown wind based on information fusion. Journal of Aerospace Engineering. 2018;31(5):04018072.
184. Farid MS, Lucenteforte M, Grangetto M. Evaluating virtual image quality using the side-views information fusion and depth maps. Information Fusion. 2018;43:47-56.
185. Fang H, Zhou A, Zhang H. Information fusion in offspring generation: A case study in DE and EDA. Swarm and Evolutionary computation. 2018;42:99-108.
186. Benzerouk H, Nebylov A, Nebylov V. Distributed consensus cubature information fusion in saturated inertial sensors network. IFAC-PapersOnLine. 2018;51(12):26-31.
187. Zhou N, Xu G, Wei J, Tang L. Relative height measurement based on collaborative information fusion of acceleration and barometric pressure. Ferroelectrics. 2018;530(1):73-81.
188. Li B, Pang F. Innovative assessment scheme of navigation risk based on improved multi-source information fusion techniques. International Journal of Distributed Sensor Networks. 2018;14(4):1550147718772543.
189. Elmadany NED, He Y, Guan L. Information fusion for human action recognition via biset/multiset globality locality preserving canonical correlation analysis. IEEE Transactions on Image Processing. 2018;27(11):5275-87.
190. An J, Zhang J, Wu M, She J, Terano T. Soft-sensing method for slag-crust state of blast furnace based on two-dimensional decision fusion. Neurocomputing. 2018;315:405-11.
191. Al-rimy BAS, Maarof MA, Prasetyo YA, Shaid SZM, Ariffin AFM. Zero-day aware decision fusion-based model for crypto-ransomware early detection. International Journal of Integrated Engineering. 2018;10(6).
192. Chen Z, Li X, Zheng H, Gao H, Wang H. Domain adaptation and adaptive information fusion for object detection on foggy days. Sensors. 2018;18(10):3286.
193. Gao L, Zhang R, Qi L, Chen E, Guan L. The labeled multiple canonical correlation analysis for information fusion. IEEE Transactions on Multimedia. 2018;21(2):375-87.
194. Al-Jarrah MA, Al-Dweik A, Kalil M, Ikki SS. Decision fusion in distributed cooperative wireless sensor networks. IEEE Transactions on Vehicular Technology. 2018;68(1):797-811.
195. Chandra BS, Sastry CS, Jana S. Robust heartbeat detection from multimodal data via CNN-based generalizable information fusion. IEEE Transactions on Biomedical Engineering. 2018;66(3):710-7.
196. Gupta K, Merchant SN, Desai UB. Inherence of Hard Decision Fusion in Soft Decision Fusion and a Generalized Radix-2 Multistage Decision Fusion Strategy. IEEE Access. 2018;6:55701-11.
197. Hu J, Huang T, Zhou J, Zeng J. Electronic Systems Diagnosis Fault in

Gasoline Engines Based on Multi-Information Fusion. Sensors. 2018;18(9):2917.
198. Huang P, Qiu W. A robust decision fusion strategy for SAR target recognition. Remote Sensing Letters. 2018;9(6):507-14.
199. Li J, Si Y, Xu T, Jiang S. Deep convolutional neural network based ECG classification system using information fusion and one-hot encoding techniques. Mathematical Problems in Engineering. 2018;2018.
200. Lang X, Li P, Cao J, Li Y, Ren H. A small leak localization method for oil pipelines based on information fusion. IEEE Sensors Journal. 2018;18(15):6115-22.
201. Zhou K-p, Bai X-f, Bi W-h. Determination of ethanol content in ethanol-gasoline based on derivative absorption spectrometry and information fusion. Optoelectronics Letters. 2018;14(6):442-6.
202. Liu Y, Wang H, Zhao W, Zhang M, Qin H, Xie Y. Flexible, stretchable sensors for wearable health monitoring: sensing mechanisms, materials, fabrication strategies and features. Sensors. 2018;18(2):645.
203. Tidriri K, Tiplica T, Chatti N, Verron S. A generic framework for decision fusion in fault detection and diagnosis. Engineering Applications of Artificial Intelligence. 2018;71:73-86.
204. Liu A LJ, Li L. Study on indoor positioning method based on subchannel information fusion. Yi Qi Yi Biao Xue Bao/Chinese Journal of Scientific Instrument. 2018;39(3):242-9.
205. Liu S, Yang J. Target recognition in synthetic aperture radar images via joint multifeature decision fusion. Journal of Applied Remote Sensing. 2018;12(1):016012.
206. Shu Y, Zhang H. Multimodal information fusion based human movement recognition. Multimedia Tools and Applications. 2020;79(7):5043-52.
207. Shrivastava S, Kothari D. SU throughput enhancement in a decision fusion based cooperative sensing system. AEU-International Journal of Electronics and Communications. 2018;87:95-100.
208. Meng Z, Han S, Liu P, Tong Y. Improving speech related facial action unit recognition by audiovisual information fusion. IEEE transactions on cybernetics. 2018;49(9):3293-306.
209. Shaban M, Mahmood A, Al-Maadeed SA, Rajpoot N. An information fusion framework for person localization via body pose in spectator crowds. Information Fusion. 2019;51:178-88.
210. ZHANG C-W, CHEN L-M, RUI W, ZENG H-J, XU D-M. TARGET POSITIONING AND TRACKING METHOD OF THE AIRBORNE TRACKER BASED ON MULTI-INFORMATION FUSION.
211. Mu N, Xu X, Zhang X, Lin X. Discrete stationary wavelet transform based saliency information fusion from frequency and spatial domain in low contrast images. Pattern Recognition Letters. 2018;115:84-91.
212. Lu F, Huang Y, Huang J, Qiu X. Gas turbine performance monitoring based on extended information fusion filter. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering. 2019;233(2):483-97.
213. Li C, Wang P, Dong H. Kriging-based multi-fidelity optimization via information fusion with uncertainty. Journal of Mechanical Science and Technology. 2018;32(1):245-59.
214. Karanikola L, Karali I. Towards a Dempster–Shafer Fuzzy Description Logic—Handling Imprecision in the

Semantic Web. IEEE Transactions on Fuzzy Systems. 2018;26(5):3016-26.
215. Li S, Ma H, Saha T, Wu G. Bayesian information fusion for probabilistic health index of power transformer. IET Generation, Transmission & Distribution. 2017;12(2):279-87.
216. Zhang X, Mahadevan S, Lau N, Weinger MB. Multi-source information fusion to assess control room operator performance. Reliability Engineering & System Safety. 2018;194:106287.
217. Zhang L, Zhang M, Sun X, Wang L, Cen Y. Cloud removal for hyperspectral remotely sensed images based on hyperspectral information fusion. International Journal of Remote Sensing. 2018;39(20):6646-56.
218. Wang M, Li Z, Huang D, Guo X. Performance analysis of information fusion method based on bell function. International Journal of Performability Engineering. 2018;14(4):729.
219. Shrinivasan L, Raol JR. Interval type-2 fuzzy-logic-based decision fusion system for air-lane monitoring. IET Intelligent Transport Systems. 2018;12(8):860-7.
220. Sarabi-Jamab A, Araabi BN. How to decide when the sources of evidence are unreliable: A multi-criteria discounting approach in the Dempster–Shafer theory. Information Sciences. 2018;448:233-48.
221. Fatemipour F, Akbarzadeh-T M. Dynamic Fuzzy Rule-based Source Selection in Distributed Decision Fusion Systems. Fuzzy Information and Engineering. 2018;10(1):107-27.
222. Saadi I, Farooq B, Mustafa A, Teller J, Cools M. An efficient hierarchical model for multi-source information fusion. Expert Systems with Applications. 2018;110:352-62.
223. Dabrowski JJ, de Villiers JP, Beyers C. Naïve Bayes switching linear dynamical system: A model for dynamic system modelling, classification, and information fusion. Information Fusion. 2018;42:75-101.
224. Paggi H, Lara JA, Soriano J. Structures generated in a multiagent system performing information fusion in peer-to-peer resource-constrained networks. Neural Computing and Applications. 2018:1-19.
225. Li H, Huang H-Z, Li Y-F, Zhou J, Mi J. Physics of failure-based reliability prediction of turbine blades using multi-source information fusion. Applied Soft Computing. 2018;72:624-35.
226. Chahine C, Vachier-Lagorre C, Chenoune Y, El Berbari R, El Fawal Z, Petit E. Information fusion for unsupervised image segmentation using stochastic watershed and Hessian matrix. IET Image Processing. 2018;12(4):525-31.
227. Che X, Mi J, Chen D. Information fusion and numerical characterization of a multi-source information system. Knowledge-Based Systems. 2018;145:121-33.
228. Paggi H, Soriano J, Lara JA. A multi-agent system for minimizing information indeterminacy within information fusion scenarios in peer-to-peer networks with limited resources. Information Sciences. 2018;451:271-94.
229. Li S, Zhao S, Cheng B, Chen J. Accelerated particle filter for real-time visual tracking with decision fusion. IEEE Signal Processing Letters. 2018;25(7):1094-8.
230. Wang L, Li Y, Liao Y, Pan K, Zhang W. Course control of unmanned wave glider with heading information fusion. IEEE Transactions on Industrial Electronics. 2018;66(10):7997-8007.
231. Mu Z, Zeng S. Some novel intuitionistic fuzzy information fusion

methods in decision making with interaction among attributes. Soft Computing. 2019;23(20):10439-48.
232. Luo H, Lan W, Chen Q, Wang Z, Liu Z, Yue X, et al. Inferring microRNA-environmental factor interactions based on multiple biological information fusion. Molecules. 2018;23(10):2439.
233. Sultana M, Paul PP, Gavrilova ML. Social behavioral information fusion in multimodal biometrics. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2017;48(12):2176-87.