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A Comprehensive Overview of Decision Fusion Technique in Healthcare: A Systematic Scoping Review

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Abstract

Context: Decision fusion has emerged as a data management technique due to the diversity and scalability of data in health care. This first-scope review aimed to investigate the use of this technique in health care.
Evidence Acquisition: A query was carried out on PubMed, Science Direct, and EMBASE within 1960-2017 using such keywords as decision fusion, information fusion, symbolic fusion, distributed decisions, expert fusion, and sensor fusion, in conjunction with med-* and health-care. The articles were analyzed in terms of methodology and results.
Results: The literature search yielded 106 articles. Based on the results, in the field of health care, the articles were related to image processing (29%), sensors (22%), diagnosis area(10%), biology (6%), health informatics (8%), and signal process (15%). The majority of articles were published in 2011, 2012, and 2015, and the USA had the largest number of articles. Most of the articles were about engineering and basic sciences. Regarding healthcare, the majority of studies were conducted on the diagnosis of diseases (80%), while 9% and 11% of articles were about prevention and treatment, respectively. These studies applied the following methods: intelligent methods (44%), new methods (36%), probabilistic (13%), and evidential methods (7%). The dataset was as follows: research project data (49%), online dataset (42%), and simulation (9%). Furthermore, 49% of articles mentioned the applied software, among which classification and interpretation were reportedly the most and the least used methods.
Conclusion: Decision fusion is a holistic approach to evaluate all areas of health care and elucidate diverse techniques that can lead to improved quality of care.

Keywords: Decision fusion, Expert fusion, Health care, Information fusion, Medicine, Sensor fusion

1. Context

In recent decades, massive amounts of data are generated in all industries due to the emergence of technological advancements, such as the Internet, computers, and mobile phones (1, 2). As one of the largest and most vital industries, healthcare is expanding rapidly along with its digital data (1, 3). The unpredictable growth of this type of data, known as Big Data, has posed a daunting challenge to all industries, with healthcare being no exception. Moreover, production and storage are relatively easy, as compared to the efficient processing of data and extraction of useful information. Our information and their efficient use are equally important; therefore, new techniques for data management are desirable in healthcare (4, 5).

Healthcare costs have been increasing dramatically (6), and we are witnessing a prevalence of chronic diseases with the growth of the aging population across the globe. Studies have highlighted the increased costs of both public and long-term health care systems despite healthcare technology advancements (7). The analysis of healthcare data is crucial for reducing health care costs, anticipating the spread of contagious diseases, preventing disease outbreaks, and improving the overall quality of life (3, 7). In addition, through robust analysis and pipelined decision-making architectures, health service providers can extract insights from the available data faster; thereby, achieving higher provision scores than competitors.

The application of Big Data techniques in health care faces numerous challenges, one of which is the distributed nature of medical data. Data is stored by different providers, such as insurers and depends on the city and country, rather than a single care unit. The aggregation of data sources would require the development of new infrastructure to facilitate data exchange and interaction among all data providers (4, 8). Another challenge is the variety of data which would require decision making under uncertainty and fuzziness. The complexity of health care and quality variance are other problems in this field.

A promising way of overcoming these challenges is information fusion techniques common in computer science, math, statistics, machine learning, and data mining (9). Although information fusion has been extensively used in the military and sensor research (10), it has recently received multidisciplinary attention (11, 12). In digital health care, the use of information fusion has become a critical element in generating suitable solutions. These techniques can be useful in the diagnosis, predictions, recommender systems, and interpretation of medical imagery (7).

The application of these processes brings some major advantages, including the easy management and aggregation of structured data sources, dimensionality reduction, noise reduction, and increased accuracy. Equally important, it provides interpretability with displays and summarization, meaningful information immediately adapted in clinical environments to make decisions, reduce costs, and production of more effective results (13). In information fusion, different methods, algorithms, sources, or classifiers could be integrated to provide higher quality and unbiased estimates. This allows Decision Fusion to process the diversity of features found in large datasets and means of providing high scalability; nonetheless, this is so poorly performed that it would be almost impossible (14).

Given the variety of complex conditions in the healthcare systems (12, 15-17), the current scope review study aimed to evaluate the use of Decision Fusion in health care and inform appropriate methodologies based on the data types and domains.

2. Evidence Acquisition

A query was carried out on PubMed, Science Direct, and EMBASE databases based on published articles in English within 1960-2017. The keywords included Decision Fusion, information fusion, symbolic fusion, distributed decision, expert fusion, and sensor fusion which were then combined with med- and healthcare. These keywords were used in related studies in this field for the description of the Decision Fusion technique. Among the published articles (n=2098), the duplicates were removed, and the articles unrelated to the title of the study were filtered. Eventually, the articles that were not available in full-text or their full-text did not meet the study criteria were screened. It is noteworthy that the full-text of PubMed articles was provided to the researchers by asking the authors for each article.

The summary of the research process is as follows. Firstly, the articles were categorized by the analytical domain and level of care, including prevention, diagnosis, treatment, and rehabilitation. Thereafter, they were categorized based on methodology, desired data, software, and the results. Furthermore, the author's discipline and the publication dates were studied. The summary of the research process is illustrated in Figure 1.

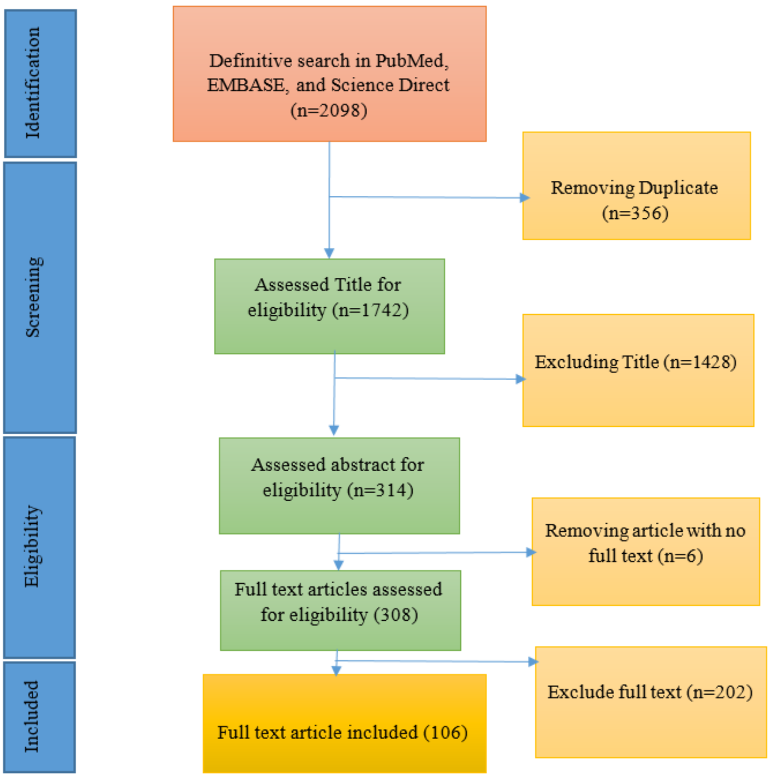

Figure 1. Summary of the research process

3. Results

After the extraction of the target items, the following information was imported into an Excel file: method, the type of the used data, research outcome, and the general metadata of the articles, including the year of publication, country, and author's expertise. Analysis of the field and levels of health care are presented below.

3.1. Frequency of articles in specified fields in healthcare

Various health care areas that used Decision Fusion techniques were categorized into six areas of image processing, sensor, biology, diagnosis, signal processing, and health informatics. Signal processing is a relevant area where Decision Fusion aggregates signal from different sources and chooses the best option among them (18). This area is used in health care fields, for instance, to analyze the signals from electroencephalogram and electromyography of patients to diagnose their diseases. In sensors, studies use sensor data to monitor a person's vital signs. In image processing, studies have been also carried out using data from magnetic resonance imaging, computed tomography, and other modalities for the early diagnosis of diseases. In biology, gene information is used for diagnosis, and in health informatics, efforts have been taken to improve the care quality by retrieving or ranking health-related documents. In area diagnoses, by analyzing the patient data or the electronic health record, diseases could be diagnosed or treated. Figure 2 demonstrates the percentage of articles in each of the six areas in which the technique was used.

As depicted in Figure 2, the number and percentage of articles ordered in frequency are image processing, sensors, biology, signal processing, diagnosis, and health informatics, respectively.

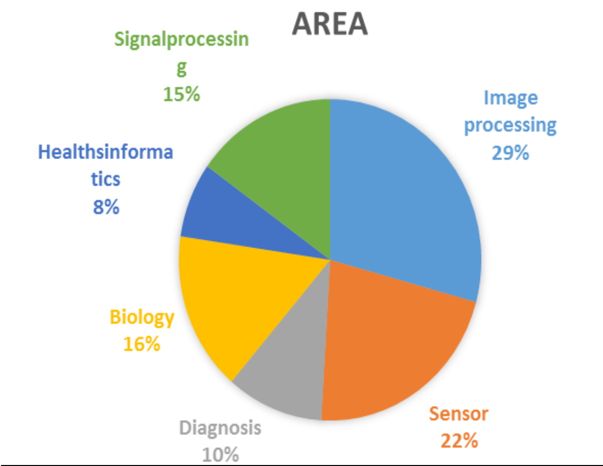

Figure 2. Relative frequency percent of articles by specified fields of healthcare

3.2. Frequency of articles within 1999-2017

As presented in Figure 3, the number of articles on the use of Decision Fusion has grown significantly between 2010 and 2017. This is due to the fact that 2010 is often cited as the beginning of Big Data growth in industries, along with the influence of the internet and smartphones. In fact, health care often lags behind other industries in integrating Decision Fusion . Given the changing landscape of emerging large data, the analysis of prior data does not paint a full picture.

3.3. Frequency of articles by healthcare subfields and the publication date

Based on Figure 4, the use of Decision Fusion has witnessed a dramatic growth in all areas since 2010. Moreover, image processing and sensor areas show

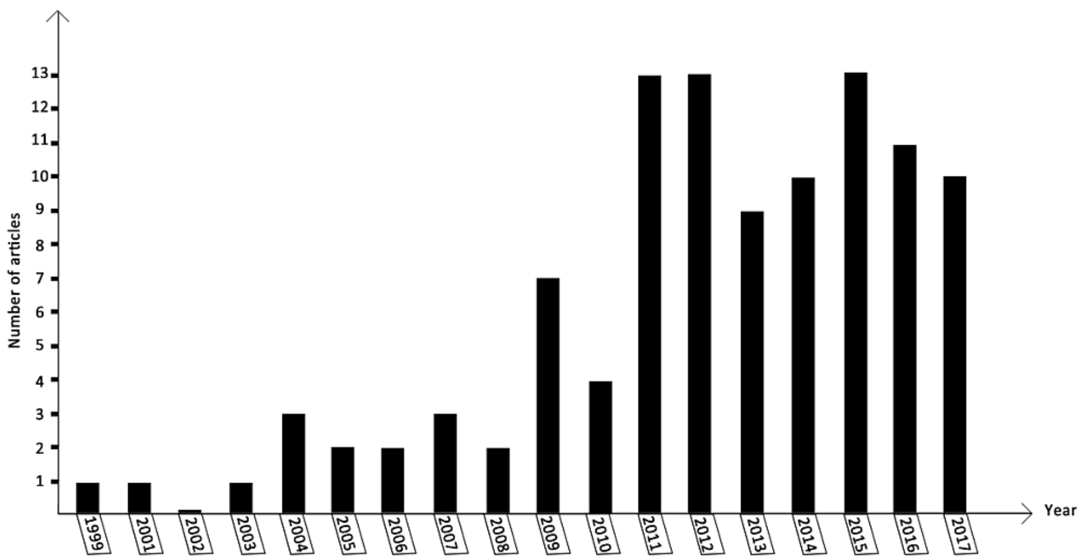

Figure 3. Frequency of articles within 1999-2017

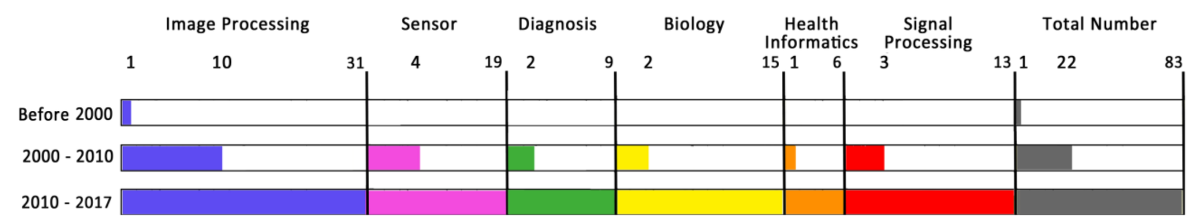

Figure 4. Frequency of articles in specified fields of healthcare in different time periods

the most growth and contemporary usage.

3.4. Frequency of articles in specified fields of healthcare by continent

Figure 5 demonstrates that Europe uses Decision Fusion predominantly in the area of image processing, sensor, and signal processing, the US extensively uses this method in the sensor, diagnosis, signal processing, and health informatics areas. Asia has used the technique most often in diagnosis and biology areas. Australia has had the least study on the use of these techniques, compared to others. In the table 1, the countries are ranked according to the technique in each area.

3.4.1. Countries with the highest rank in articles conducted in specific healthcare fields

The USA and France ranked first and second in image processing; Germany and the USA in sensors; China and the USA in diagnosis and biology; the USA and France in health informatics and signal processing. Canada, China, and the USA topped, and the USA held the top two across all areas.

3.5. Frequency of articles in specified fields of healthcare by author expertise

The Decision Fusion technique was introduced in the 1960s, and since then has been extensively used in the sensor area for collecting information related to military affairs. In those years, the use of this technique was limited to engineering expertise. The expansion of Decision Fusion in subsequent years requires domain knowledge. After reviewing the specialties of the authors in different areas, the following figure was obtained:

The written number on the Venn diagrams signifies the number of authors in each area; therefore, it could be interpreted as an indicator of interest and diversity. Based on Figure 6, in image processing, most specialties are in engineering, basic science, and a combination of medical and basic science. In the sensor area, most of the specialties are in a combination of basic science and engineering, as well as a combination of engineering science and medical science. In signal processing, most of the specialties are in medical sciences, basic sciences engineering, including specific engineering domains.

Basic sciences and engineering are dominant in biology. The predominant specialties in the diagnosis area are engineering, basic sciences, and their overlap, including the overlap of medical and engineering, as well as the three-way intersection of medical, basic sciences, and engineering. Finally, engineering is dominant in the area of health informatics. Engineering and basic science are the most prevalent specialties, and health informatics shows up the least. The next figure displays the authors' specialty in the use of the technique.

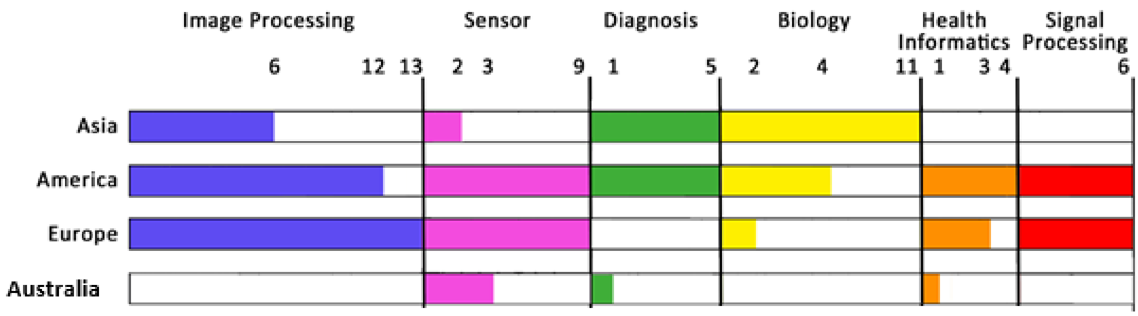

Figure 5. Frequency of articles in specified fields of healthcare and continents

Table 1. The countries with the highest rank in articles conducted in specific healthcare fields

<table>
<tr><th>Rank</th><th>Image Processing</th><th>Sensor</th><th>Diagnosis</th><th>Biology</th><th>Health Informatics</th><th>Signal</th></tr>
<tr><td>1</td><td>USA</td><td>Germany</td><td>China</td><td>China</td><td rowspan="3">USA and France</td><td>Canada</td></tr>
<tr><td>2</td><td>France</td><td>USA</td><td rowspan="2">USA</td><td rowspan="2">USA</td><td rowspan="2">China and USA</td></tr>
<tr><td>3</td><td>Canada and Netherlands</td><td>Australia</td></tr>
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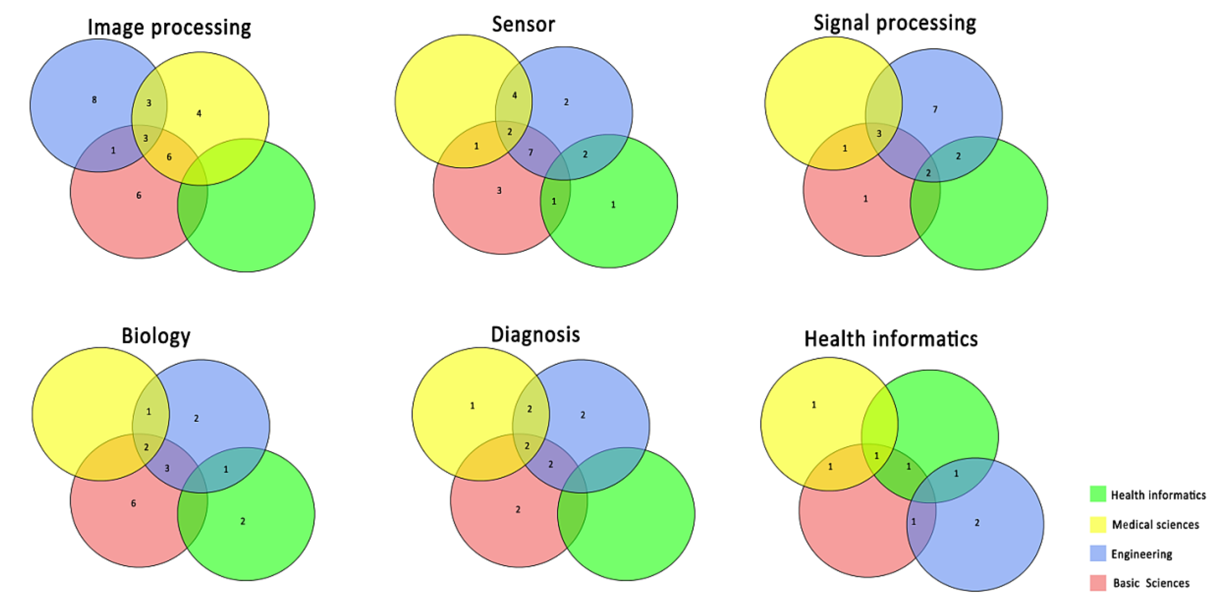

Figure 6. Frequency distribution of articles in specified fields of healthcare by author expertise

3.5.1 Frequency of articles by authors' expertise

According to the information obtained from Figure 7, the most prevalent specialties are related to engineering, basic sciences, followed by a combination of engineering and basic Science, respectively.

3.6. Frequency distribution of articles by health promotion levels (prevention, diagnosis, treatment, and rehabilitation)

As it is known, health care could be provided at different levels, including prevention, diagnosis, treatment, and rehabilitation. After reviewing the related articles, the contribution of the articles (in percent) was determined at each of the three levels of health promotion. Thereafter, various health care articles were categorized at each level of health promotion services. This categorization is depicted in the following figures.

As illustrated in Figure 8, regarding healthcare, the majority of studies were conducted on the diagnosis of diseases (80%), while 9% and 11% of articles were about prevention and treatment, respectively.

3.6.1. Studies in the area of image processing

According to the three levels of health promotion, Figure 9 shows that 90% of imaging studies are about brain diseases, digestion, breast cancer, and other cancers are on the level of diagnosis, 7% of which are related to the health promotion level in the prevention, and 3% fall in the level of treatment.

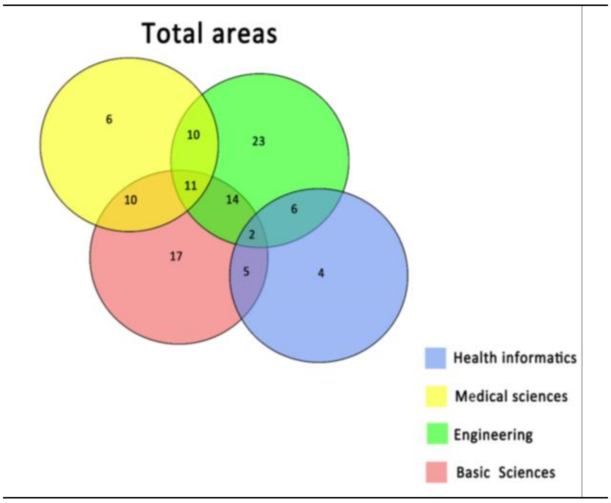

Figure 7. Frequency of articles by authors' expertise

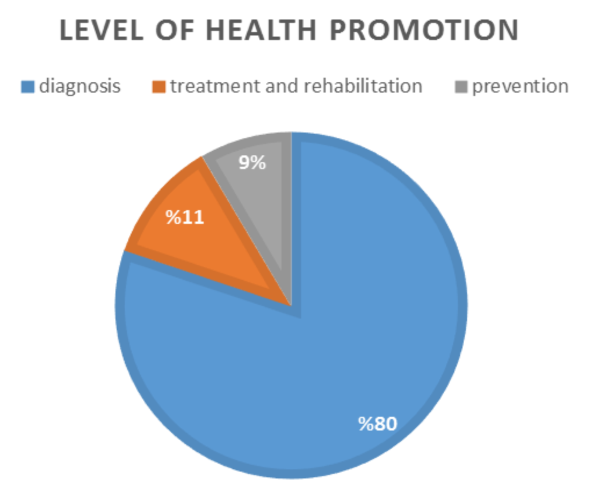

Figure 8. Frequency distribution of articles by health promotion levels

3.6.2. Studies in the area of the sensor

According to Figure 10, 48%, 26%, and 26% of articles are related to the levels of diagnosis, prevention, and treatment, respectively. For diagnosis, sensors are used for surgical affairs, brain diseases, digestive system, and heartbeat rate. For treatment, sensors are used for rehabilitation and monitoring.

3.6.3. Studies in the area of diagnosis

In the diagnostic area, studies have examined the diagnosis of Alzheimer's disease, emphysema, hypoxia, hypertension, acupuncture, and traditional medicine and medical diagnosis by using data.

3.6.4. Studies in the area of health informatics

Studies at the diagnosis level within health informatics were conducted to investigate the effect of environmental variables and create a health database. This requires the retrieval of information, encoding, and ranking, and the construction of advisory systems. Moreover, 25%, 37%, and 38% of the studies were related to the levels of health promotion in prevention, diagnosis, and treatment, respectively.

3.6.5. Studies in the area of signal processing

Studies in the diagnosis area for signal processing were conducted on epilepsy, seizures, and head-related diseases, cardiorespiratory diseases, skeletal rehabilitation diseases, and stress. In this area, 94 % and 6% of these studies were related to diagnosis and treatment, respectively.

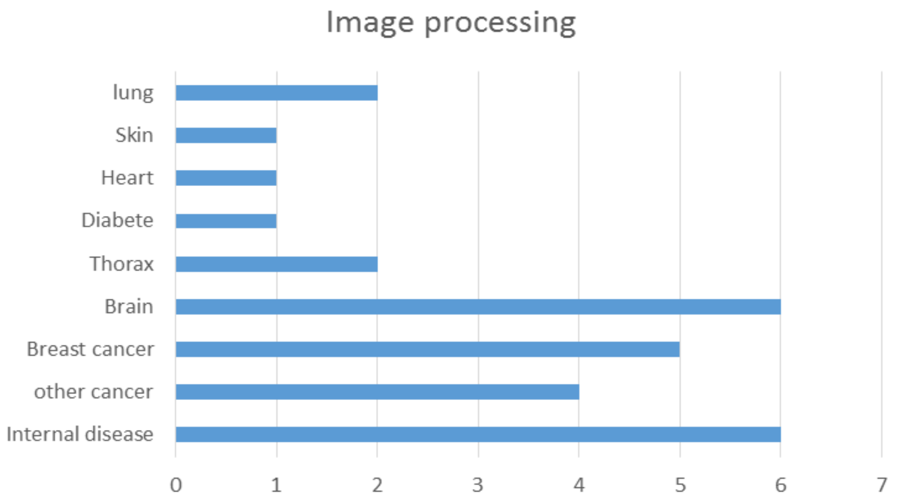

Figure 9. Frequency of articles of diagnosis level in image processing

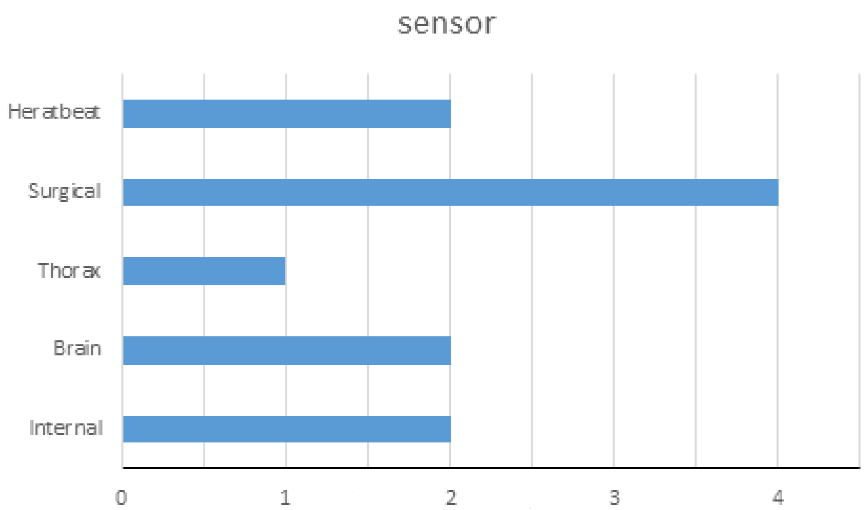

Figure 10. Frequency of diagnosis level articles in the sensor area

3.6.6. Studies in the area of biology

In the area of biology, studies have been conducted to cluster diverse genomic data through extensive integration of various sources of biological data. A primary motivation is drug design. The initial aim of these studies is the prediction of protein interaction sites, HIV-1 protease cleavage sites, protein function, genes function, protein-protein interactions, and the localization of subcellular processes.

3.7. Summary of Decision Fusion methods

In general, Decision Fusion methods fall into three broad categories:

1) Probabilistic methods
2) Evidential methods
3) Intelligent methods

A brief description of each category is presented below (Figure 11):

1) Probabilistic methods use probabilistic and statistical foundations. An example of these methods is Bayesian theory which is effectively used in event fusion and is an efficient method for managing randomness in the Decision Fusion technique.

2) The theory of evidence relates to a combination of evidence to calculate the probability of an event. For instance, the Dempster-Shafer (DS) theory uses the belief-to-pure attribute (as an opposed probability). The most important part of this theory is Dempster's rule of combination, which combines evidence from two or more sources to produce an inference. DS theory is a generalization of the Bayesian theory of subjective probability. It is clear that Bayesian and DS theories deal with a kind of randomness and uncertainty. These two methods are part of statistical methods.

3) Fuzzy methods and artificial neural networks are examples of intelligent methods. Fuzzy-logic theory has been effectively used in fuzziness information processing. Fuzzy-logic theory succeeds in making decisions and fusion systems for identifying and managing health care systems. Fuzzy methods are suitable for qualitative information; nonetheless, they are weak in randomness management (14, 19, 20)

The used methods in studies of each area (image processing, sensors, biology, signal processing, diagnosis, and health informatics) is as follows (Table 2 to Table 7):

The relative frequency of the methods used in articles according to the main category and based on the health care areas are listed in Table 8.

As observed in Table 8, the intelligent method was the most extensively used one in such a way that nearly half of all articles have benefited from the capabilities of this method. In the area of image processing, the intelligent and evidential methods were the most and least used techniques, respectively. In the area of sensors, intelligent and new methods were most extensively used, while probabilistic methods were the least used methods. In signal processing, the new method has been used the most, and the evidential method was the least used one. In biology, the most frequently used method was intelligent, while the evidential and

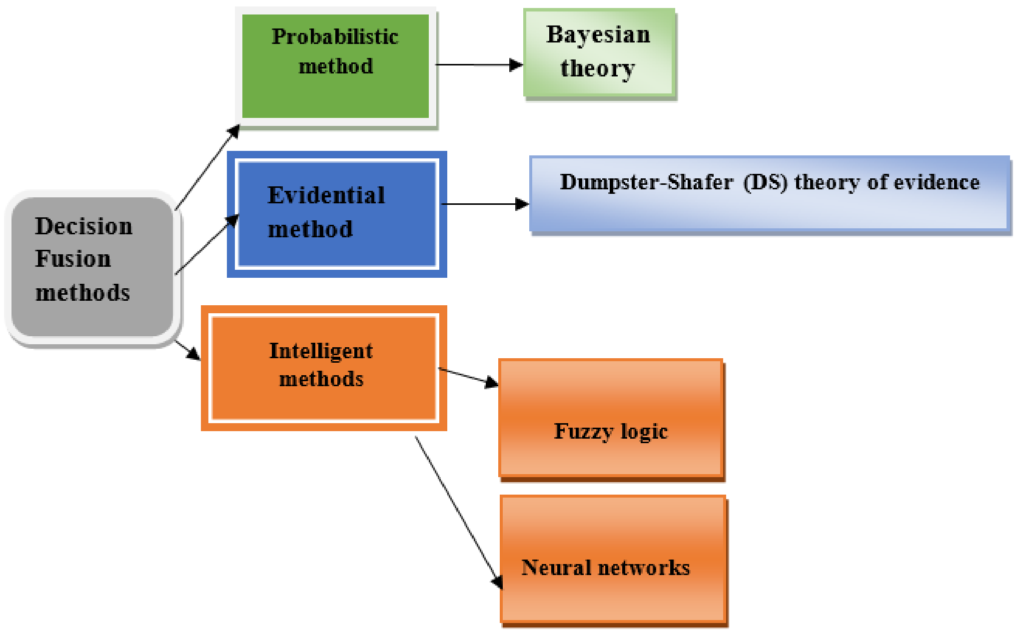

Figure 11. Summary of Decision Fusion methods

Table 2. Methods of Decision Fusion used in the image processing area

Main category method	Methods (Reference number)
Probabilistic method	Causal independence model (21) Belief function theory (22) Bayesian (23) Model estimation and voxel label probability (24)
Intelligent method	PSO[1] (25) Fuzzy(26, 11) LDA[2]-majority voting (27) Label propagation and weighted Decision Fusion (WDF) (28) Linear discriminant classifier, quadratic discriminant classifier, SVM[3], KNN[4], Likelihood distribution normalization(PPDN[5]) (29) Multiple kernel learning method-SVM-majority (30) SVM-LDA(31) SVM-Gaussian approach, KNN (32) SVM-Hidden Markov Models (33) CNN[6] model (34) CNN ensemble (35) SVM (36) Wavelet theory& random forest (37) Decision Trees (38) Fuzzy k-mean (39) Multi content fuzzy clustering(40)
Evidential method	(41, 42)
New methods	(43-48)

NOTE:
[1] Particle Swarm Optimization
[2] Latent Dirichlet Allocation
[3] Support Vector Machine
[4] K-Nearest Neighbors Algorithm
[5] Power Function-Based Power Distribution Normalization Algorithm
[6] Convolutional Neural Network

Table 3. Methods of Decision Fusion used in the sensor area

Main category method	Methods (Reference number)
Probabilistic method	Discrete Bayes classifier(49) Bayesian (50)
Intelligent method	Kalman filtering and ANNS (51) Kalman (52-54) K-means((55-57) SVM(58) Conventional Ensemble Methods (59)
Evidential method	(60-62)
New methods	(63-70)

Table 4. Methods of Decision Fusion used in the biology area

Main category approach	Methods (Reference number)
Probabilistic method	Bayesian (71, 72)
Intelligent method	PCA[1]-SVM (73) PCA- SVM (74) NN[2] (75) RBF[3] –SOM[4]76) SVM (77) Pairwise kernel function and Support Vector Machines (SVM) (78) Markov (79) RF[5] and HMM[6]-SVM DS evidence theory[7] (80) MLP[8], SMO[9], KNN, RF, ARF[10] and RARF[11](64)
Evidential method	(81)
New methods	(82-84)

NOTE:
[1] Principal Component Analysis
[2] Neural Network
[3] Radial Basis Function Network
[4] Self-Organizing Map
[5] Random Forest
[6] Hidden Markov Model
[7] Dempster–Shafer Theory
[8] Multilayer Perceptron
[9] Sequential Minimal Optimization
[10]AdaBoost Random Forest
[11] Real AdaBoost Random Forest

Table 5. Methods of Decision Fusion used in the signal processing area

Main category approach	Methods (Reference number)
Probabilistic method	Likelihood Ratio Test and Heuristic Test Statistic (85) Bayesian (86)
Intelligent method	ANN[1] classifier with a Gaussian RBF (87)
New methods	(88-96,18)

NOTE:
[1]Artificial Neural Network

Table 6. Methods of Decision Fusion used in the diagnosis area

Main category approach	Methods (Reference number)
Probabilistic method	Bayesian (97) Likelihood (98)
Intelligent method	KNN(99) SVM, Neural network, Multi-label learning (100) Ensemble (101, 102)
Evidential method	(103)
New methods	(104-107)

Table 7. Methods of Decision Fusion used in the health informatics area

Main category approach	Methods (Reference number)
Probabilistic method	Bayesian (108)
Intelligent method	PSO (109)
New methods	(110-116)

probabilistic methods were the least used ones. In diagnosis, the intelligent was the most widely used method, and the evidential method was the least used one. Finally, in health informatics, the new and evidential methods were the most and the least used ones.

3.8. Relative frequency of dataset type used in articles with different area

In the studied articles, three data sources were used to test the method as presented in the following:

a) In some studies, online datasets are used to test the method. These data are usually available online. For example, the digital database for screening mammography.

b) Simulation: In some studies, simulated data are used to test the method that has been generated from real data.

c) Research project data: In some studies, clinical data is used to test the desired method. For example, real data of 12 men and 10 women.

The frequency of used data to test the proposed study methods is presented in Table 9:

As displayed in Table 9, in image processing, research project data was most widely used, while simulated data had the minimum application. In the sensor, research project data was the most used source, while simulated data was used the least. In signal processing, the data was mainly sourced from research projects, whereas the simulated data was the least used source of data. In the area of biology, the online dataset was most extensively used, whereas simulation data was the least used source. In diagnosis, research project data was the major source, while the simulation data has had the minimum application. In the area of health

Table 8. Relative frequency of used Decision Fusion methods in the article with different area

Main category/Area	Probabilistic method	Evidential method	Intelligent method	New methods
Image processing	16%	7%	58%	19%
Sensor	9%	13%	39%	39%
Signal processing	12%	0%	25%	63%
biology	11%	11%	61%	17%
diagnosis	18%	9%	37%	36%
Health informatics	12%	0%	13%	75%
Total percentage	13%	7%	44%	36%

Table 9. Relative frequency of used dataset type in articles with different areas

Area	Online Dataset	Simulation	Research project data
Image processing	42%	6%	52%
Sensor	26%	13%	61%
Signal	25%	12%	63%
Biology	59%	9%	32%
Diagnosis	45%	0%	55%
Health informatics	37%	13%	50%
Total	42%	9%	49%

informatics, research project data were the most widely used source, whereas simulation data was the least used one. Apart from biology, where online datasets were used to test the method, the other areas featured research project data the most. In general, in the reviewed studies, datasets included research project data (49%), dataset (42%), and simulation (9%). As a final note, research project data was the most extensively used source of data, while simulation had the minimum application.

3.9. Sample of used software in articles within different fields

According to the results of the review of the software used in the studies, 49% of the studies mentioned the software intended for the implementation, and 51% did not refer to it.

The numbers of the software used in the studies are provided in Table 10.

According to Table 10, 34% of the studies that used the software applied MATLAB software.

3.10. Frequency distribution of goals in published articles

According to the results of the studies, the methods are summarized in the table below, along with their frequency. Different studies have used this technique to classify, predict, interpret, represent, segment, discover, and display information, along with managing uncertainties, variability, and outliers. These techniques improve our understanding and comprehension of complexities, estimation, data retrieval, information quality management, conflict management, and decision making.

The classification was most commonly used in image processing, signal processing, biology, and diagnosis, respectively. Prediction/function is mostly used in diagnosis, biology, and sensor areas; however, it is not applicable in health informatics. Uncertainty and variability management has been most prominent in image processing, sensor, and diagnosis, respectively, and has not been applied in other areas. The maximal use of localization was observed in image processing; nonetheless, it did not show any growth in biology, diagnosis, and signal processing, and it was not used in other areas.

The interpretation was most widely used in image processing and was not applied in other areas. Representation is most and solely used in biology and image processing. The widest application of segmentation has been in image processing and has not been used in other areas. The maximal use of information has been detected in image processing, signal processing, and health informatics and is not used in the biology area. Detection has been mostly applied in the sensor areas, image processing, and signal processing.

Understanding complexity has been only applied in image processing and biology, and estimation is mostly and only used in the area of sensors. Tracking has been used in the sensor area and not in other areas, while retrieval has been applied in image processing and health informatics. Quality has been only used in sensors and image processing and has not been applied in other areas, and conflict management was used in image processing and biology. Decisions have been applied in sensor areas, health informatics, and diagnosis, while it has not been used in the rest of the areas. The frequency of each category is depicted in Figure 12.

Table 10. Sample of used software in the article within different fields

Software name	Reference	Software name	Reference
C++	(25, 65, 116)	Matlab	(88,63,117,31,59,46,33,98,102,67,96,39)
R	(98, 102)	IBM SPSS	(45)
c#	(82)	C	(26)
WEKA	(36, 64, 110)	Netlab	(102)

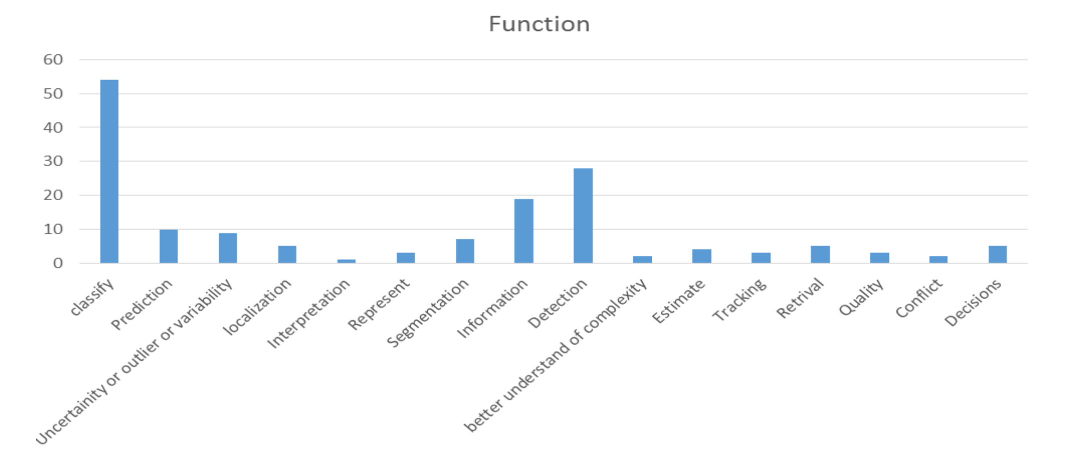

Figure 12. Frequency distribution of goals of Decision Fusion methods used in published articles

As observed, the most widely performed techniques are classification, detection, information provision, and prediction, whereas the least used ones are complexity and conflict.

4. Discussion

The present study aimed to investigate the application of the Decision Fusion technique in health care in the form of a systematic scoping review. It assessed and analyzed the performance of the health care field, the applied methods, the implementation environment, the used data, and the required expertise in different health care areas and levels of health promotion. To the best of our knowledge, the current study was the first scope review that has assessed the applicability of Decision Fusion in the field of health care.

Nowadays, the dramatic increase in the variety, scalability, and complexity of data in the health care field has led to a growing interest in the application of Decision Fusion techniques to manage this massive amount of data. This technique brings numerous advantages, including high-quality results, summarized information, and unbiased estimates. This technique was introduced by the US Department of Defense in 1960 to collect data from, and most of its applications have been long restricted to the sensor area. There has not been much research on Decision Fusion technology in the field of health care until the year 2000. Nonetheless, since then, especially from 2010 with the growth of data due to the emergence of new technologies, research in this area has witnessed a dramatic growth in a way that these techniques are referred to in almost all articles in recent years.

Our first step is to identify the subfields in healthcare in which Decision Fusion can be applied since domain knowledge is required before diving deeper. They were identified based on the objectives of the studies, and the results indicated that the majority of articles were related to image processing, sensors, diagnosis, biology, health informatics, signal processing, respectively. The pioneer countries in the publication of articles in these subfields are as follows: image processing: the USA and France, the sensor area: Germany and the USA, diagnosis: China and USA, biology: China and the USA, health informatics: the USA and France, and signal processing: Canada, China, and the USA. The development of countries appears to be an indicator, and a question is raised concerning the organizations responsible for a special emphasis on particular areas.

After identifying the area and the use environment, since the study aimed to apply this technique in the field of health care, the articles in each area were categorized into prevention, diagnosis, treatment, and rehabilitation, according to the type of health care service and the levels of the health provision. The results of this categorization reflected that the majority of studies in healthcare are related to diagnosis, followed by prevention and treatment. Since the early diagnosis of the disease, especially in such diseases as breast cancer, prostate cancer, and pneumonia, is critical for treatment (98, 107), most studies emphasized early detection and proper diagnosis. Moreover, the accurate diagnosis in health care positively affects the selection of the most appropriate treatment and cost management both for the patient and for the health care system, pursuing the twin goals of upgrading the quality of care and cost reduction (3, 7).

After identifying the problem space, it is of utmost importance to select the appropriate method for data management. Therefore, in the present study, they were classified according to the general categorization of methods for Decision Fusion (three general categories plus new methods) and the areas (six domains). Based on the results, the most frequently used methods in each area are as follows: image processing, diagnosis, and biology: intelligent methods, sensor area: intelligent methods and new methods, signal processing and health informatics: new methods. Furthermore, except for the sensor area which made the least use of probabilistic methods, the evidential method was least frequently applied in all other areas. Across all areas, the intelligent method was the most and the evidential method was the least used technique indicating the importance of intelligent methods in health care.

Today, intelligent methods are often the first choice due to modeling capabilities, such as easy modeling, data type matching, and noise data management (21). Therefore, it is evident that this method should be considered in the use of Decision Fusion in health care. Given the complexities that exist in the field of health care, it is essential to use new methods, combine the existing methods, or design algorithms for optimizing the existing methods.

Deep learning and advanced fuzzy techniques have been recently recommended in the category of intelligent methods. Deep learning uses a set of machine-learning algorithms at multiple levels to apply different layers of nonlinear transformations to enhance the abstraction of a complicated environment. Since Decision Fusion provides a variety of methodologies for merging data from multiple sources, using deep learning along with Decision Fusion paradigms can enhance large data analytics with a more systematic design and more efficient processes.

It is noteworthy that deep learning systems require more computing power and memory storage. For instance, in mammogram analyses, its use is often limited to image analysis; nonetheless, it can be applied in other domains as well. In the case of fuzzy methods, the advanced concepts, including Type-2 fuzzy logic and computing with words (CWW), attempt to manage fuzziness and randomness in events. Recently, Cloud Computational Theory (CCT) has been introduced as a computational methodology for combining randomness and fuzziness in the information used in decision making (14, 19).

The results on test methodology showed that in all areas, except for biology which uses an online dataset for method testing, research project data has been used predominantly. This is due to the absence of research project data in the area of biology. The analysis also demonstrated that simulated data is the least widely used data in health care, highlighting the need for more emphasis on this kind of data.

Regarding the functions of Decision Fusion or our expectation of this technique, different categories were obtained after reviewing the goals and results obtained from the articles. Based on the results, the most dominant functions of this technique were observed in classification, detection, providing information, and prediction, whereas it had the minimum use in interpreting, complexity, and conflict management. Furthermore, it was found that the most efficient use of this technique has been observed in the detection area for the discovery of abnormal conditions, and the use of the most appropriate information for the correct decision.

Regarding the implementation environment considered in the studies, the results showed that the environment of MATLAB was the most used one, and other studies applied other environments, such as C ++, and R. The use of MATLAB environment can be ascribed to its numerous capabilities in a variety of statistical and engineering toolbar (118). Nonetheless, despite the remarkable capabilities of such software as Hadoop, Spark, and Flink, no studies have used them due to people's unfamiliarity or ready-made data analytic tools which eliminated the need for an advanced environment.

It is recommended that these environments be considered in future studies concerning the subsequent benefits. The Hadoop environment is easy to detect. Spark can also process a large data set in memory with a very fast response time. It has fault tolerance capability and uses local memory in the event of a lack of memory. Flink allows users to store data in memory and load them several times. A mechanism provides continuous fault tolerance for restoring the flow of data, and in case of a failure, it can return to snapshots of the system and be used to rebuild the missing data set (119-121). Given its popularity, Python and its growing number of packages should also be taken into consideration, especially with deep learning, for which specialized languages, such as Tensor flow is necessary (122).

In terms of authors' expertise, the results indicated that the most frequent expertise was related to engineering sciences, basic science, and a combination of both. Moreover, a combination of expertise in the medical and other sciences was observed in some studies. This is probably due to the fact that Decision Fusion techniques matured within the field of engineering; therefore, it became the source of transfer, justifying its scarcity in medical informatics. Considering the importance of health care, it is recommended that Decision Fusion n be used in the future by combining methods in engineering, basic sciences, and medical sciences. Individualization is suggested to be used in this technique (tailored and customized treatment. For instance, one study used individualization to determine the sleep stages of a person (66). It is also recommended that this technique be used more thoroughly to manage individual treatment, which allows care services to provide closer care using an individualization approach.

As a final note, we acknowledge that there is no general approach to determining which method is the best in the field of health care and the application of this technique. Therefore, providing and addressing this framework will be of great help for future research. More detailed, domain-specific review articles will support researchers in understanding benefits and help overcome challenges in adopting Decision Fusion technology, especially in health care.

This article was the first scope review article about using the Decision Fusion technique in the field of health care, building on an established protocol (123).

5. Conclusion

The Decision Fusion technique has been widely used in various area. These techniques have been quite successful in diagnosis of disease. This technique can be performed in the future management such as hospital resource management as well as admission and discharge services. The adoption of this technique has proved indispensable since it holds great promise for cost reduction of medical care and health care quality improvement. Therefore, this article can help care providers understand the benefits of this technique and overcome challenges in adopting Decision Fusion technology.

Vitae

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Footnotes

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