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A comprehensive survey of data classification based on evidence theory

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Abstract: Data classification is a fundamental task in machine learning and data analysis, with applications across many fields. In practice, uncertainty often arises due to weakly discriminative features, missing values, distribution shift, class imbalance, inconsistent label spaces, and class overlap. Traditional classification methods, which typically rely on probabilistic frameworks, may not explicitly represent or reduce such uncertainty. Evidence theory (ET), also known as Dempster–Shafer theory, provides a flexible framework for modeling uncertainty and imprecision through basic belief assignments and the evidence combination rule, and has attracted growing attention in the data classification field. Consequently, data classification based on ET (DCET) has become an active research topic. This paper provides a comprehensive survey of DCET, systematically categorizing DCET methods by feature- and label-based uncertainty scenarios. We first review ET fundamentals and summarize the evidential K-nearest-neighbor classifier and its variants. We then survey ET-based methods for tabular data classification under six major uncertainty scenarios: high-dimensional features, missing attribute values, feature distribution shift, imbalanced label distribution, inconsistent label spaces, and class overlap. Next, we review ET-based methods for image (unstructured) classification, highlighting the integration of ET with deep neural networks. We further summarize representative applications, including human activity recognition, medical image segmentation, remote sensing image classification, and remote sensing image change detection. Finally, we discuss future research directions for DCET.

Key words: Evidence theory; Uncertain data classification; Belief functions; Evidential reasoning; Dempster–Shafer theory; Multi-source information fusion

1 Introduction

In data classification, patterns are assigned to predefined classes based on their features (Huang LQ, 2024; Ahmad et al., 2025; Gu et al., 2025; Guan et al., 2025; He HF et al., 2025; Liu D et al., 2025; Sehar et al., 2025; Sun QR et al., 2025; Xu NJ et al., 2025; Zhang JW et al., 2025). Many classification models implicitly assume that the collected data are of high quality and that the training and test data follow similar conditions (Fan et al., 2022, 2023; Fu YM et al., 2023, 2024; Wang GX et al., 2024; Wu et al., 2024; Yan et al., 2024; Fan et al., 2025; Li ZY et al., 2025; Wang X et al., 2025; Zhou N et al., 2025; Feng J et al., 2026; Zhu TY et al., 2026). In practice, however, data quality is often imperfect. For example, features extracted by algorithms or experts may be weakly discriminative, making some patterns difficult to classify accurately. As a result, uncertainty is inherent in many real-world classification problems (Huang LQ and Liu, 2024; Huang LQ et al., 2024a, 2025a, 2025f; Zhang Z et al., 2025).

Evidence theory (ET), also known as belief functions (BFs), evidential reasoning (ER), or Dempster–Shafer theory (DST) (Dempster, 1967; Shafer, 1976), provides a general framework for representing and reasoning with uncertain information (Zhou QL et al., 2023, 2024; Denœux, 2025; Zhou QL et al., 2025a, 2025b; Zhou K et al., 2026; Zhu YC et al., 2026). ET extends beyond both set-theoretic and probabilistic uncertainty frameworks by allowing belief mass to be assigned to sets of hypotheses, enabling an explicit representation of

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ambiguity and imprecision. These properties make ET attractive for uncertainty-aware classification and have motivated a growing body of research on data classification based on ET (DCET) (Ma CX et al., 2024; Shi et al., 2025; Jiao et al., 2026a).

Tabular (structured) data classification problems often involve uncertainty arising from the following scenarios:

1. High-dimensional feature (HDF): When feature dimensionality is high, the complex relationships among features can increase uncertainty, often leading to overfitting, difficulty in identifying informative patterns, and high computational cost (Lian et al., 2015, 2016b; Su et al., 2021).

2. Missing attribute values (MAVs): Missing values reduce the available feature information for classification and may introduce bias, making label prediction less reliable and increasing uncertainty in decision-making (Liu ZG et al., 2015a, 2015b; Liu ZG et al., 2016).

3. Feature distribution shift (FDS): FDS, also known as domain shift or covariate shift, occurs when the feature distributions of the training and test datasets differ, which can cause learned decision rules to generalize poorly, thereby degrading classification performance (Huang LQ et al., 2020; Liu ZG et al., 2021a; Huang L et al., 2023b).

4. Imbalanced label distribution (ILD): In many real datasets, classes are imbalanced. This imbalance can bias classifiers toward majority classes and increase uncertainty for minority-class prediction, thereby reducing reliability and generalizability (Fu C et al., 2021; Niu JW et al., 2022; Grina et al., 2023).

5. Inconsistent label spaces (ILSs): In some settings, training and test datasets may use inconsistent label definitions, which prevents direct transfer of learned decision rules and introduces additional uncertainty (Geng XJ et al., 2020; Liu ZG et al., 2021b, 2022a).

6. Class overlap (COL): COL occurs when samples from different classes share similar feature representations, which increases ambiguity near decision boundaries and makes classification more uncertain (Liu ZG et al., 2013b, 2014b, 2017).

This survey contributes to the field of DCET by providing a comprehensive overview of recent research progress under the above-mentioned scenarios, as well as ET applications in deep neural networks (DNNs) and representative real-world applications. It also highlights the advantages of ET in handling uncertain and imprecise information and identifies potential future research directions. Specifically, this survey makes the following major contributions:

1. It provides a comprehensive overview of DCET, covering its theoretical foundations, key concepts, and classical methods. It includes a comparative discussion of different DCET methods and an analysis of their strengths and weaknesses.

2. It provides an in-depth analysis of various DCET methods, including the evidential K-nearest-neighbor (EKNN) classifier and its variants. The advantages and limitations of these methods are discussed, and potential improvements and extensions are explored.

3. It explores real-world applications of DCET in various domains, including human activity recognition (HAR), medical image segmentation (MIS), remote sensing image classification (RSIC), and remote sensing image change detection (RSICD). It also provides classical examples and case studies to illustrate the effectiveness of DCET in these fields.

4. It identifies key challenges and potential future research directions in DCET, and discusses the need to develop new and efficient combination rules, to embed ET into structured and unstructured data representations, and to address issues such as limited training data, scalability, and interpretability.

Recently, several surveys on ET and its applications (Table 1) have been published (Denœux, 2019b; Ma LY and Denœux, 2021; Campagner et al., 2022; Huang L et al., 2023a; Li XD et al., 2024; Liu Z and Letchmunan, 2024). Denœux (2019b) revisited the relationship between ET and other classification rules. Specifically, this paper shows that generalized logistic regression classifiers can be viewed as evidence combiners within the ET framework, with output probabilities interpretable as normalized plausibilities based on mass functions, thereby offering a new perspective for classifier analysis and design. Ma LY and Denœux (2021) explored partial classification within the ET framework. They introduced the utility of set-valued predictions using ordered weighted average operators and analyzed different decision criteria. Huang L et al. (2023a) reviewed the use of ET in MIS, highlighting its ability to model uncertainty and fuse multiple sources of evidence, which can lead to more accurate and reliable segmentation. Campagner et al. (2022) surveyed connections between rough set theory and belief function theory (i.e., ET), highlighting applications in knowledge representation and machine learning, particularly for clustering and handling uncertain or imprecise data. Liu Z and Letchmunan (2024) reviewed the application of belief functions in machine learning, with an emphasis on uncertainty and imprecision reasoning in clustering, classification, and information fusion. Li XD et al. (2024) provided a comprehensive overview of multi-source information fusion (MSIF), covering definitions, architectures, theories, methodologies, and applications in both military and civilian domains. They also briefly introduced and discussed the use of ET for MSIF.

These works review ET-based classification problems and methods to varying extents. However, there is still a lack of a comprehensive overview that specifically summarizes DCET. Unlike previous surveys that focus mainly on general ET principles or scattered application scenarios without systematic uncertainty-oriented categorization, our survey is the first to structure DCET systematically around six uncertainty scenarios from feature- and label-based perspectives. To be specific, we organize DCET problems and corresponding ET-based methods into different categories. Each category is supplemented with a detailed analysis of representative research cases, including the adopted theoretical basis and experimental design, so that readers can understand the implementation pipeline and practical performance of each method. Furthermore, this survey summarizes the challenges faced by DCET and outlines potential future research directions to provide guidance for subsequent research.

The remainder of this paper is organized as follows. Section 2 reviews ET. Section 3 introduces the most popular classification model based on ET, i.e., the EKNN classifier, and its classical variants. To address uncertainty arising from

Table 1 Summary of related surveys

Reference	Title	Publication	Description
Denœux (2019b)	Logistic regression, neural networks and Dempster–Shafer theory: a new perspective	KBS	This survey explores how logistic regression and neural networks can be understood through ET.
Ma LY and Denœux (2021)	Partial classification in the belief function framework	KBS	This survey systematically investigates decision rules for partial classification using ET.
Campagner et al. (2022)	Belief functions and rough sets: survey and new insights	IJAR	This survey explores the connections between the belief function (i.e., ET) and rough set theories and highlights their relationships and applications in knowledge representation and machine learning.
Huang L et al. (2023a)	Application of belief functions to medical image segmentation: a review	INFFUS	This survey comprehensively explores the application of ET in medical image segmentation.
Li XD et al. (2024)	Multi-source information fusion: progress and future	CJA	This survey provides a comprehensive overview of multi-source information fusion technologies and briefly introduces ET aiming to combine multi-source uncertain information.
Liu Z and Letchmunan (2024)	Representing uncertainty and imprecision in machine learning: a survey on belief functions	JKSU-CIS	This survey explores the application of ET in machine learning to effectively represent and reason with uncertainty and imprecision in clustering, classification, and information fusion.

different causes, several important ET-based tabular (structured) data classification methods are introduced in Section 4. Section 5 reviews representative frameworks that embed ET into deep convolutional neural networks (DCNNs) for unstructured data (i.e., image) classification. Section 6 introduces real-world DCET applications, such as human activity recognition (HAR), medical image segmentation (MIS), remote sensing image classification (RSIC), and remote sensing image change detection (RSICD). Sections 7 and 8 outline possible future research directions and conclude this survey, respectively. The logical framework connecting the main sections is presented in Fig. 1.

2 Evidence theory

ET was introduced by Dempster (1967) and developed by Shafer (1976). As a generalization of both set-theoretic and probabilistic uncertainty representations, ET provides a principled framework for modeling and reasoning with uncertainty and imprecision. ET has been applied in many areas (Denœux, 2016; Shafer, 2016; Tong et al., 2019), including regression (Petit-Renaud and Denœux, 2004; Laanaya et al., 2010; Su et al., 2013; Su and Wang, 2014; Amini et al., 2020; Gong et al., 2020b; Ramel et al., 2020; Liu C et al., 2022; Meinert et al., 2023), classification (Denœux, 1995, 1997, 2000; Zouhal and Denœux, 1998; Denœux and Smets, 2006; Liu ZG et al., 2014d; Tong et al., 2021b), clustering (Denœux and Masson, 2004; Masson and Denœux, 2008; Zhou K et al., 2015, 2016, 2018; Su and Denœux, 2019; Gong et al., 2020a, 2021b, 2022b; Yu et al., 2021; Zhou K et al., 2022; Ju et al., 2024), multi-source information fusion (Frikha and Moalla, 2015; Xiao, 2019, 2020; Laghmara et al., 2020; Wang JY and Yu, 2020; Deng and Wang, 2021; Denœux, 2021; Hu ZT et al., 2023; Liu Z, 2023; Qiao et al., 2023), decision making (Strat, 1990; Attoh-Okine, 2002; Denœux, 2019a; Denœux and Shenoy, 2020; Fei et al., 2020), expert systems (Jiao et al., 2015a, 2016; Zhou ZJ et al., 2015, 2018; Chang et al., 2019; Feng ZC et al., 2019, 2021; Cao et al., 2021; Tang et al., 2022, 2023; Wang J et al., 2022; Zhang CL et al., 2023), and medical image segmentation (Lian et al., 2018, 2019; Huang L et al., 2022b, 2023c). Here, we briefly review ET concepts most relevant to DCET: frame of discernment (FoD), basic belief assignment (BBA), combination rule, and discounting technique.

2.1 FoD and BBA

Let $\Omega = \{\omega_1, \omega_2, \cdots, \omega_C\}$ be a finite set of mutually exclusive and exhaustive hypotheses for a given problem domain, called FoD. The power set of Ω, which is denoted by 2^Ω, is the set of all subsets of Ω. For example, if FoD is $\Omega = \{\omega_1, \omega_2, \omega_3\}$, then the power set is $2^\Omega = \{\varnothing, \{\omega_1\}, \{\omega_2\}, \{\omega_3\}, \{\omega_1, \omega_2\}, \{\omega_1, \omega_3\}, \{\omega_2, \omega_3\}, \Omega\}$. BBA, also known as the mass function, is a mapping from the power set 2^Ω to the interval $[0, 1]$, satisfying the following conditions:

$$\begin{cases} \sum\limits_{A \in 2^\Omega} m(A) = 1, \\ m(\varnothing) = 0, \end{cases} \tag{1}$$

where $m(A)$ denotes the measure of belief degree to element A and not to any of its subsets. Element A is called a focal element if $m(A) > 0$.

In classification tasks, uncertainty and ambiguity usually arise due to various factors such as incomplete data and overlapping class boundaries. ET addresses these challenges by modeling uncertainty through BBA. Specifically, BBA assigns a belief to a set of hypotheses or classes instead of assigning a single probability to each hypothesis or class. This allows a more flexible representation of uncertainty. For a C-class classification problem, FoD can be considered as the label space. Then, $m(A)$ denotes the support degree for a query pattern $\boldsymbol{x}$ belonging to a singleton class, e.g., $A = \{\omega_1\}$, or the union of several classes, e.g., $A = \{\omega_1, \omega_2\}$. In such a case, we can find $\sum\limits_{c=1}^{C} m(\{\omega_c\}) \leq 1$; i.e., the sum of mass values of focal elements whose cardinality is 1 may be less than or equal to 1. Here, $m(A)$, where $1 < |X| < C$, represents the local uncertain information, and the global uncertainty can be measured by $m(\Omega)$ if Ω is a focal element.

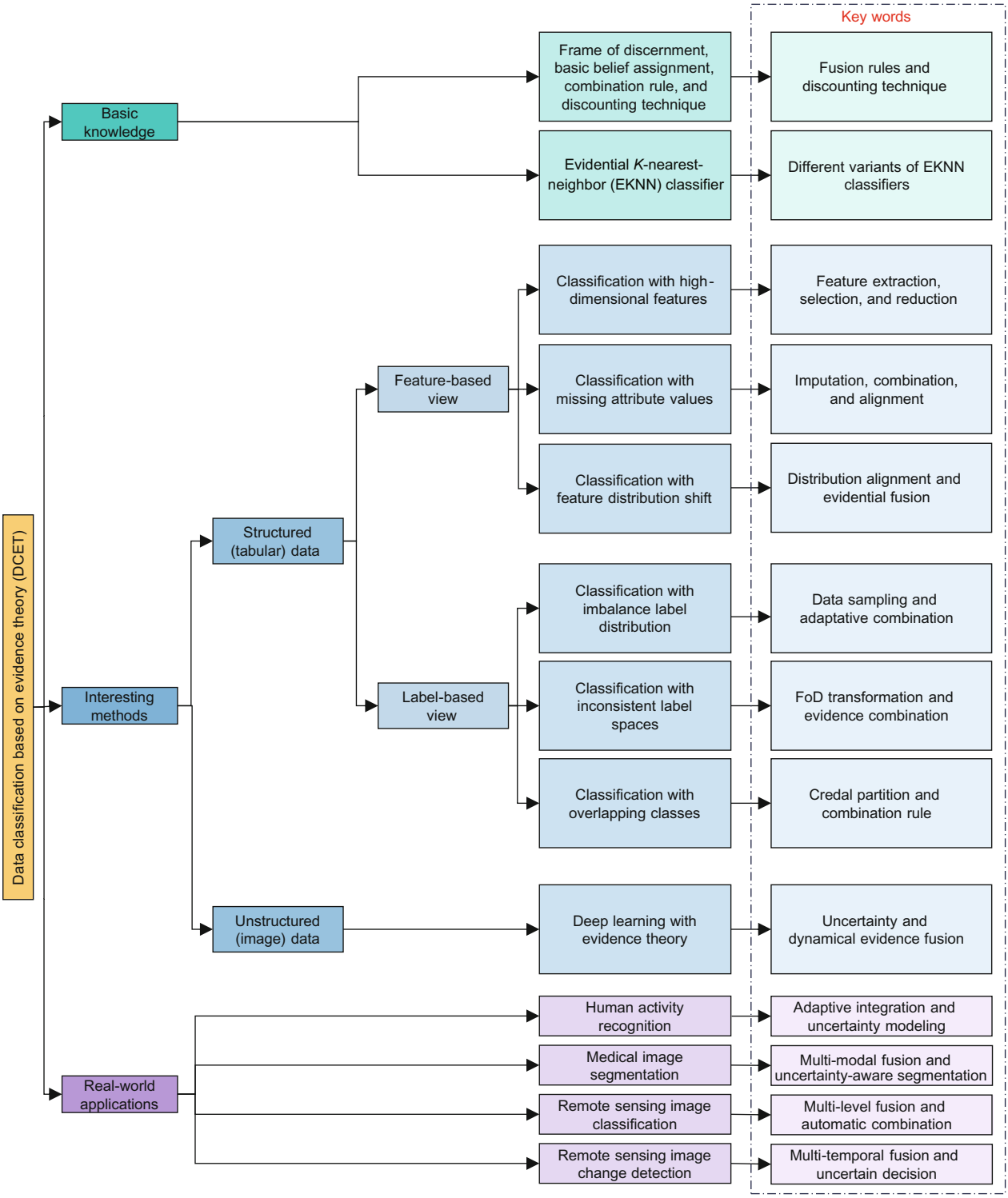

Fig. 1 Flowchart of the logical framework connecting the different sections of this survey

When all focal elements are singletons, the BBA is also called a Bayesian BBA. The soft outputs yielded by some commonly used classifiers, e.g., KNN, support vector machine (SVM), and convolutional neural networks (CNNs) with a softmax layer, are usually regarded as Bayesian BBAs in ET because the cardinality of each focal element equals 1. In such a case, we can obtain $\sum_{c=1}^{C} m(\{\omega_c\}) = 1$. However, these classifiers cannot effectively represent the local and global uncertainties for classification tasks. Thus, some novel classifiers based on ET (Liu ZG et al., 2014b) use the power set of the label space, i.e., 2^{Ω}, to model the final label space for the representation of local uncertain information.

2.2 Classical combination rule and discounting technique

When dealing with multiple sources of BBAs, ET enables their combination to obtain a new BBA. The well-known Dempster (DS) rule (Dempster, 1967) integrates belief functions based on their overlapping or conflicting areas of support. This combination process takes into account the uncertainties and inconsistencies among different information sources. Let $\boldsymbol{m}_1$ and $\boldsymbol{m}_2$ be two distinct BBAs. A new BBA $\boldsymbol{m}_{\mathrm{DS}}$ is yielded by employing the DS rule as

$$\begin{aligned} m_{\mathrm{DS}}(A) &= m_1(B) \oplus_{\mathrm{DS}} m_2(C) \\ &= \begin{cases} \frac{\sum\limits_{B\cap C=A} m_1(B)m_2(C)}{1-K}, & A \in 2^{\Omega}\backslash\varnothing, \\ 0, & A=\varnothing, \end{cases} \end{aligned} \tag{2}$$

where $\oplus_{\mathrm{DS}}$ denotes the DS combination operator and $K = \sum\limits_{B\cap C=\varnothing} m_1(B)m_2(C)$ is the conflicting degree between $\boldsymbol{m}_1$ and $\boldsymbol{m}_2$. The DS rule has been widely employed in many real-world applications because it is commutative and associative. In other words, we can obtain the following combination results: $\boldsymbol{m}_1 \oplus_{\mathrm{DS}} \boldsymbol{m}_2 = \boldsymbol{m}_2 \oplus_{\mathrm{DS}} \boldsymbol{m}_1$ and $(\boldsymbol{m}_1 \oplus_{\mathrm{DS}} \boldsymbol{m}_2) \oplus_{\mathrm{DS}} \boldsymbol{m}_3 = \boldsymbol{m}_1 \oplus_{\mathrm{DS}} (\boldsymbol{m}_2 \oplus_{\mathrm{DS}} \boldsymbol{m}_3)$.

We can see that the DS rule can be used if and only if $K \neq 1$ because there is a logical contradiction when $K = 1$. Moreover, the DS rule usually yields unreasonable combination results when the conflicting degree is very large. For example, if FoD is $\Omega = \{\omega_1, \omega_2, \omega_3\}$, and one obtains two Bayesian BBAs $\boldsymbol{m}_1 = [0.9\ 0.1\ 0]$ and $\boldsymbol{m}_2 = [0\ 0.1\ 0.9]$, then the DS combination result is $\boldsymbol{m} = \boldsymbol{m}_1 \oplus_{\mathrm{DS}} \boldsymbol{m}_2 = [0\ 1\ 0]$. The mass values of $\{\omega_2\}$ of two BBAs, $m_1(\{\omega_2\}) = 0.1$ and $m_2(\{\omega_2\}) = 0.1$, are very small, but the DS combination rule makes it the largest. This counterintuitive behavior has motivated extensive research (Shafer, 1976; Yager, 1987; Dubois and Prade, 1988) , which can be broadly divided into two categories: (1) designing the new combination rule, e.g., Yager's rule (Yager, 1987) and Dubois–Prade (DP) rule (Dubois and Prade, 1988); (2) adopting the BBA discounting technique (Shafer, 1976).

For an alternative combination rule, Yager (1987) argued that the conflicting information is completely unreliable, and it should be redistributed to the element Ω. Thus, the combination result, i.e., $\boldsymbol{m}_{\mathrm{Y}} = \boldsymbol{m}_1 \oplus_{\mathrm{Y}} \boldsymbol{m}_2$, using Yager's rule (Yager, 1987), is defined by

$$\begin{cases} m_{\mathrm{Y}}(\varnothing) = 0, \\ m_{\mathrm{Y}}(A) = \sum\limits_{B\cap C=A} m_1(B)m_2(C), \\ m_{\mathrm{Y}}(\Omega) = m_1(\Omega)m_2(\Omega) + \sum\limits_{B\cap C=\varnothing} m_1(B)m_2(C). \end{cases} \tag{3}$$

Dubois and Prade (1988) believed that the two sources of BBAs are reliable when they are not in conflict, but one of them is right when a conflict occurs. That is, if one observes a value in set A, and the other observes this value in set B, then the truth lies in $B \cap C$ as long as $B \cap C \neq \varnothing$. If $B \cap C = \varnothing$, then the truth lies in $B \cup C$. The following hybrid rule of combination, also known as the DP rule (Dubois and Prade, 1988), is obtained:

$$\begin{aligned} m_{\mathrm{DP}}(A) &= m_1(B) \oplus_{\mathrm{DP}} m_2(C) \\ &= \begin{cases} m_{\mathrm{DP}}(\varnothing) = 0, \\ m_{\mathrm{DP}}(A) = \sum\limits_{B\cap C=A} m_1(B)m_2(C) \\ \qquad\qquad + \sum\limits_{B\cap C=\varnothing, B\cup C=A} m_1(B)m_2(C). \end{cases} \end{aligned} \tag{4}$$

The above two alternative rules can, to some extent, reduce the negative influence of conflicts among BBAs for combination, but they are not associative. As a result, these rules are not widely employed in real-world applications.

Another common strategy is the BBA discounting technique. Shafer (1976) suggested that the unreliability of information sources is a major cause of intense conflicts, and that BBA with low reliability should have limited influence on the DS combination. For BBA $\boldsymbol{m}$, the discounting operation is defined by

$$\begin{cases} {}^{\beta}m(A) = \beta \cdot m(A), & A \in 2^{\Omega}\backslash\Omega, \\ {}^{\beta}m(\Omega) = 1 - \beta + \beta \cdot m(\Omega), \end{cases} \tag{5}$$

where $\beta \in [0, 1]$ is the weight/reliability of $\boldsymbol{m}$, and ${}^{\beta}\boldsymbol{m}$ denotes the discounted result. Specifically, BBA is completely reliable and unreliable when $\beta = 1$ and $\beta = 0$, respectively. In other words, the larger the weight, the higher the importance. For two BBAs $\boldsymbol{m}_1 = [0.9\ 0.1\ 0]$ and $\boldsymbol{m}_2 = [0\ 0.1\ 0.9]$, if their weights are $\beta_1 = 0$ and $\beta_2 = 1$, then $\boldsymbol{m}_{\mathrm{DS}} = {}^{\beta_1}\boldsymbol{m}_1 \oplus_{\mathrm{DS}} {}^{\beta_2}\boldsymbol{m}_2 = \boldsymbol{m}_2 = [0\ 0.1\ 0.9]$. Here, the discounted result ${}^{\beta_1}\boldsymbol{m}_1$ plays a negligible role in the combination.

The discounting technique preserves commutativity and associativity, and has been widely employed. In practice, the DS rule and BBA discounting technique are usually used together to integrate complementary information in classification. As a decision-level fusion tool, ET differs from data- and feature-level methods (Hu JW et al., 2020; Xu PL et al., 2025; Yang DP et al., 2025) by modeling uncertain beliefs via BBA. It explicitly quantifies aleatoric and epistemic uncertainties, and this can preserve uncertainties and enable interpretable multi-source decisions.

In practice, the combined BBA is usually transformed into a pignistic probability distribution, i.e., BetP(·) (Smets, 2005), to make the final class decision when a singleton label is required. It is defined by

$$\mathrm{BetP}(\{\omega_c\}) = \sum_{X\in 2^{\Omega}, \{\omega_c\}\in X} \frac{m(X)}{|X|}, \tag{6}$$

where $|X|$ denotes the cardinality of element $X \in 2^{\Omega}$.

In summary, uncertainty in classification can be explicitly represented and managed using BBA, the DS combination rule, and the discounting technique, providing a robust framework for analyzing complex data.

3 ET-based K-nearest-neighbor classification

The most popular classification method based on ET is the EKNN classifier, first proposed by Denœux (Denœux, 1995, 1997; Zouhal and Denœux, 1998). It has been shown to usually outperform KNN and fuzzy KNN (FKNN) classifiers (Keller et al., 1985), and several variants have been developed. In

EKNN, each neighbor of a query pattern is treated as an item of evidence (i.e., BBA) that supports certain hypotheses regarding the class membership. The support degree is defined as a function of distance between this query pattern and its neighbors, and the K BBAs yielded by the K nearest neighbors (NNs) are then combined by the DS rule. The specific process is shown below.

3.1 Evidential K-nearest-neighbor classifier

Let $D_{\rm tr}=\{(\boldsymbol{x}_p,y_p)\}_{p=1}^{M}$ and $\Omega=\{\omega_1,\omega_2,\cdots,\omega_C\}$ be the M labeled training patterns and the label space (i.e., FoD), respectively. Given a query pattern $\boldsymbol{x}_q$, its class label can be assigned in two stages.

1. Its neighbor $\boldsymbol{x}_p$ with actual label $y_p=\{\omega_c\}$ provides a BBA for query pattern $\boldsymbol{x}_q$. This BBA is computed by

$$\begin{cases} m_{q,p}(\{\omega_c\})=\tilde{\alpha}{\rm e}^{-\gamma_c d_{q,p}^{\tilde{\beta}}}, \\ m_{q,p}(\Omega)=1-\tilde{\alpha}{\rm e}^{-\gamma_c d_{q,p}^{\tilde{\beta}}}, \\ m_{q,p}(A)=0, \quad \forall A\in 2^{\Omega}\setminus\{\Omega,\{\omega_c\}\}, \end{cases} \tag{7}$$

where $d_{q,p}$ denotes the Euclidean distance between $\boldsymbol{x}_q$ and its neighbor $\boldsymbol{x}_p$, i.e., $d_{q,p}=\|\boldsymbol{x}_q-\boldsymbol{x}_p\|_2$, and $\tilde{\alpha},\gamma_c$, and $\tilde{\beta}$ denote the tuning parameters. Denœux suggested to set $\tilde{\alpha}=0.95$ and $\tilde{\beta}=1$ as the default values, and γ_c is determined by $1/d_c$, where d_c is the mean distance between two patterns belonging to $\{\omega_c\}$.

2. The DS rule is employed to combine K BBAs provided by K NNs of query pattern $\boldsymbol{x}_q$. Finally, $\boldsymbol{x}_q$ will be assigned to the class with the largest BetP$(\cdot)$ value computed using Eq. (6).

To clearly illustrate the principle of the EKNN classifier, let us consider a simple example. Assume that the label space is $\Omega=\{\omega_1,\omega_2,\omega_3\}$, and that there are several labeled training data and a query pattern $\boldsymbol{x}_q$. These patterns are shown in Fig. 2.

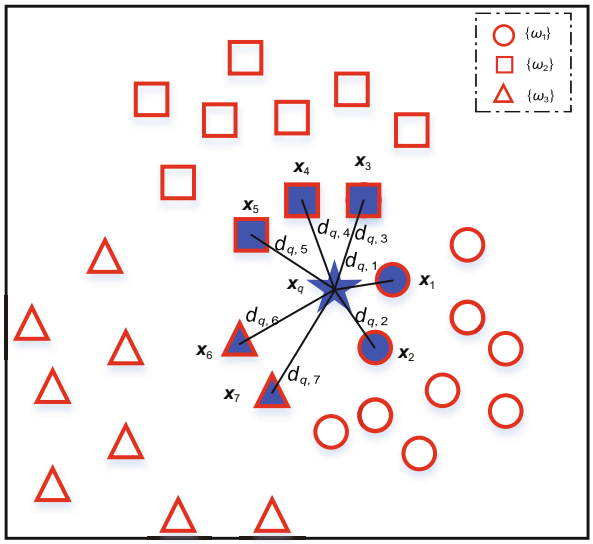

Fig. 2 Training and query patterns

The seven NNs of query pattern $\boldsymbol{x}_q$ are $\boldsymbol{x}_1$, $\boldsymbol{x}_2$, $\boldsymbol{x}_3$, $\boldsymbol{x}_4$, $\boldsymbol{x}_5$, $\boldsymbol{x}_6$, and $\boldsymbol{x}_7$. Then, we can obtain the distances: $d_{q,1}$, $d_{q,2}$, $d_{q,3}$, $d_{q,4}$, $d_{q,5}$, $d_{q,6}$, and $d_{q,7}$. The BBAs provided by these seven NNs can be computed using Eq. (7). Suppose that the resulting BBAs are

$$\boldsymbol{m}_{q,1}: m_{q,1}(\{\omega_1\})=0.90, m_{q,1}(\Omega)=0.10;$$
$$\boldsymbol{m}_{q,2}: m_{q,2}(\{\omega_1\})=0.85, m_{q,2}(\Omega)=0.15;$$
$$\boldsymbol{m}_{q,3}: m_{q,3}(\{\omega_2\})=0.70, m_{q,3}(\Omega)=0.30;$$
$$\boldsymbol{m}_{q,4}: m_{q,4}(\{\omega_2\})=0.70, m_{q,4}(\Omega)=0.30;$$
$$\boldsymbol{m}_{q,5}: m_{q,5}(\{\omega_2\})=0.65, m_{q,5}(\Omega)=0.35;$$
$$\boldsymbol{m}_{q,6}: m_{q,6}(\{\omega_3\})=0.60, m_{q,6}(\Omega)=0.40;$$
$$\boldsymbol{m}_{q,7}: m_{q,7}(\{\omega_3\})=0.55, m_{q,7}(\Omega)=0.45.$$

Their DS combination is computed by $\boldsymbol{m}_{\rm DS}=\boldsymbol{m}_{q,1}\oplus_{\rm DS}\boldsymbol{m}_{q,2}\oplus_{\rm DS}\boldsymbol{m}_{q,3}\oplus_{\rm DS}\boldsymbol{m}_{q,4}\oplus_{\rm DS}\boldsymbol{m}_{q,5}\oplus_{\rm DS}\boldsymbol{m}_{q,6}\oplus_{\rm DS}\boldsymbol{m}_{q,7}$:

$$\begin{aligned}\boldsymbol{m}_{\rm DS}:\quad & m(\{\omega_1\})=0.6440, m(\{\omega_2\})=0.3015,\\ & m(\{\omega_3\})=0.0447, m(\Omega)=0.0098.\end{aligned}$$

The BetP$(\cdot)$ value for each class is computed as follows:

$$\text{BetP}(\{\omega_1\})=m(\{\omega_1\})+\frac{m(\Omega)}{3}=0.6473;$$
$$\text{BetP}(\{\omega_2\})=m(\{\omega_2\})+\frac{m(\Omega)}{3}=0.3048;$$
$$\text{BetP}(\{\omega_3\})=m(\{\omega_3\})+\frac{m(\Omega)}{3}=0.0479.$$

Thus, the query pattern $\boldsymbol{x}_q$ is assigned to class $\{\omega_1\}$ because BetP$(\{\omega_1\})$ has the largest value.

3.2 Variants of the evidential K-nearest-neighbor classifier

From the above introduction and example, we can find that this mechanism provides a global treatment of imperfect information regarding the class membership of training data. This idea has inspired researchers to develop a variety of ET-based methods to address different data mining issues. The basic information of these methods is summarized in Table 2.

Table 2 Summary of different variants of the EKNN classifier

Reference	Method	Publication
Su et al. (2010)	IGA-EC	ESWA
Jiao et al. (2015b)	CCW	Neurocomputing
Su et al. (2018)	EKNN-PCTRs	KBS
Denœux et al. (2019)	CD-EKN	IJAR
Jiao et al. (2019)	EEKNN	Electronics
Gong et al. (2021a)	EIS	IJAR
Gong et al. (2022a)	GE-EKNN	BELIEF
Gong et al. (2022c)	JEKNN	ICDE
Gong et al. (2024)	LA-EKNN	IEEE TBD
Gong et al. (2025)	MvEKNN	INFFUS

When EKNN is applied to the data classification problem, the parameters used to define the weighting factor as a function of distance are often fixed heuristically. To address this issue, Zouhal and Denœux (1998) proposed to learn the parameters by minimizing the mean-squared error between pignistic probabilities and class indicator variables. Moreover, Su et al. (2010) proposed an immune genetic algorithm-based adaptive evidential classification rule (IGA-EC), which adaptively searches for globally optimal parameters. As a result, the classification

performance of EKNN can be significantly improved because the learned parameters are obtained to make the combination results closer to the ground truth.

In EKNN, the DS rule is employed to integrate useful information from the K NNs. This rule can be applied when the sources of evidence (i.e., BBAs) are distinct, but this assumption may be difficult to satisfy in some cases. Denœux (2008) proposed a cautious rule to combine non-distinct evidence, which is expected to further improve the classification performance of EKNN. Inspired by this, Su et al. (2018) proposed a new EKNN classification method by optimizing a class of parametric conjunctive t-rules (i.e., cautious rules), namely EKNN with parametric conjunctive t-rules (EKNN-PCTRs). For a query pattern, PCTRs were employed to combine the BBAs provided by its neighbors.

In practice, another major limitation in the KNN classifier is that all training data are considered equally important in the assignment of the class label to the query pattern. To address this issue, the evidential editing version of KNN (EEKNN) (Jiao et al., 2019) was proposed to reassign the original training patterns with new labels represented by an evidential membership structure. Then, a t-norm rule was optimized to combine these BBAs yielded by the K NNs of a query pattern. By doing this, the patterns situated in overlapping regions will have less influence on the final class decision.

As is well known, the classification performance of the KNN classifier usually depends on the neighborhood size K and the distance metric used. The EKNN classifier can be improved if we can automatically learn the optimal K value and distance metric. Gong et al. (2022c) designed a joint EKNN (JEKNN) classifier to simultaneously learn the adaptive K value and distance matrix based on the feedback from an objective function. Jiao et al. (2015b) designed a class-conditional weighted (CCW) distance metric, where feature weights are linked to a prototype's actual class and a query's hypothesized class, derived by training set statistics. The method builds a multi-hypothesis classifier, performs sub-classification under each hypothesis, and then fuses results via ET to obtain the final classification decision.

To apply EKNN in big data classification, Gong et al. (2022a) developed a distributed processing strategy on Apache Spark, called global exact EKNN (GE-EKNN), to reduce time and memory constraints. The training dataset is divided into multiple partitions, with candidate K NNs identified for each testing pattern through map operations applied to the corresponding split. Subsequently, candidate K NNs from these splits are consolidated to determine the exact K NNs, and the classification result is obtained by combining the BBAs produced by the exact K NNs. Gong et al. (2024) proposed a local approximate EKNN (LA-EKNN) classifier using the distributed gradient algorithm to estimate the parameters. This approach can reduce the negative influence caused by distribution differences across multiple datasets. The evidential instance selection (EIS) method for KNN classification (Gong et al., 2021a) uses ET to fuse information from neighbors and identify boundary instances. Furthermore, a distributed version with Apache Spark effectively balances scalability and classification accuracy, making it suitable for big data applications.

To improve EKNN interpretability and performance on multi-view data, Gong et al. (2025) developed a multi-view EKNN (MvEKNN) classifier, which uses ET to address challenges like soft labels and overlapping feature spaces. To adapt EKNN to partially supervised data where only imprecise class information is available, Denœux et al. (2019) developed a contextual discounting EKNN (CD-EKNN) classifier using the conditional evidential likelihood and the contextual discounting operation.

Overall, all EKNN classifier variants are developed with targeted optimizations to address the key limitations of the original EKNN classifier in practical applications, covering multiple research directions and application scenarios. In future work, dynamic conflict-aware evidence fusion can be incorporated into EKNN to achieve deep integration with deep learning for complex unstructured data classification, and to expand EKNN to hierarchical or multi-objective classification.

4 Classification rules in shallow learning using evidence theory

In tabular data classification, uncertainties often arise for many reasons. They can be divided into two major categories: (1) attribute/feature-based view, e.g., high-dimensional feature (HDF), missing attribute values (MAV), and feature distribution shift (FDS); (2) label-based view, e.g., imbalanced label distribution (ILD), inconsistent label spaces (ILSs), and class overlap (COL). As ET can handle uncertain information, many classification methods based on ET are proposed to represent and reduce uncertainty.

4.1 Tabular data classification with high-dimensional features

In practice, feature dimensionality of patterns in real data usually affects classification performance. When the Euclidean distance is used, the curse of dimensionality may cause classification methods that rely on computing distances between patterns to perform poorly (He YL et al., 2022; Song et al., 2022; Xue et al., 2023). The training and test data with N-dimensional features are shown in Fig. 3, and the corresponding trend of classification accuracy with respect to (w.r.t.) dimension N is shown in Fig. 4. In general, classification performance decreases when N becomes very large. How to apply ET-based classification rules to accurately recognize high-dimensional tabular data remains an important research topic.

In recent years, various methods have been proposed to address this issue, as summarized in Table 3.

Table 3 Summary of ET-based high-dimensional tabular data classification methods

Reference	Method	Publication
Lian et al. (2015)	TCS	PR
Lian et al. (2016b)	EDML	IEEE TFS
Geng XJ et al. (2021)	EARC-HD	ICCBDA
Su et al. (2021)	REKNN	IEEE TFS
Ju et al. (2022)	NHEI-AR	INS
Gong et al. (2023)	SEKNN	IEEE TKDE
Liu YW et al. (2025)	GEKNN	BDCC

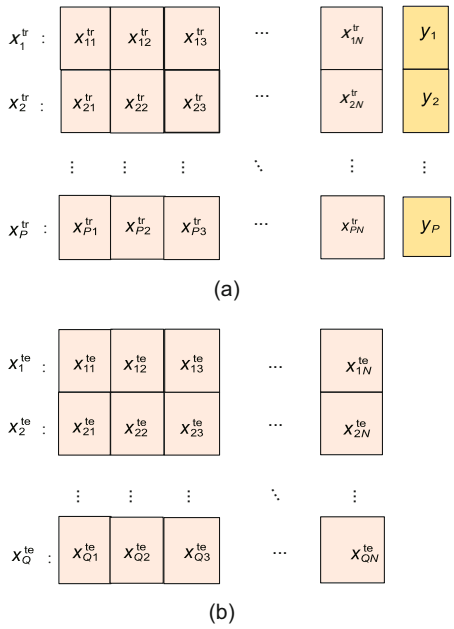

Fig. 3 Training (a) and test (b) data with N-dimensional features

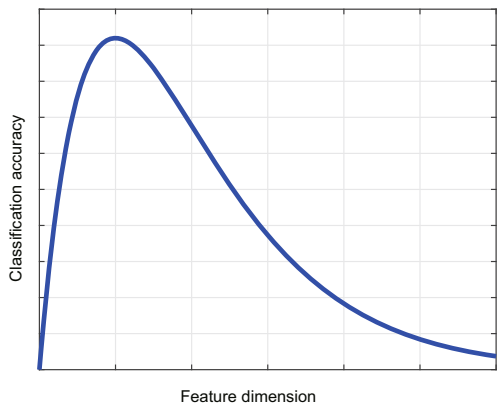

Fig. 4 Classification accuracy w.r.t. feature dimension (N)

Metric learning and feature selection/extraction approaches can be embedded into EKNN to improve the classification performance on high-dimensional features. Lian et al. (2016b) addressed this problem by employing low-dimensional feature transformation, i.e., extracting features from the original high-dimensional feature space. EKNN embedded with their method, called evidential dissimilarity metric learning (EDML), can improve both classification accuracy and efficiency. Moreover, it is often desirable to identify which features play crucial roles in classification; therefore, it is meaningful to alleviate the curse of dimensionality through feature selection rather than feature extraction. Accordingly, an evidential classifier based on feature selection and a two-step classification strategy was proposed in Lian et al. (2015). This method aims to select a subset of useful features to facilitate data interpretation and improve classification performance. However, the computational complexity of these methods may limit their applicability to very large datasets. To address this issue, Su et al. (2021) proposed a rough EKNN (REKNN) rule. REKNN selects useful features and reduces computational complexity by minimizing the neighborhood pignistic decision error, considering both the Bayes decision error and spatial information. This rule can usually achieve good classification performance and efficiency, especially when the feature dimension is high and the dataset is large. Nevertheless, feature extraction (or selection) may result in the loss of structural information in the original data. Gong et al. (2023) further developed a sparse reconstructive EKNN (SEKNN) classifier to preserve the local structural information for high-dimensional data classification. In SEKNN, an appropriate K value for each pattern and the dissimilarity matrix measured by correlation coefficients rather than a distance function are first learned. Then, each query pattern is reconstructed using the training data and classified based on the DS combination results of BBAs.

Attribute reduction (AR) is also a promising strategy for high-dimensional data classification, and several ET-based AR methods have been proposed in recent years. Ju et al. (2022) developed a method called neighbor homogeneous evidence information-based attribute reduction (NHEI-AR). In NHEI-AR, a mutual neighborhood rough set module is first introduced to allocate different neighborhood radii to objects in regions with different densities, and to describe the bidirectional relationship during information granularity processing. Then, evidence information is used to establish a coverage criterion for justifiable granularity, i.e., to obtain an adaptive neighborhood radius.

In addition, association rule-based classification (ARC) has been widely used in practice (Ribeiro et al., 2008; Alcala-Fdez et al., 2011; Hadi et al., 2018), but it is often less effective for high-dimensional data. Therefore, several ARC methods integrated with ET have been developed. Geng XJ et al. (2021) presented an evidential association rule-based classification method for high-dimensional data (EARC-HD). Specifically, an entropy-based fuzzy partition strategy is developed to generate a set of adaptive fuzzy regions, which helps model the high-dimensional feature space using fewer rules. Then, a genetic rule selection process is employed to obtain a compact set of rules with high classification accuracy.

In conclusion, these studies collectively demonstrate the potential of ET-based approaches in classifying tabular data with high-dimensional features. The proposed methodologies, including dissimilarity metric learning, feature selection or extraction, sparse reconstruction, attribute reduction, and association classification, illustrate diverse strategies to address the challenges posed by high-dimensional feature spaces in classification tasks. Further exploration and refinement of these methods may contribute to improved classification accuracy and efficiency in high-dimensional data scenarios.

4.2 Tabular data classification with missing attribute values

In pattern classification, missing attributes are common and can arise for various reasons (Williams et al., 2007; Liew et al., 2011; Deb and Liew, 2016; Zhang WA et al., 2017; Wang LC et al., 2018). A schematic of incomplete data is shown in Fig. 5.

The missing attribute issue degrades the quality of data, and the uncertainty will become high. Thus, many data-driven

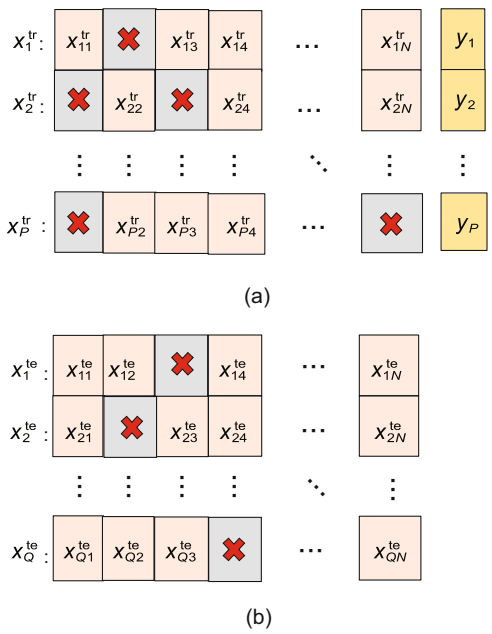

Fig. 5 Training (a) and test (b) data with missing attribute values

classification methods cannot perform well on tabular data with missing attribute values. In general, their classification performance would be significantly improved if ET is employed to represent and reduce uncertain information. For the past few years, many ET-based methods have been developed to make accurate class decisions as much as possible for data classification with missing attribute values. The basic information of these methods is shown in Table 4.

Table 4 Summary of ET-based missing attribute tabular data classification methods

Reference	Method	Publication
Liu ZG et al. (2015a)	CCI	KBS
Liu ZG et al. (2015b)	PCC	IEEE TCYB
Liu ZG et al. (2016)	CCAI	PR
Zhang ZW et al. (2021)	EICA	INS
Zhang ZW et al. (2022a)	BCC	IEEE/CAA JAS
Zhang ZW et al. (2022b)	OAME	IEEE TSMC-S
Huang LQ et al. (2025b)	MICA	IEEE TNNLS
Huang LQ et al. (2025e)	DAF	ICASSP
Huang LQ et al. (2026b)	IDAC	MIR
Huang LQ and Liu (2026)	DJCA	IEEE TNNLS

4.2.1 Credal partitioning with evidential fusion

In practice, the evidential combination of soft classification results of query patterns with multiple estimated missing values, which are yielded by imputation methods, can effectively reduce uncertainty and improve classification performance. Liu ZG et al. (2015b) developed a method called prototype-based credal classification (PCC) to solve the incomplete data classification issue. In PCC, the prototypes obtained from complete training data are employed to estimate multiple values of the missing attributes for an incomplete pattern, and the soft classification results of these patterns with different estimations are combined by ET. To further improve the performance, a new credal classification method for incomplete patterns (CCI) (Liu ZG et al., 2015a) is designed. The major difference from PCC is that CCI employs the K NNs of an incomplete pattern to estimate its missing attribute values. Afterwards, K soft classification results, which are yielded with K versions of estimated values, are combined by ET. Moreover, Liu ZG et al. (2016) developed a method called credal classification with adaptive imputation (CCAI) for incomplete data to obtain lower error rates. In CCAI, some incomplete patterns are directly classified (i.e., the estimation of missing values is not considered) if the specific classification result can be obtained, and then the self-organizing map and KNN techniques are applied to estimate the missing attribute values for the remaining incomplete data. CCAI has achieved a good compromise between estimation accuracy and computation burden compared with PCC and CCI.

In the data classification field, a reliability matrix can be employed to correct the soft classification of query patterns. The performance of incomplete data classification methods could be further improved if we can embed the reliability matrix into the incomplete data classification issue. Zhang ZW et al. (2021) developed a method called the evidence integration credal classification algorithm (EICA). In EICA, the dataset is first divided into several subsets, and the missing values in each subset are estimated by similar sub-patterns with different weights. The greater the variation in distribution across classes, the greater the weight. The classification results of the edited subpatterns with different discounting factors obtained by the optimization function are globally fused to make the class decision. An optimized and adaptive multi-estimation (OAME) (Zhang ZW et al., 2022b) method is further designed to obtain high classification accuracy. To be specific, some incomplete training patterns are estimated with multiple versions by global optimization, and the test pattern is adaptively estimated with one or multiple versions by neighbors. The classifiers' soft outputs with different weights are combined for a credal decision. The method called belief combination of classifiers (BCC) (Zhang ZW et al., 2022a) first regards attributes as independent sources to yield multiple subsets, and then multiple classifiers are trained with each subset independently. It allows each observed attribute to provide a sub-classification result. Finally, these sub-classification results are combined using the DS rule for a class decision.

4.2.2 Distribution alignment with evidence combination

In practice, imputed attribute values are not actual attribute values, so the attribute imputation process will change data distributions. This phenomenon is illustrated in Fig. 6.

In other words, the distribution function of imputed data is not the same as that of complete data. Fig. 7 illustrates this issue.

A novel solution to incomplete data classification is that we can reduce the distribution difference (of training and test data) caused by missing attributes. For example, the dual joint covariance alignment (DJCA) method (Huang LQ and Liu, 2026) is designed to address the problem of incomplete data classification when both the training and test data are incomplete, from the perspective of distribution alignment. In DJCA, the differences in the global and local covariance

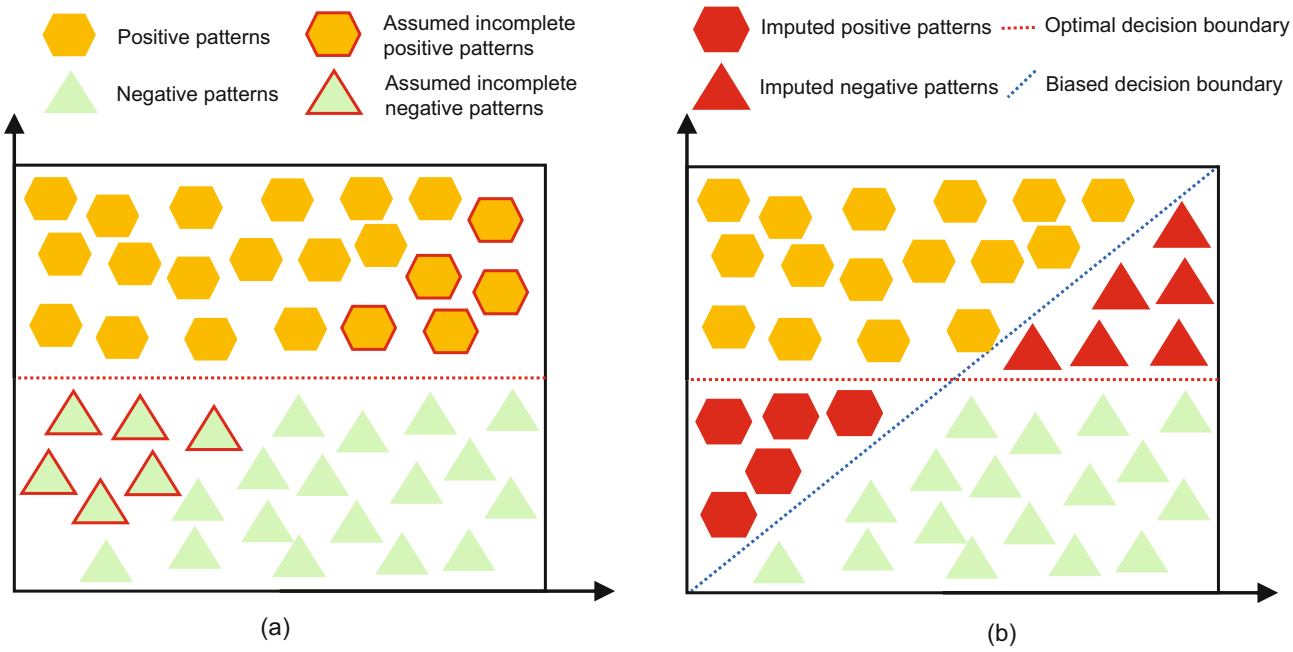

Fig. 6 Schematic of complete (a) and imputed (b) data

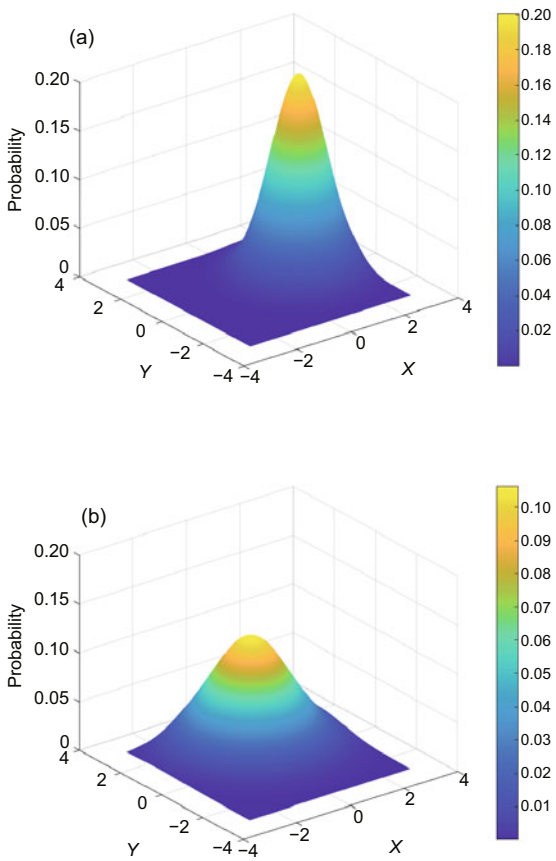

Fig. 7 An example illustrating the distribution functions of complete (a) and imputed (b) data

matrices between the imputed training data and the imputed test data are reduced to achieve distribution alignment. For the classification issue with incomplete training and complete test data, a method called integration of multi-kind imputation with covariance adaptation based on ET (MICA) (Huang LQ et al., 2025b) is developed. To be specific, incomplete training datasets are imputed by multiple kinds of missing value estimation methods, and then we can obtain multiple imputed incomplete training datasets. Afterwards, the covariance difference between each imputed incomplete training dataset and test dataset is reduced to yield multiple soft classification results. Finally, the evidence combination of these soft classification results is employed to make the class decision. In practice, the quality of imputed attribute values significantly affects the performance of downstream classification, so the imputed values should be improved if we want to achieve higher classification accuracy. For this purpose, a new method called incomplete data classification based on distribution alignment with evidence combination (IDAC) (Huang LQ et al., 2025e, 2026b) is developed for the classification problem with complete training data but incomplete test data. In IDAC, the missing values in the test data are first imputed based on the mean vectors computed from the complete training data. It can guarantee that the first-order distribution difference is small. Then, the second-order statistical distributions of training data and imputed test data are aligned to learn two feature transformation matrices. For a query pattern, two soft classification results obtained with the aid of transformation matrices are fused via ET to determine the final class.

To sum up, ET-based incomplete data classification methods exhibit advantages in handling missing attribute values within tabular data. While these studies offer innovative approaches, further research is needed to explore their practical applications in greater depth and optimize their performance across different fields. The continuous exploration and refinement of ET-based methods could significantly enhance their utility in the incomplete data classification field.

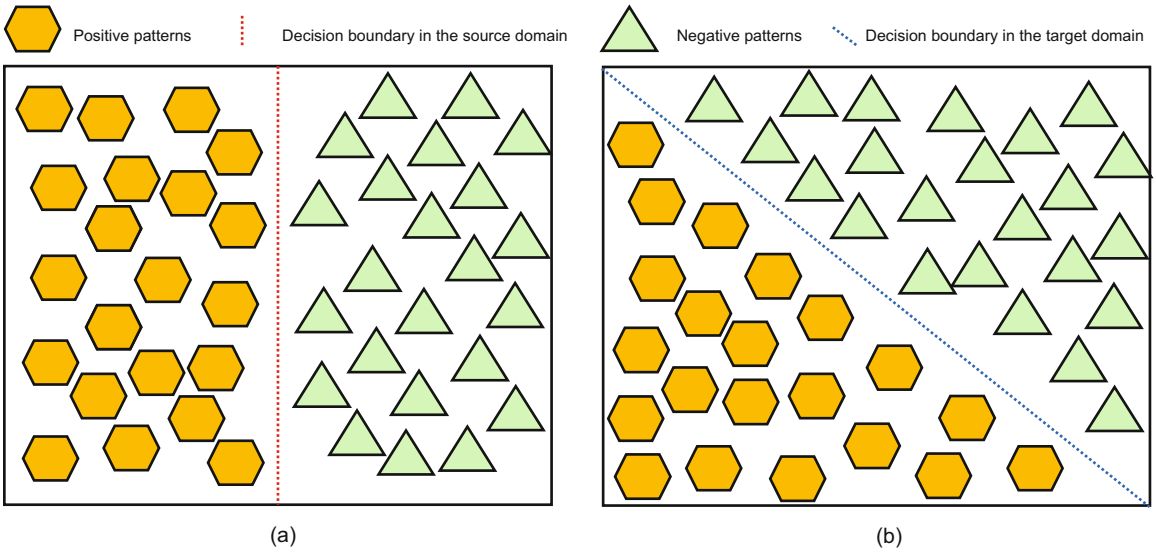

Fig. 8 Schematic of source-domain (a) and target-domain (b) data

4.3 Tabular data classification with feature distribution shift

In data classification, we usually assume that training and test data have the same distributions. However, the FDS issue (i.e., distributions of training and test data are different) often arises because of many common reasons (Niu ST et al., 2020; Chen M et al., 2021; Zhuang et al., 2021). A schematic is shown in Fig. 8.

In real-world applications, FDS will result in uncertainty, degrading downstream classification performance. Thus, designing ET-based methods for tabular data classification with FDS becomes a hot research topic. As for data classification with distribution shift, training data and test data are usually called source- and target-domain data, respectively. Thus, it is also known as a cross-domain classification task if we train a classification model using source-domain data to classify target-domain data. Recently, many ET-based cross-domain classification methods have been proposed to handle this task. Their basic information is shown in Table 5.

Table 5 Summary of ET-based distribution shift tabular data classification methods

Reference	Method	Publication
Huang LQ et al. (2020)	ECAMI	SCIS
Liu ZG et al. (2021a)	CTC	IEEE TNNLS
Liu ZG et al. (2021c)	EHTC	IEEE TSMC-S
Chen L et al. (2022)	TNT	AAAI
Dai et al. (2022)	GCL-OSDA	KBS
Huang M and Zhang (2022)	MAN-DS	Mathematics
Liu ZG et al. (2022b)	BDTC	IEEE TCYB
Lv et al. (2022)	SVMU	Entropy
Huang LQ et al. (2023a)	MTWF	KBS
Huang L et al. (2023b)	DAET	IEEE TCYB
Huang LQ et al. (2024b)	EMDA	IEEE TNNLS
Lv et al. (2023)	Lv et al. (2023)'s	CIKM
Huang LQ et al. (2025c)	MMET	IEEE TIM
Huang LQ et al. (2025d)	MET	IEEE TSMC-S
Huang LQ et al. (2026a)	RMST	IJAR

A method called distribution adaptation with ET (DAET) (Huang L et al., 2023b) is developed for cross-domain data classification when one single source domain and one single target domain are available. The core idea of DAET is that ET is employed to combine supervised information in the source domain and pseudo supervised information in the target domain. To solve the cross-domain classification problem with multiple source domains and one single target domain, a new framework called combination of transferable classification (CTC) (Liu ZG et al., 2021a) is designed. To be specific, the soft classification results after employing domain adaptation techniques, which aim to reduce the distribution difference between each source domain and target domain, are effectively combined by ET for class decision-making. Moreover, an evidential combination of augmented multi-source of information (ECAMI) method (Huang LQ et al., 2020) is developed to improve the data classification performance from multiple source domains to a single target domain. In ECAMI, the source domains are augmented by simple merging of different source domains, and then some augmented source domains are selected. The soft classification results yielded by the assistance of the selected source domains are combined by ET with a weighted DS rule. A new method called multi-source transfer learning based on two-stage weighted fusion (MTWF) (Huang LQ et al., 2023a) is further proposed to represent and reduce the local uncertain information when some classes are not easy to classify. In MTWF, EKNN is extended to output BBAs for the union of two classes, and this operation can well measure the local uncertainty. Afterwards, the weighted DS rule is employed to combine these BBAs yielded by different source domains. The robust multi-source transfer (RMST) method (Huang LQ et al., 2026a) employs the classifier fusion strategy to obtain high-quality distribution alignment results, and then the soft classification results (i.e., BBAs) yielded by multiple source domains are combined by ET. The corresponding weights of these BBAs are estimated by classification

accuracy in the source domain and distribution discrepancy across domains.

When one single source domain and multiple target domains are available, an evidential multi-target domain adaptation (EMDA) method was developed in Huang LQ et al. (2024b) to integrate the complementary information in different domains using ET. In EMDA, multiple target domains are first merged as a new target domain, and then the distributions of the source domain and this target domain are aligned to select some high-confidence target-domain patterns. The two classifiers trained by source-domain data and these high-confidence target-domain patterns are combined by ET to classify query patterns in each target domain. To effectively extract and combine the useful information in different target domains, a method called multi-target domain adaptation based on ET (MET) (Huang LQ et al., 2025d) is further designed. Specifically, for a certain target domain, the remaining target domains are randomly combined to yield some new target domains, and then the distribution discrepancies between the source domain and these new target domains are separately reduced. Multiple soft classification results will be obtained after aligning the distributions, and a weighted DS rule in ET is employed to combine these soft classification results to make the final class decision. In some extreme cases, multiple source domains and multiple target domains are usually available, so the multi-source multi-target domain adaptation based on ET (MMET) method (Huang LQ et al., 2025c) is proposed to deal with this issue. The useful information in source and target domains is combined from the decision-level view, i.e., by a weighted DS rule in ET.

For deep domain adaptation problems, Lv et al. (2023) proposed a fusion strategy based on feature simulation. Specifically, the nearest neighbor features of ImageNet data are used to represent target-domain patterns, and then BBAs are constructed through the reproducing kernel Hilbert space (RKHS) distance. The fused simulated feature vectors are optimized with the coordinate ascent method for a class decision. Similarly, based on the RKHS distance, the SVM with uncertainty measure (SVMU) (Lv et al., 2022) method calculates mass values for similar and dissimilar patterns separately, focusing on source-domain patterns and their corresponding labeled target-domain neighbor sets. It obtains the final fusion result through the multi-fusion ET network. A new method called multi-source-domain adaptation network with Dempster–Shafer ET (MAN-DS) (Huang M and Zhang, 2022) designs the domain-specific subnetworks aligned with MMD, and outputs classification results through a classical evidence fusion process. To improve the robustness of the model, the evidential neighborhood contrastive learning (TNT) framework (Chen L et al., 2022) introduces an adversarial mechanism based on classical evidence fusion classification. It performs high–low adversarial optimization on the uncertainty generated by ET and the converted predicted class probability. In the more complex open-set domain adaptation scenario, a new method called graph collaborative learning for open-set domain adaptation (GCL-OSDA) (Dai et al., 2022) combines an evidence network with multiple binary classifiers to screen unknown classes together. It uses the graph neural network for pseudo-label supervision to enhance the learning effect.

ET also performs well in the traditional machine learning framework on constructed data. The method called evidence-based heterogeneous transfer classification (EHTC) (Liu ZG et al., 2021c) adopts a non-deep learning strategy. It first processes samples using self-organizing map (SOM) clustering and conditional K-means clustering, and then applies evidence fusion to the prediction probabilities of the random forest. The belief-based bidirectional transfer classification (BDTC) method (Liu ZG et al., 2022b) proposes a bidirectional prediction framework (from the source domain to the target domain and from the target domain to the source domain). It uses an SOM to learn clustering reliability weights from labeled target-domain samples, and performs evidence discounting and final fusion on bidirectional prediction results via these weights.

To sum up, the above-mentioned ET-based methods address the FDS issue in tabular data classification through distribution alignment, multi-source evidence fusion, and explicit uncertainty modeling. They can effectively leverage ET's strengths in handling ambiguity and conflicts to bridge the gaps between the source and target domains, adapting to single/multi-source or single/multi-target scenarios. These methods are integrated with traditional domain adaptation techniques to enhance cross-domain classification performance. Future research should focus on adaptive combination rules, deep learning integration for non-linear shifts, and scalable fusion strategies to overcome current limitations in complex real-world applications.

4.4 Tabular data classification with imbalanced label distribution

ILD is a prevalent source of uncertainty in tabular data classification, characterized by significant disparity in the number of patterns across different classes, and has attracted much attention (Gao M et al., 2014; Koziarski, 2020; Mullick et al., 2020; Thabtah et al., 2020; Xie YX et al., 2022). Fig. 9 shows the difference between ILD and balanced label distribution (BLD). It is more challenging to build an unbiased classifier in the ILD setting than in the BLD setting.

The imbalance issue will bias classifiers toward the majority class, leading to insufficient learning of minority class patterns and compromised generalization to unseen data, thereby undermining the reliability and robustness of classification results. ET, which effectively models the uncertainty induced by class imbalance, offers a robust framework for addressing ILD. In recent years, many researchers have proposed various ET-based methods that target ILD from different perspectives, including evidential modeling, evidential resampling, and evidential decision fusion, significantly enhancing the performance of imbalanced data classification. The basic information of these methods is shown in Table 6.

From the perspective of evidential modeling, Kadir et al. (2020) proposed a proximity-weighted EKNN (PEKNN) classifier for imbalanced data. It treats each neighbor as a piece of evidence and assigns higher weights to closer neighbors. The discounted evidence is then fused using the DS rule to reduce the majority bias while keeping uncertainty explicit. In the rule-based family, Fu YG et al. (2021) proposed a novel extended belief rule-based (EBRB) system based on

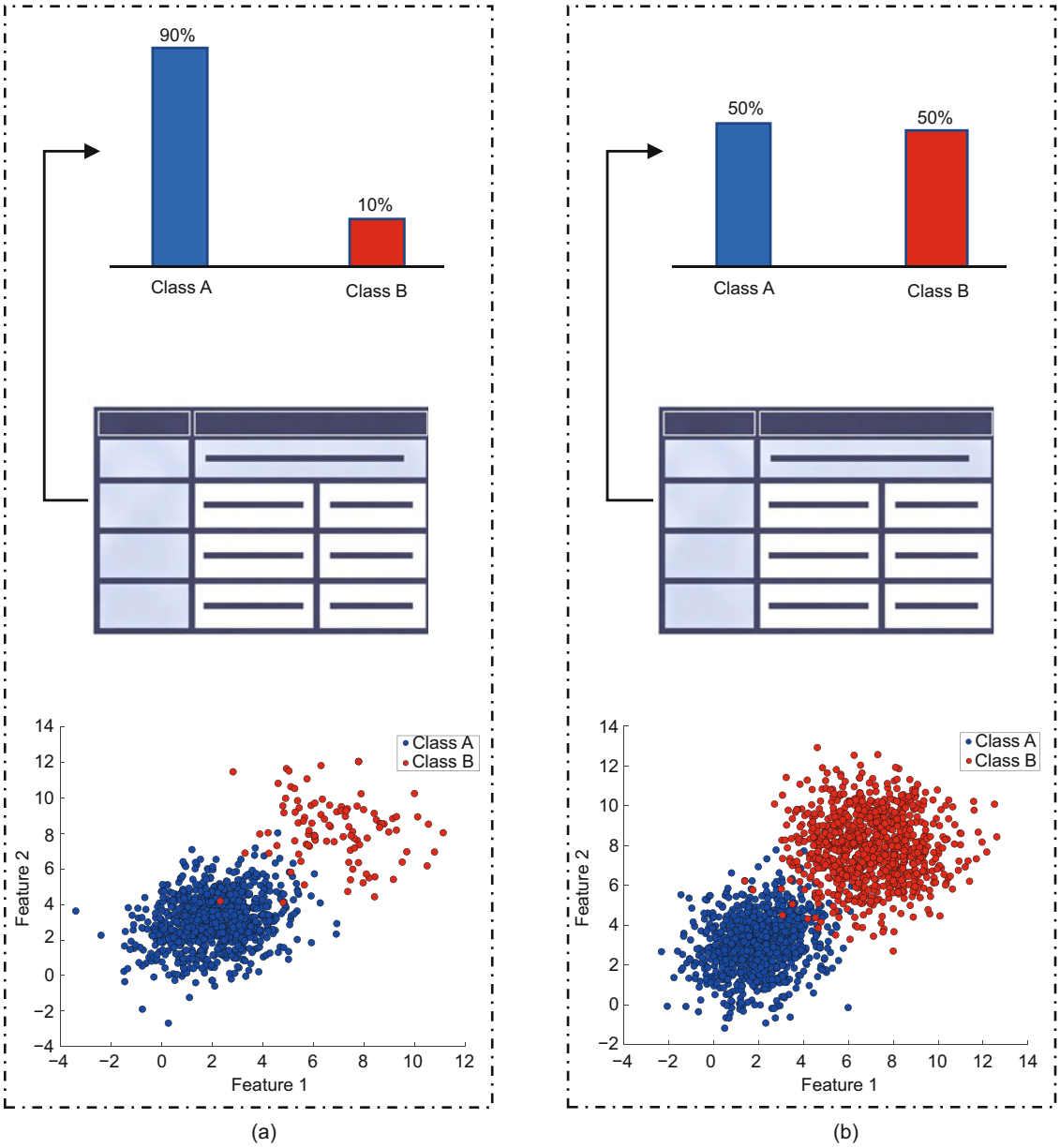

Fig. 9 Data with imbalanced (a) and balanced (b) label distributions

fuzzy C-means clustering (FCM-EBRB). FCM clustering is used to re-balance the data, and the membership degrees are used to generate rules. This produces a belief rule base that is more balanced and more compact. Yang LH et al. (2022) proposed an ensemble EBRB framework. They built diverse base EBRBs using multiple over-sampling techniques. During inference, they also considered the consistency among the activated rules.

Table 6 Summary of ET-based imbalanced tabular data classification methods

Reference	Method	Publication
Kadir et al. (2020)	PEKNN	PAKDD
Fu C et al. (2021)	EREC	INS
Fu YG et al. (2021)	FCM-EBRB	KBS
Zhang JF et al. (2021)	FILM	IEEE TCST
Grina et al. (2022)	E-EVUS	ICSUM
Niu JW et al. (2022)	ECC	IEEE TSMC-S
Tian HP et al. (2022)	RIC	BELIEF
Yang LH et al. (2022)	Ensemble EBRB	KBS
Grina et al. (2023)	E-EVRS	IJAR
Lin and Leony (2024)	EVA	KIS

At the data level, evidential resampling methods use belief functions to decide which samples to remove or generate. For binary classification, Grina et al. (2022) proposed ensemble-based evidential under-sampling (E-EVUS). They assigned soft evidential labels to majority patterns and selectively removed noisy and overlapping patterns. The evidential under-sampling method was then incorporated into a bagging ensemble to learn from the resulting balanced subsets. For the multi-class case, Grina et al. (2023) proposed the ensemble-based evidential

hybrid re-sampling (E-EVRS) method. They defined evidential labels over all classes to detect ambiguous majority samples for under-sampling and to guide borderline over-sampling for minority classes. Then they used a classifier-independent evidential ensemble to combine the results. Lin and Leony (2024) proposed the evidence-based adaptive over-sampling algorithm (EVA). It represents the uncertainty of each minority instance using BBAs, and this reduces the number of low-quality synthetic samples in extremely imbalanced data.

Evidential decision fusion treats different sampling strategies or trained models as heterogeneous evidence sources and combines them based on their estimated reliability. Niu JW et al. (2022) proposed an evidential combination of classifiers (ECC) method, which combines classifiers trained with over-sampling, under-sampling, and hybrid sampling. It uses a reliability matrix to revise the belief degree for each instance, and the revised outputs are then fused using ET. Tian HP et al. (2022) proposed a reliability-based imbalanced data classification (RIC) approach, which creates multiple balanced training sets via repeated random under-sampling of the majority class and trains multiple classifiers. For each test instance, it estimates each classifier's local reliability from neighborhood information, revises the outputs, and fuses them with the DS rule. When reliability is low, neighbor labels are used for an extra correction. Fu C et al. (2021) proposed an evidential reasoning-based ensemble classifier (EREC). It uses re-sampling to reduce class imbalance and then trains an ensemble of ER-based classifiers on the balanced data. Zhang JF et al. (2021) proposed a fused imbalance learning machine (FILM) algorithm for compound fault diagnosis of rotating machinery under severe class imbalance. FILM converts classifier outputs into basic probability assignments and then uses the DS rule to fuse multiple evidence sources for the final fault decision.

In conclusion, these ET-based methods address the ILD issue in tabular data classification through diverse strategies such as sampling optimization, ensemble fusion, and rule base adjustment. These methods leverage ET's strengths in uncertainty modeling and multi-source information fusion to effectively mitigate the negative impact of class imbalance, improving the performance of minority class classification while maintaining the overall classification accuracy. Future research could focus on integrating ET with deep learning for end-to-end imbalanced data classification, developing dynamic evidence combination rules adaptive to class distribution changes, and enhancing the scalability of ET-based methods for large-scale imbalanced datasets. These advancements will further expand the applications of ET in ILD.

4.5 Tabular data classification with inconsistent label spaces

In pattern classification, we usually assume that the training and test datasets have the same FoD, i.e., consistent label space (CLS). It is an interesting research topic to solve the classification problem with inconsistent FoDs, i.e., ILSs, using evidential classifiers (Scheirer et al., 2014; Geng CX et al., 2021; Gil-Gonzalez et al., 2021). The schematic in Fig. 10 shows the ILS issue.

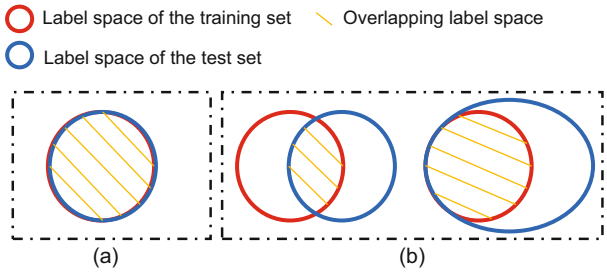

Fig. 10 Schematic of consistent (a) and inconsistent (b) label spaces

Actually, the uncertainty caused by inconsistent label spaces will result in performance degradation for downstream classification tasks. Therefore, we can represent and combine the uncertain information by ET to enhance classification accuracy. Recently, many ET-based methods have been designed for tabular data classification with inconsistent label spaces, and their basic information is shown in Table 7.

Table 7 Summary of ET-based tabular data classification methods with inconsistent label spaces

Reference	Method	Publication
Jiang et al. (2017)	IFoD-GET	MPE
Sun RL and Deng (2019)	MST	IEEE Access
Geng XJ et al. (2020)	RMDF	ASC
Liu F and Deng (2021)	KME	IEEE TFS
Liu ZG et al. (2021b)	CCDF	IEEE TFS
Chen ZC and Cai (2022)	FGS	EAAI
Liu ZG et al. (2022a)	CCIF	CJA
Cui et al. (2023)	Cui et al. (2023)'s	INS
Skau et al. (2023)	Complementary DST	ISIPTA

In Liu ZG et al. (2021b), a credal transformation rule was proposed to transform BBAs over one FoD to those over another FoD, and the transformation matrix was learned to model the relationships between two inconsistent FoDs. The rule mining-based multi-frame decision fusion (RMDF) method (Geng XJ et al., 2020) uses an evidential association rule mining algorithm to discover the relationships among different FoDs, and then these mined rules are properly combined with uncertain decision information by ET. This method successfully models the uncertain relationships among inconsistent FoDs for deriving more accurate decision results. Liu ZG et al. (2022a) developed a new method called combination of classifiers with incomplete frames of discernment (CCIF) to progressively detect the unknown class, improving the overall classification performance. Here, ET is employed to combine the useful information with inconsistent FoDs. Jiang et al. (2017) proposed a new method called identification of incomplete FoDs under the generalized ET framework (IFoD-GET). The empty set is allowed to carry non-zero mass, interpreted as a form of unknown support. Their method first generates evidence from the attributes of each sample, and then employs three parameters related to the empty-set mass to judge whether the FoD is incomplete. These parameters are the mass of the empty set in weight average evidence from the generated pieces of evidence, as a focal element in the generated pieces of evidence, and in the combination of the generated pieces of evidence. In contrast to criteria-driven detection, Sun RL and Deng (2019) developed a graph-based

approach with the minimum spanning tree (MST). For a new sample, they assigned the empty-set mass through an MST covering model and used this mass value as an indicator of FoD incompleteness.

Once an incomplete FoD is detected, a key question is how many unknown classes exist in the open world. Liu F and Deng (2021) proposed a method to detect the number of unknown targets in the open world based on the K-means clustering with elbow method (KME). Specifically, they applied K-means clustering and adopted the elbow method to infer the number of unknown targets, and then updated the FoD accordingly. While this approach is conceptually simple, it may suffer from subjectivity and instability when the elbow point is not visually clear. Chen ZC and Cai (2022) proposed to update an incomplete framework of the target recognition database based on fuzzy gap statistic (FGS). Their method leverages fuzzy C-means (FCM) to handle fuzzy information, and uses FGS to select the number of clusters more objectively. Monte Carlo sampling was further introduced to mitigate local-minimum issues in FCM. Cui et al. (2023) proposed a bidirectional analysis framework that combines gap statistic with isolation forest. Their method first performs forward clustering and then uses isolation-based anomaly detection to split the data into a normal domain and an abnormal domain. Next, reverse clustering focuses on the abnormal domain to extract candidate novel clusters, and a novelty validation standard is defined to confirm truly new clusters. Finally, the sum of base clusters (normal domain) and validated novel clusters (abnormal domain) yields the total target number and enables completion of FoD.

Instead of attributing open-world uncertainty primarily to the empty set, Skau et al. (2023) explored an alternative formulation of DST using complementary sets. They expanded the framework to include the complement of every set of propositions, thus enabling the dynamic inclusion of new propositions as the problem space evolves. Importantly, this approach differs from many previous open-world interpretations that mainly assign openness to the empty set. It uses complementary sets to represent the unspecified propositions in a more structured way. In our opinion, ET uniquely enables open-set classification under incomplete frames of discernment by assigning belief masses to the full frame, explicitly quantifying epistemic uncertainty about unknown classes. Unlike probabilistic models constrained to closed label spaces, ET supports credal decisions and unknown rejection, offering rigorous open-world modeling.

To sum up, the above-mentioned ET-based methods address ILS in tabular data classification through FoD transformation, evidential association rule mining, incremental unknown class detection, and multi-source fusion. These methods effectively leverage ET's strengths in modeling uncertain relationships and fusing heterogeneous information to reduce the negative impact of label space inconsistencies, usually enabling consistent and reliable classification. Future research could focus on developing end-to-end learning frameworks integrated with ET for ILS, enhancing the interpretability of cross-FoD belief transformations.

4.6 Tabular data classification with class overlap

COL constitutes a prominent source of uncertainty in tabular data classification. It arises when different classes share significant common features (i.e., the observed features lack discriminative power), and this issue often leads to ambiguous decision boundaries. Such ambiguity makes it difficult for classifiers to distinguish between overlapping classes, resulting in uncertain predictions and a notable decline in classification accuracy. The COL issue is illustrated by Fig. 11.

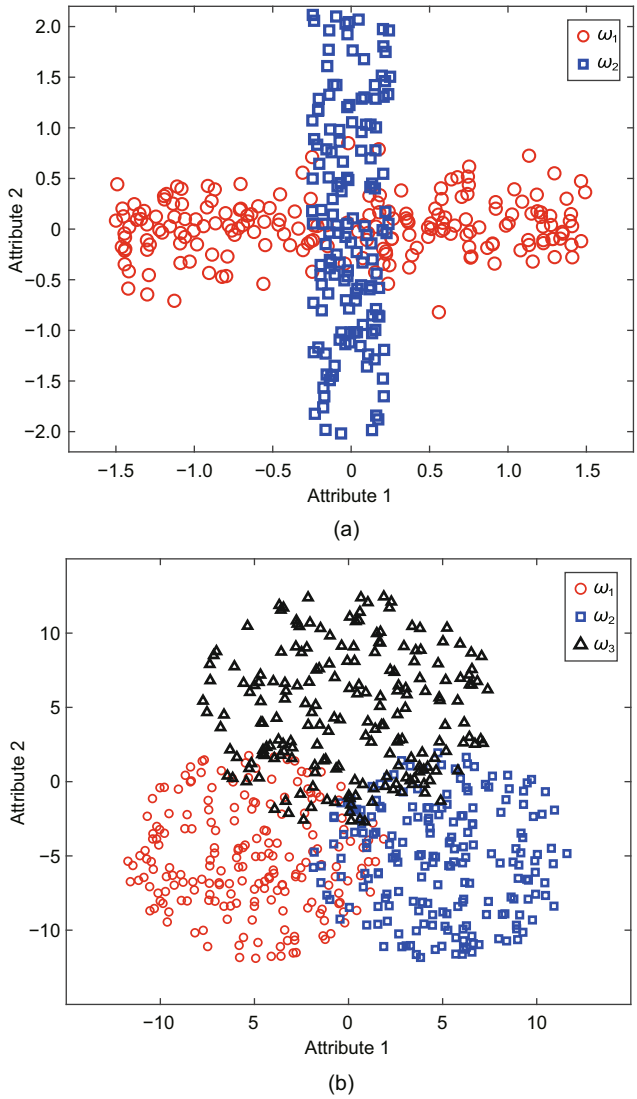

Fig. 11 Data under different class overlap (COL) settings: (a) COL with two categories; (b) COL with three categories

ET excels at modeling ambiguous and uncertain information by allowing BBAs to subsets of classes (rather than a single class), making it well-suited for addressing the COL issue. Recent ET-based methods for COL in tabular data classification focus mainly on credal partition, improved combination rules, and hybrid classification systems. Their basic information is shown in Table 8.

Starting from the neighbor-based evidential classification model, Liu ZG et al. (2013b) proposed a new belief-based KNN (BKNN) classifier. It treats each neighbor as one piece

Table 8 Summary of ET-based tabular data classification methods with overlapping classes

Reference	Method	Publication
Liu ZG et al. (2013a)	EC	KBS
Liu ZG et al. (2013b)	BKNN	PR
Liu ZG et al. (2014a)	BCR	APIN
Liu ZG et al. (2014b)	CCR	PR
Liu ZG et al. (2014d)	BCKN	Neurocomputing
Liu ZG et al. (2017)	HCS	IEEE TSMC-S

of evidence and converts neighbor distances into belief masses based on acceptance and rejection thresholds. Similarly, a new evidential classifier (EC) (Liu ZG et al., 2013a), which introduces an imprecision threshold to allocate BBAs, is designed. It adopts a two-step combination strategy together with discounting to perform evidence fusion. To enrich neighborhood evidence under overlap, Liu ZG et al. (2014d) presented a new belief $C \times K$ neighbor (BCKN) classifier. It searches for K NNs within each class, expands neighborhood evidence into $C \times K$ evidence sources, and performs global fusion to obtain comprehensive support for each class and class set.

In terms of belief-based decision rules, the belief classification rule (BCR) (Liu ZG et al., 2014a) designs a new fusion rule that integrates the strengths of DS and DP rules. Liu ZG et al. (2014b) presented a new credal classification rule (CCR), which introduces a method to compute meta-class centers and further incorporates the distance between an object and the corresponding meta-class center to allocate BBAs. A hybrid classification system (HCS) for partially overlapping classes was developed in Liu ZG et al. (2017), adaptively choosing an appropriate classification method for each pattern based on its KNN information in the weighting vector space obtained by SOMs.

In conclusion, the above-mentioned methods leverage ET's ability to model ambiguity and uncertainty, effectively mitigating the harmful influence of class overlap on classification performance. Future research could focus on developing dynamic combination rules that adapt to varying degrees of class overlap. What is more, exploring the combination of ET with feature selection techniques could further reduce the number of redundant features that exacerbate the class overlap issue.

5 Classification rules in deep learning using evidence theory

DNNs have demonstrated remarkable performance in unstructured data classification, particularly in image analysis. Despite their success, they frequently exhibit critical limitations in modeling aleatoric uncertainty stemming from inherent data randomness, such as ambiguous visual patterns and label noise, and in modeling epistemic uncertainty arising from insufficient training data. These uncertainties (Abdar et al., 2021; He WC et al., 2026), which are pervasive in real-world scenarios, are often overlooked by conventional deep learning models, compromising their reliability in some real-world applications.

ET provides a rigorous framework to quantify and fuse uncertain information, making it a natural complement to deep learning. By integrating ET with DCNNs, researchers have developed a range of evidential deep learning (EDL) methods that enhance the reliability and robustness of image classification. Here, EDL adopts ET to construct BBAs, explicitly distinguishes between aleatoric and epistemic uncertainty, and realizes interpretable uncertainty quantification. These methods focus mainly on belief function modeling, evidential fusion of multi-modal or multi-scale features, and uncertainty-aware training. Their basic information is summarized in Table 9.

Table 9 Summary of ET-based end-to-end image data classification methods

Reference	Method	Publication
Lee et al. (2016)	DBF	WACV
Sensoy et al. (2018)	EDL	NeurIPS
Tong et al. (2019)	ConvNet-BF	SUM
Yuan et al. (2020)	EviNet-UC	KSEM
Han et al. (2021)	TMC	ICLR
Lee and Kwon (2021)	DBF-CMOD	IEEE TPAMI
Tong et al. (2021a)	EDLC	Neurocomputing
Tong et al. (2021b)	MFE-CNN	BELIEF
Han et al. (2022)	MD	CVPR
Li BL et al. (2022)	TLC	CVPR
Liu W et al. (2022)	TMDL	AAAI
Han et al. (2023)	ETMC	IEEE TPAMI
Liu W et al. (2023)	SMDC	AAAI
Xie MY et al. (2023)	UIMC	CVPR
Jiao et al. (2026b)	EDNN	TAI

Among classification methods based on the prototype distance, the CNN with belief functions (ConvNet-BF) classifier (Tong et al., 2019) initially constructs evidence by calculating the distance between features and class prototypes to perform fusion prediction. This concept was subsequently expanded by incorporating fuzzy or credal prediction to output the class–group affiliation of samples (Tong et al., 2021a, 2021b; Jiao et al., 2026b). The mass-fusion evidential CNN (MFE-CNN) (Tong et al., 2021b) fuses pre-trained evidential CNNs via the DS rule. Specifically, each CNN extracts features to generate mass functions on compatible frames, a fusion module aggregates them on a common refinement, and end-to-end fine-tuning with soft labels optimizes all parameters, outperforming other fusion strategies in heterogeneous dataset-based image classification. The evidential deep-learning classifier (EDLC) (Tong et al., 2021a) extracts features via CNN, generates aggregated mass functions through a DS layer, realizes set-valued classification with an expected utility layer, and uses end-to-end training to boost accuracy and cautiousness. Evidential DNN (EDNN) (Jiao et al., 2026b) integrates CNNs with ET, extracting hierarchical features via a CNN-based feature representation module and constructing open-world BBAs through a generalized evidential classifier module. It adopts a utility-based decision module for decision-making, is trained in an end-to-end manner, and yields precise classification, set-valued classification, and novelty detection within a unified framework.

Reliable uncertainty estimation has become a crucial requirement for the deployment of deep learning algorithms (Gao JY et al., 2026), and it is feasible to use ET to measure the uncertainty. Researchers have studied the joint working of deep learning and ET. EDL (Sensoy et al., 2018) designs the

classical framework, which replaces the softmax layer of the network with an ReLU layer. This directly predicts the parameters of the Dirichlet distribution to quantify classification uncertainty. Numerous applications have been derived from this framework (Yuan et al., 2020; Li BL et al., 2022). The EDNN for uncertain data classification (EviNet-UC) method (Yuan et al., 2020) introduces an evidence adjustment term for medical detection scenarios to prioritize false alarms over missed detections. This makes the judgment of high-risk uncertain samples more conservative, thereby improving the recall rate. The trustworthy long-tailed classification (TLC) method (Li BL et al., 2022) uses the inherent uncertainty of ET in long-tail classification to distinguish between easy and hard samples, dynamically determining the number of expert modules to employ.

ET also plays a core role in multi-view and multi-modal scenarios. The uncertainty-induced incomplete multi-view data classification (UIMC) method (Xie MY et al., 2023) completes missing views by sampling based on the nearest neighbor distribution. It jointly optimizes single-view and multi-view representations through evidential loss. The trusted multi-view classification (TMC) method (Han et al., 2021) and its extended version, the enhanced trusted multi-view classification (ETMC) method (Han et al., 2023), use standard evidential deep learning operations to automatically assign weights to different views for fusion. As for multi-modal medical data, multi-modal dynamics (MD) (Han et al., 2022) proposes a sparse gating mechanism to screen important features. It predicts the true class probabilities to evaluate the modality importance for feature discounting, finally concatenating features of each modality to complete the classification. Notably, to reduce the complexity of traditional evidence fusion algorithms and resolve conflict issues, Liu W et al. (2022, 2023) chose to convert network outputs into evidence and directly added them to generate global evidence. The trusted multi-view deep learning (TMDL) method (Liu W et al., 2022) formulates multi-view learning results as opinions via ET, aggregates them through evidence accumulation to reduce uncertainty, adds consistency regulation via opinion entropy, and ensures accurate outcomes. Liu W et al. (2023) further introduced safe multi-view deep classification (SMDC), a safe multi-view deep classification approach that leverages ET for multi-view evidence integration, adopted KL divergence regularization to address the uncertainty issue, and offered theoretical assurance of non-increasing empirical risk to achieve accurate classification without performance degradation. The evidential deep partial label learning (ED-PLL) method (Fan et al., 2026) extends evidential deep learning to PLL by modeling candidate labels as evidence, updating label confidence with belief and credibility, and introducing non-candidate suppression and conflict-aware regularization to quantify disambiguation uncertainty.

As for the object detection task, the dynamic belief fusion (DBF) method (Lee et al., 2016) and its extended version, the dynamic belief fusion for combining multiple object detectors (DBF-CMOD) method (Lee and Kwon, 2021), design the score-level late fusion rule for combining multiple object detectors. They build confidence models based on each detector's precision–recall relationship to dynamically assign basic probabilities to target, non-target, and intermediate hypotheses, and fuse these probabilities via the DS rule to achieve enhanced detection accuracy. This framework gives a way to effectively improve the object detection performance.

In conclusion, integrating ET with deep learning significantly improves the classification accuracy of unstructured image data. This integration enables models to estimate predictive uncertainty more accurately and to fuse information from multiple sources more effectively. It also addresses several key limitations of traditional deep learning models, such as overconfident predictions on ambiguous data and insufficient capacity to handle incomplete information. Future research could develop faster BBA generation methods to reduce computational costs when processing large-scale datasets. Researchers could also integrate ET with emerging deep learning models, such as foundation models and diffusion models, to develop new frameworks for better uncertainty handling and data generation. Moreover, this improved framework can be extended to additional unstructured data types, including text and video, thereby expanding its applicability and practical value.

6 Real-world data classification applications of evidence theory

6.1 Human activity recognition

HAR aims to identify daily or specific actions (e.g., walking and running) from data collected by different sensors. A schematic of HAR using multi-source sensors is shown in Fig. 12.

HAR systems often face challenges like noisy sensor data and multi-source information redundancy. ET excels at handling uncertain information and fusing heterogeneous data, making it a valuable tool for improving HAR performance. In other words, ET explicitly models conflict-aware uncertainty and heterogeneous multi-sensor evidence fusion that cannot be well handled by conventional probabilistic approaches. The designed ET-based HAR methods usually focus on multi-sensor data fusion, uncertainty modeling of ambiguous activities, and adaptive integration of domain knowledge. The basic information of these methods is summarized in Table 10.

Table 10 Summary of ET-based HAR methods

Reference	Method	Publication
Sebbak et al. (2012)	CREF	UbiComp
Sebbak et al. (2013)	Sebbak et al.	RAS
Dong YL et al. (2020)	DSmT-HAR	IEEE TII
Dong YL et al. (2021a)	HFBS	IEEE TFS
Dong YL et al. (2021b)	MCASR	IEEE Sensors Journal
Dong YL et al. (2022)	HHAR	IEEE Sensors Journal
Dong YL et al. (2023a)	w-MSDAER	IEEE TII
Dong YL and Zhou (2023)	Hie-BKNN	CCC
Zhao C et al. (2023)	MULE	CVPR
Zuo et al. (2023)	CDGB	IEEE Sensors Journal
Dong YL et al. (2024)	MGBF	IEEE TNNLS
Geng XJ et al. (2024)	Multi-EARF	IEEE Sensors Journal
Dong YL et al. (2025)	MVUAGCN	IEEE TII

To integrate source reliability into evidence generation, Dong YL et al. (2021b) proposed the multi-criterion analysis

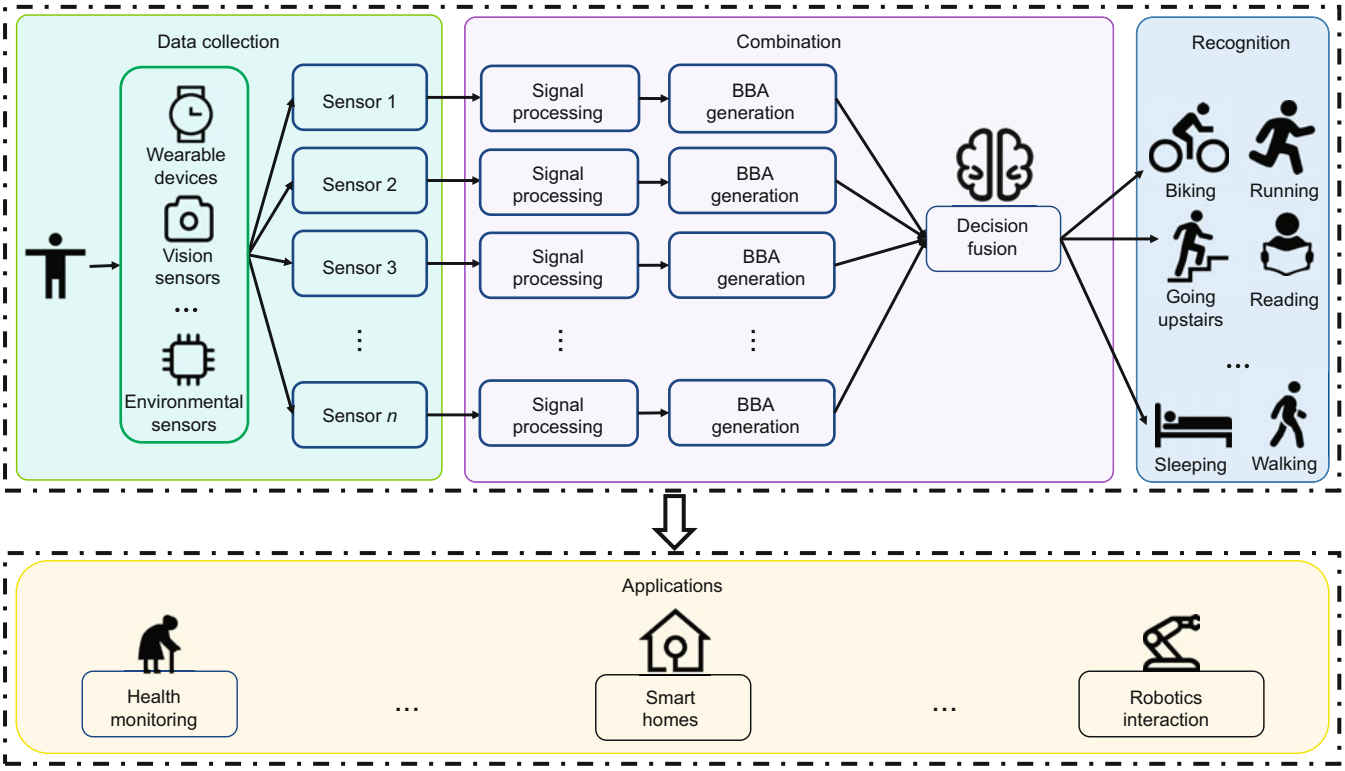

Fig. 12 Schematic of human activity recognition (HAR) using multi-source sensors

framework of sensor reliability (MCASR). In MCASR, sensor reliability weights are derived through a multi-criterion evaluation based on BBAs, which improves the recognition accuracy with uncertainty transparency. Building on reliability assessment, they further developed a method called multi-source weighted domain adaptation with evidential reasoning (w-MSDAER) (Dong YL et al., 2023a). For adaptation from multiple labeled source domains to an unlabeled target domain, the belief function-based technique for order preference by similarity to an ideal solution (BF-TOPSIS) is used to assign reliability weights to different source domains, and weighted evidential reasoning is conducted to enhance stability in the target domain. Compared with MCASR, w-MSDAER extends BF-TOPSIS reliability weighting from sensor-level evidence generation to domain-level source selection. In this way, reliability shifts from serving as an in-domain fusion prior to acting as a cross-domain adaptation mechanism. In addition, Dong YL et al. (2025) designed a multi-view uncertainty-aware graph convolutional network (MVUAGCN) to enhance multi-view information extraction. The major difference from conventional time-series feature learning is that MVUAGCN organizes sliding-window sensor sequences as graph-structured representations and applies graph convolutional networks for feature extraction.

Beyond improving sensor-level data quality, Sebbak et al. (2012, 2013) introduced a new evidential fusion rule. Rather than being discarded simply, conflicting evidence is explicitly defined and converted into a discounting factor to suppress conflict-dominated erroneous decisions. Dong YL et al. (2020) developed a DSmT-based fusion framework that constructs BBAs via kernel density estimation and models missing observation values directly as vacuous BBAs, reducing the imputation bias with improved stability. Dong YL et al. (2021a) proposed the hesitant fuzzy belief structure (HFBS), where the belief assigned to each activity is expressed as a set of all plausible values rather than a single number, and accordingly developed a combination. It enables a finer-grained characterization of ambiguity.

To better distinguish fine-grained activities, Dong YL et al. (2022) proposed a hierarchical activity recognition (HHAR) method, which organizes recognition into a hierarchical process and leverages more reliable coarse-grained decisions to alleviate ambiguities among similar fine-grained activities. Along similar lines, a hierarchical belief KNN (Hie-BKNN) approach (Dong YL and Zhou, 2023) operates on a data-driven hierarchical tree. At each node, it selects K NNs to generate local BBAs and then fuses the outputs to obtain the final decision. A new method called combination of different-granularity beliefs (CDGB) (Zuo et al., 2023) explicitly distinguishes coarse- and fine-grained FoDs. Specifically, the coarse-grained BBAs mapped to fine-grained FoDs help achieve in-domain fusion of different-granularity evidence. Geng XJ et al. (2024) proposed a multi-framework evidential association rule fusion-based activity recognition method (Multi-EARF), which fuses the association rules of different granularity frameworks. It supports more explainable and stable reasoning.

The above-mentioned methods often enlarge the focal-element set and increase combination complexity. To reduce fusion complexity and accelerate the fusion process, Dong YL et al. (2024) designed a novel efficient multi-granular belief fusion (MGBF) method, which treats focal elements as nodes in a graph and selects decision-community nodes based on node

distances to enable efficient fusion. In practical applications, there are open-world deployment scenarios where unknown activities may occur. Thus, Zhao C et al. (2023) proposed the multi-label evidential learning (MULE) method. In MULE, multi-action uncertainty is estimated from feature representations using a Beta evidential network, and the representations are optimized under an evidence-debiasing constraint. Task-specific training and evaluation procedures are adopted to support recognition under single/multiple actors and single/multiple concurrent actions.

To sum up, these ET-based methods enhance HAR performance by addressing key challenges such as multi-sensor data redundancy, activity ambiguity, and domain adaptation. These methods leverage ET's strengths in uncertainty modeling and multi-source fusion to extract reliable information from heterogeneous sensor data. Future research could focus on developing real-time evidential fusion algorithms for low-power wearable devices and extending these methods to recognize complex interactive activities by fusing human–object interaction data. It will expand the application of ET in practical scenarios, e.g., healthcare monitoring.

6.2 Medical image segmentation

MIS refers to the process of partitioning medical images (e.g., CT and MRI) into clinically meaningful regions (e.g., tumors, organs, and tissues). It often serves as a critical step for disease diagnosis. A schematic of MIS is shown in Fig. 13.

In practical applications, MIS faces many significant challenges: low image contrast, blurred anatomical boundaries, noise from imaging equipment, and inter-patient anatomical variations. These factors usually result in high uncertainty in segmentation tasks, making accurate boundary delineation difficult. ET provides a powerful framework for modeling and fusing uncertain information from multiple sources. The ambiguous tissue boundaries and multi-modal imaging uncertainty cannot be well captured by standard probabilistic models, while employing ET can obtain more reliable segmentation results. Recently, researchers have developed a variety of ET-based MIS methods, and this field has experienced rapid evolution. Specifically, it has moved beyond the traditional reliance on feature or cluster methods to realize deep integration with modern deep learning architectures. Their basic information is shown in Table 11.

Table 11 Summary of ET-based MIS methods

Reference	Method	Publication
Lelandais et al. (2014)	SECM	MIA
Lian et al. (2016a)	iEFS	MIA
Lian et al. (2018)	ECM-MS	IEEE TBE
Lian et al. (2019)	CC-BFT	IEEE TIP
Huang L et al. (2021a)	EUNet	MLMI
Huang L et al. (2021b)	ES-UNet	BELIEF
Huang L et al. (2022a)	MMEF	MICCAI
Huang L et al. (2022b)	ENN-UNet	IJAR
Xu SX et al. (2022)	DEF	IJAR
Zhou XQ et al. (2022)	PENet	Methods
Huang L et al. (2023c)	SEFNet	Neurocomputing
Pan et al. (2026)	EviVLM	IEEE TMI

Traditional methods primarily employ ET at the feature engineering or clustering stage. For instance, Lian et al. (2018) developed a method called evidential C-means clustering with an adaptive distance metric and spatial regularization (ECM-MS) for tumor segmentation in three-dimensional (3D) FDG-PET images. ECM-MS applies ET to fuse intensity and texture features within a regularized clustering framework,

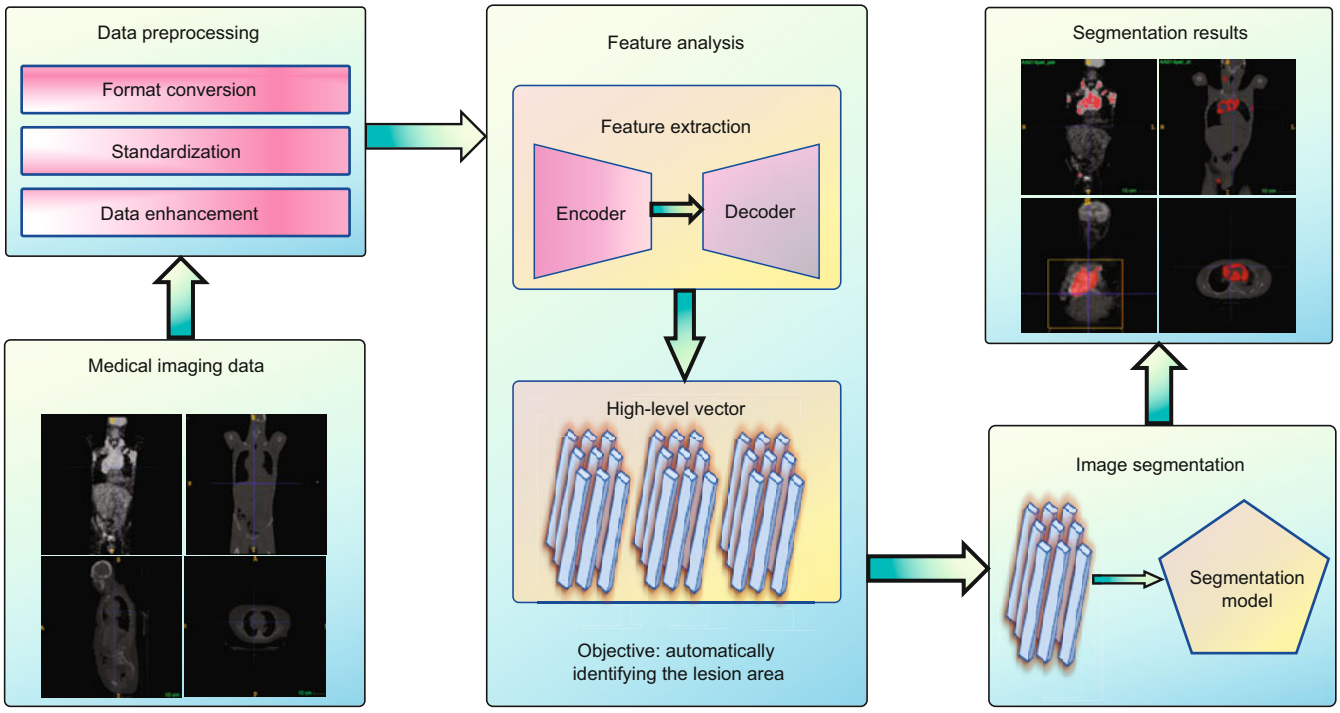

Fig. 13 Schematic of medical image segmentation (MIS)

effectively enhancing segmentation accuracy and robustness. As for multi-modal PET-CT analysis, the co-clustering and fusion based on belief functions (CC-BFT) method (Lian et al., 2019) separately clusters features from PET and CT modalities, and then employs the DS rule to fuse the clustering results. Lian et al. (2016a) designed an improved evidential feature selection (iEFS) framework, which uses ET with an optimization algorithm to identify robust features from PET images. Similarly, Lelandais et al. (2014) introduced the spatial evidential C-means (SECM) algorithm for radiotherapy dose painting, which fuses multi-tracer PET images by explicitly modeling uncertainty and integrating neighborhood information. While these traditional approaches demonstrate the potential of ET, they often remain limited by their dependence on handcrafted features and multi-stage processing pipelines.

The rapid advancement of deep learning is fundamentally transforming this field, enabling the direct integration of ET into end-to-end trainable networks. Current deep evidence-based segmentation methods can be systematically classified into three categories based on their architecture and evidence fusion mechanisms: (1) single-modality evidential segmentation networks; (2) multi-modality evidence fusion networks; (3) evidence networks that incorporate prior knowledge.

Single-modality evidential segmentation networks incorporate standard segmentation backbones into evidential output layers to quantify prediction uncertainty. Representative works include evidential U-Net (EUNet) (Huang L et al., 2021a) and evidential segmentation-based U-Net (ES-UNet) (Huang L et al., 2021b), and they are designed for lymphoma segmentation in 3D PET-CT images. These models replace the conventional softmax layer with an evidence-based output layer, which directly produces BBAs for each class. This design not only yields segmentation maps but also provides uncertainty estimates. For instance, Huang L et al. (2022b) proposed an evidential neural network integrated with the U-Net backbone (ENN-UNet), where an evidential layer uses distances to prototypes in the feature space to compute belief functions. The joint optimization allows the network to balance accuracy and reliability, making it particularly suitable for clinical applications where uncertainty awareness is critical.

Multi-modality evidence fusion networks use ET to combine information from different data sources within a deep learning framework. For brain tumor segmentation with multi-parametric MRI, Huang L et al. (2023c) introduced the semi-supervised multiple evidence fusion network (SEFNet), which operates under limited supervision. SEFNet employs an image transformation strategy to generate diverse evidence from a probabilistic segmentation module and an evidential segmentation module. Then, SEFNet fuses them via the DS rule to reduce the overall uncertainty. Another notable approach is the multi-modality evidence fusion framework (MMEF) (Huang L et al., 2022a), which incorporates a contextual discounting mechanism to assign and adaptively learn the reliability weights for each MRI modality before the evidence combination. This weighting strategy aligns the learned importance of modalities with clinical prior knowledge, thereby improving accuracy and robustness. To address the practical challenge of missing modalities, Xu SX et al. (2022) proposed the deep evidential fusion (DEF) network, which builds upon evidential deep learning and uses the DS combination rule to fuse evidence from any available subset of modalities. It further introduces techniques such as base rate modeling and weighted mass calibration to enhance robustness and performance in small-scale, multi-modal classification tasks. To push the boundaries of multi-modal fusion, Pan et al. (2026) proposed the evidential vision language model (EviVLM), a novel framework that integrates ET with a vision language model (VLM) for medical image segmentation. EviVLM constructs an evidence affinity map generator to enhance the complementarity between image and text features. Then, it employs evidence differential similarity learning to improve cross-modal consistency.

Evidence networks incorporating prior knowledge explicitly integrate clinical or domain-specific priors into the evidential reasoning process. A prominent example is the prior-embedded evidential network (PENet) (Zhou XQ et al., 2022) for bladder cancer staging. PENet encodes clinical rules as prior evidence and combines them with image-derived evidence using a Bayesian fusion framework. This integration not only improves prediction accuracy but also enhances model interpretability by clarifying the contribution of clinical knowledge.

In conclusion, ET-based methods greatly improve the performance of medical image segmentation. They carefully quantify ambiguity, effectively fuse information, and reveal ambiguous lesion boundaries by integrating useful data from CT and MRI images. These methods also use existing medical knowledge to make the segmentation results more consistent. For future research, we can connect ET more closely with advanced models (e.g., medical vision-language models) to add clinical meaning. We also need to enable these methods to work across different image types and medical centers to address data heterogeneity.

6.3 Remote sensing image classification

RSIC involves identifying land cover types (e.g., forests and urban areas) or objects (e.g., ships and buildings) from satellite images. It plays an important role in environmental monitoring. A schematic of RSIC is shown in Fig. 14.

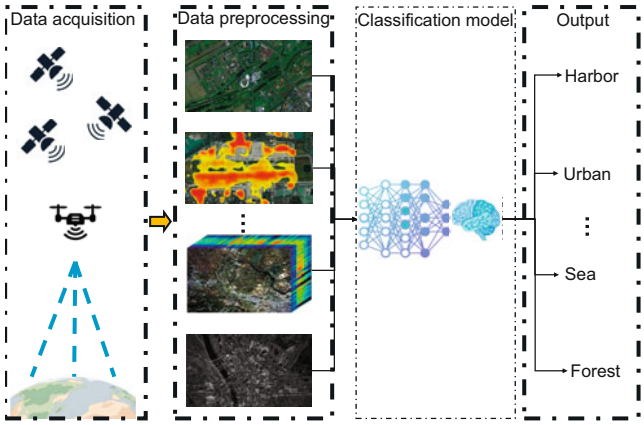

Fig. 14 Schematic of remote sensing image classification (RSIC)

RSIC faces notable challenges, including spectral variability (e.g., the same objects show different colors under

varying conditions) and noise from imaging sensors. These factors introduce high uncertainty to downstream classification tasks. ET excels at modeling uncertain information and fusing multi-source data, making it a reliable tool to enhance RSIC accuracy. Specifically, ET can better measure spectral variability and cross-domain distribution shift uncertainty compared to probabilistic classifiers. The developed ET-based RSIC methods usually focus on multi-source or multi-scale feature fusion and uncertainty-aware classification. Their basic information is shown in Table 12.

Table 12 Summary of ET-based RSIC methods

Reference	Method	Publication
Le Hegarat-Mascle et al. (1997)	ETUC	IEEE TGRS
Zhu HW and Basir (2005)	aFENN	IEEE TGRS
Laha et al. (2006)	LCCET	IEEE TGRS
Dong GG and Kuang (2015)	TRIA	IEEE GRSL
Dong YL et al. (2023b)	E-FPN	RS
Huang LQ et al. (2023b)	ECMS	INFFUS
Ji et al. (2024)	SSEL	IEEE TGRS
Zhang JX et al. (2024)	DELIC	IEEE JSTARS
Feng YB et al. (2025)	HyperEDL	IEEE TGRS
Jiao et al. (2026c)	MBHF-Net	Neurocomputing

Some early research followed the feature extraction, evidence generation, and decision fusion paradigm, focusing on integrating the spatial context or multi-view features via ET. Laha et al. (2006) developed a land cover classification via ET (LCCET) method, which validates the aggregation of pixel and spatial neighborhood information using the DS rule to enhance multi-spectral land cover classification stability. Based on this, feature fusion across multiple modalities or multiple domains has become prevalent. Huang LQ et al. (2023b) proposed the evidential combination of multi-color spaces (ECMS) framework to leverage the complementarity of different color spaces. Dong YL et al. (2023b) used sparse representation residuals to construct evidence for robust SAR target recognition via the DS rule. This methodology is also extended to unsupervised clustering (Le Hegarat-Mascle et al., 1997).

With the development of deep learning, ET has evolved from an external postprocessing tool to a core component for modeling classification uncertainty. This transition is rooted in EDL (Sensoy et al., 2018), which enables the quantification of epistemic and aleatoric uncertainties. In recent years, many remote sensing-oriented EDL methods have been designed. The spectral-spatial evidential learning (SSEL) network (Ji et al., 2024) combines generative adversarial networks with EDL to characterize category uncertainty for hyperspectral unknown class rejection. The hyperspectral EDL (HyperEDL) method (Feng YB et al., 2025) uses spatial–spectral features as evidence and employs evidential loss to suppress cross-scene uncertainty.

Concurrently, some novel mechanisms have been proposed for high-conflict scenarios. Zhang JX et al. (2024) introduced the rearrangement-invariant belief Jensen–Renyi (BJR) divergence for landslide identification. The multi-source belief hybrid fusion network (MBHF-Net) (Jiao et al., 2026c) uses reliability discounting strategies to reduce multi-source target recognition risks. The adaptive fuzzy evidential nearest neighbor (aFENN) framework (Zhu HW and Basir, 2005) treats the NNs as fuzzy evidence to bolster neighborhood classification robustness.

In conclusion, ET-based methods significantly advance remote sensing image classification. They rely on robust uncertainty modeling and flexible multi-level fusion to precisely decompose mixed pixels, effectively integrate complementary data from optical, radar, and hyperspectral sensors, and adaptively handle spectral shifts. Future research could develop edge-friendly lightweight evidential networks for real-time on-satellite processing and enhance interpretability by linking belief distributions to physical properties. These efforts will expand the impact of ET-based methods in critical domains.

6.4 Remote sensing image change detection

RSICD aims to identify differences between two or more remote sensing images of the same area captured at different times (Zhang Z et al., 2026). It serves as a core technology for environmental monitoring, disaster assessment, and urban expansion tracking. Fig. 15 gives a schematic of RSICD.

In practical applications, RSICD faces multiple critical challenges. These include spectral variability caused by different imaging conditions (e.g., weather and lighting) and ambiguous changes. This will result in high-uncertainty change detection results, making it hard to distinguish true changes from pseudo changes. ET, which can model uncertain information and fuse multi-source or multi-temporal data, enhances the accuracy of RSICD. Researchers have designed many ET-based methods to handle multi-temporal inconsistency and ambiguous change uncertainty, which cannot be effectively quantified by probabilistic fusion. They focus mainly on multi-temporal evidence fusion and uncertainty-aware change judgment. Their basic information is shown in Table 13.

Table 13 Summary of ET-based RSICD methods

Reference	Method	Publication
Le Hégarat-Mascle and Seltz (2004)	FMCD	RSE
Wang M and Zhang (2010)	ETCD	JRS
Du et al. (2012)	FMSCD	IEEE JSTARS
Liu ZG et al. (2012)	DER	IEEE TGRS
Du et al. (2013)	Du et al.	INFFUS
Liu ZG et al. (2014c)	MDER	IEEE GRSL
Liu ZG et al. (2018)	HPT	IEEE TIP
Luo et al. (2018)	D-S_Fusion	RS
Zhang YJ et al. (2018)	OB-MUSA	IEEE GRSL
Zhao JX et al. (2020)	SSIM	IEEE Access
Tian SQ et al. (2022)	CDST	IEEE TGRS

A subset of studies focuses on fusing multiple change indices or detection results through ET to address the inherent uncertainty associated with single-source detection. Le Hégarat-Mascle and Seltz (2004) proposed a method called fusion of multi-index change detection (FMCD). This approach automatically determines the number of classes (no-change or change) in each index image, and BBAs are adaptively constructed based on the derived class features, facilitating the evidential fusion of complementary indices to minimize change detection errors. Du et al. (2013) developed a two-stage sequential fusion framework: pan-sharpening is used to enhance spatial details, and ET is applied to integrate multiple preliminary change maps for mitigating commission errors. The

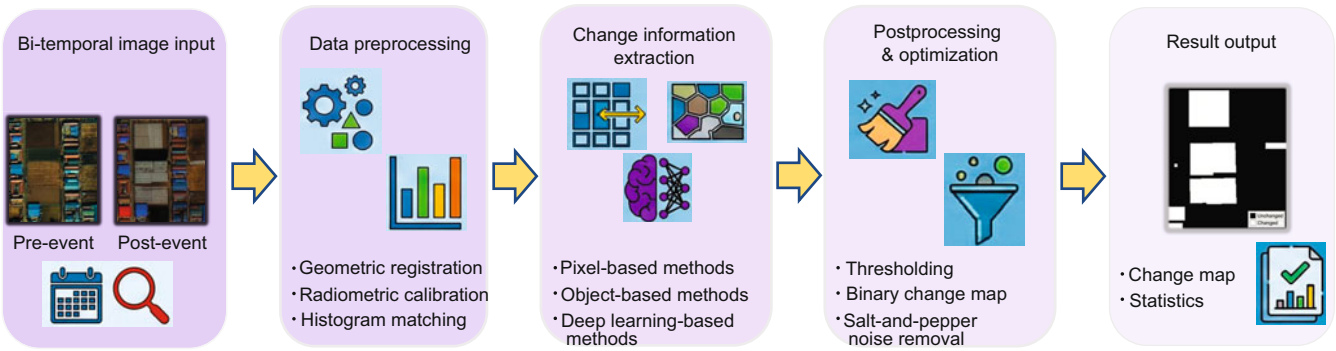

Fig. 15 Schematic of remote sensing image change detection (RSICD)

method called fusion of multiple spectral change difference images (FMSCD) (Du et al., 2012) integrates spectral change difference (SCD) images at both feature and decision levels. At the feature level, fuzzy set theory is adopted to merge SCD data, while at the decision level, ET, majority voting, and fuzzy integral are employed to generate more reliable urban change maps by leveraging complementary spectral change information.

Researchers have also used ET to tackle specific challenges in heterogeneous imagery, high-resolution imagery, and evidence conflicts in data fusion.

As for heterogeneous data, Liu ZG et al. (2012) proposed the dynamic evidential reasoning (DER) method featuring a state transition power set framework and dedicated operators at the feature level and object level. DER breaks through the limitation of the static frame of discernment in traditional ET and Dezert–Smarandache theory (DSmT), enabling precise characterization of multi-temporal change processes. Their subsequent work, multi-dimensional evidential reasoning (MDER) (Liu ZG et al., 2014c), expands the classical frame to a multi-dimensional space via Cartesian product. The homogeneous pixel transformation (HPT) method (Liu ZG et al., 2018) relies on forward–backward pixel transformation, unifying pre-event and post-event images into a common feature space based on unchanged pixel pairs. To mitigate modality differences and noise, this method first fuses complementary difference values. Then, it introduces ET into a spatial-neighbor-based noise filter, which employs the weighted DS (WDS) combination rule. This filter can effectively suppress false alarms and missing detections.

As for very high-resolution (VHR) images, Luo et al. (2018) developed the D-S_fusion method, combining three change detection results, i.e., change vector analysis (CVA), iteratively reweighted multivariate alteration detection (IR-MAD), and iterative slow feature analysis (ISFA). Specifically, stacked VHR images are first segmented into object maps. The three aforementioned methods generate change intensities that are thresholded by the Otsu algorithm to obtain candidate change maps. Then, these candidate maps are fused by ET to produce the final object-oriented change map. Other high-resolution-focused methods have also achieved notable advancements. The evidential theory and structural similarity-based change detection (ETCD) method (Wang M and Zhang, 2010) integrates ET with structural similarity. It extracts texture, gradient, and edge features from bi-temporal images, calculates their structural similarities using a moving window to construct BBAs, and then fuses them through the DS rule to identify changed areas. The structural similarity (SSIM)-based method (Zhao JX et al., 2020) fuses spectral difference images and texture difference images via ET. It confirms that texture features play a more dominant role than spectral features in high-resolution image change detection, and their combination effectively enhances detection performance. The object-based change detection for VHR images based on multi-scale uncertainty analysis (OB-MUSA) method integrates ET with SVM (Zhang YJ et al., 2018). It employs multi-scale uncertainty analysis (from coarse to fine scales) to refine object-based detection. Experimental results demonstrate that OB-MUSA can effectively reduce salt noise and improve change detection accuracy.

As for evidence conflicts in data fusion, the evidence fusion 3D change detection framework based on Dempster–Shafer theory (CDST) (Tian SQ et al., 2022) advances conflict-aware fusion by integrating the digital surface model and normalized difference vegetation index data. It employs prior knowledge to map their difference images to BBAs and converts compound BBAs via a transferable belief model. Then, they are combined by DS to classify changes into three categories: building changes, other changes, and no change.

The above-mentioned ET-based change detection methods, which leverage ET's strengths in uncertainty modeling and multi-source information fusion to extract reliable change signals from complex data, significantly improve the performance of RSICD. In the future, we could focus on integrating ET with foundation models for large-scale long-sequence change detection and extending them to multi-class change detection by distinguishing different change types. These advancements will further strengthen the role of ET in RSICD.

7 Future research directions

Despite the aforementioned progress, there are many research directions and challenges in DCET that require further analysis. This section highlights the major hurdles facing researchers and identifies areas that require further investigation.

7.1 Conflict reduction in DCET

One of the primary challenges in DCET is handling conflicts among BBAs. When different sources of evidence provide contradictory or inconsistent information, it usually leads to conflicts or confusion in assigning class labels.

Several methods have been developed to reduce conflicts, but they do not completely reduce the negative influence caused by conflicts. Resolving these conflicts effectively is crucial to obtain reliable combination results for the downstream class decision-making task. In the future, researchers can develop deep learning-driven adaptive combination rules and evidence reliability learning mechanisms to effectively resolve evidential conflicts.

7.2 Evidence combination rule in DCET

ET involves the combination of multiple sources of evidence, whereas combining evidence from various sources can be challenging, especially when the sources have different reliability levels or uncertainty degrees. Specifically, DS or weighted DS combination rules can work well when BBAs are independent or the conflict degrees are small, but are not always suitable for use in other cases.

Although some new combination rules have been developed to replace the DS rule, their versatility is limited. Developing and selecting appropriate combination rules requires careful evaluation. Researchers can design context-aware, dynamic fusion strategies that adapt to varying evidence reliability in the future.

7.3 Data representation in DCET

Representing data in a suitable form for ET-based classification can be complex. ET requires the definition of BBAs on a set of hypotheses or classes. However, assigning appropriate BBAs that reflect the uncertainty and reliability of evidence can be difficult, especially when dealing with complex unstructured data (e.g., image, text, and video).

The solution is to transform unstructured data into a structured form using different feature extraction methods or end-to-end deep learning frameworks. How to effectively embed ET into feature extraction methods or end-to-end deep learning frameworks for data representation is an important research direction. End-to-end EDL pipelines have the potential to generate high-quality BBAs from complex unstructured data.

7.4 Limited training data in DCET

As with other classification techniques, ET-based classification methods require large amounts of labeled training data. However, acquiring and labeling sufficient training data, particularly for some specialized domains or rare classes, can be a significant challenge.

Limited training data can lead to inaccurate classification results. Thus, it will be an interesting research topic to solve the classification problem using ET when the training data are very limited. In the future, few-shot and zero-shot evidential learning frameworks could be developed to mitigate uncertainty from insufficient labeled samples.

7.5 Incremental learning in DCET

Incremental learning in the context of ET-based data classification involves continuously updating the classifier as new data become available, allowing the model to adaptively change in the environment or incorporate new evidence without retraining on the entire dataset.

To address this, we can develop some algorithms that update BBAs incrementally as new evidence arrives. This allows the classifier to continuously integrate new information without reprocessing the entire dataset. Moreover, we can design methods to efficiently fuse new evidence with existing belief assignments. This could involve updating belief functions or combining new evidence with existing sources of evidence while maintaining coherence. Building online evidential fusion systems that continuously update BBAs without full retraining could be a possible solution.

7.6 Adversarial robustness in DCET

Adversarial robustness in the context of ET-based data classification refers to the ability of classifiers to maintain accuracy and reliability in the face of deliberate perturbations or manipulations introduced to input data, commonly known as adversarial attacks. It is important to investigate how adversarial attacks manifest in ET-based classifiers, and then to assess the impact of perturbations or manipulations in the evidence space and belief assignments to different hypotheses or classes. Moreover, we should develop robust evidence fusion techniques that are resilient to adversarial perturbations, and explore ways to mitigate the effects of manipulated or misleading evidence from adversarial inputs.

7.7 Scalability in DCET

ET-based classification methods can become computationally expensive, especially when the number of classes increases or when the dataset is very large. To be specific, calculating the combination of evidence and updating belief functions could be quite time-consuming if the local and global uncertainties are measured by the mass values of power set 2^{Ω}. How to significantly reduce the time and memory cost in DCET should be considered. In our opinion, reduction in the number of focal elements can reduce combination complexity, and parallel fusion using the DS rule can significantly speed up data processing and analysis.

7.8 Interpretability of DCET

ET often provides more complex decision outputs compared to traditional classification approaches. Interpreting and explaining the class decision, especially to non-experts, can be challenging due to the inherent complexity of belief functions. Thus, we need to focus on the interpretability of DCET. In the future, we can develop some explainable evidential reasoning modules to trace belief contributions for transparent decision-making.

8 Conclusions

In this paper, we provide a comprehensive overview of data classification based on evidence theory (DCET), covering ET's theoretical foundations, classical methods (e.g., EKNN classifier and its variants), and targeted solutions for structured data challenges (including high-dimensional features, missing attribute values, feature distribution shift, imbalanced label distribution, inconsistent label spaces, and class overlap), as well as its integration with deep learning for unstructured (i.e., image) data and real-world applications in human activity recognition, medical image segmentation, remote sensing image classification, and remote sensing image change detection. ET's unique strength in modeling uncertainty and fusing multi-source information enables robust classification across diverse scenarios. Several key challenges in DCET, including evidence conflict management, inefficient combination rules, limited scalability, and poor interpretability, warrant significant attention and resolution.

As noted in recent literature (Huang T et al., 2025), the outputs from large language models (LLMs) inherently contain epistemic uncertainty stemming from incomplete knowledge and potential hallucinations, which cannot be fully captured by traditional probabilistic confidence scores alone. Basic belief assignment within ET provides a more expressive mathematical tool to quantify such uncertainty in LLMs by distinguishing conflicts. Moreover, we can fuse multi-prompt or multi-model evidential masses via the DS rule, and use evidential uncertainty to mitigate LLMs' overconfidence and hallucination risks. This integration will offer an interpretable uncertainty quantification paradigm for reliable reasoning. Thus, new methods can be developed to unlock the full potential of ET when integrated with LLMs.

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Author contributions

Linqing HUANG and Jinfu FAN conceived the idea and designed the review framework. Linqing HUANG conducted the literature search and collection and drafted the paper. Jinfu FAN helped organize the paper. Gongshen LIU and Alan Wee-Chung LIEW reviewed the paper and checked the writing details. All the authors revised and finalized the paper.

Conflict of interest

Linqing HUANG is a junior editorial board member of *ENGINEERING Information Technology & Electronic Engineering*, and he was not involved in the peer review process of this article. All the authors declare that they have no conflict of interest.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used Doubao to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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