Fuzzy Logic in Surveillance Big Video Data Analysis: Comprehensive Review, Challenges, and Research Directions

KHAN MUHAMMAD*, Department of Software, Sejong University, Seoul 143-747, South Korea

MOHAMMAD S. OBAIDAT, College of Computing and Informatics, University of Sharjah 27272, UAE, KASIT, University of Jordan 11942, Jordan, and University of Science and Technology 100083, Beijing, China

TANVEER HUSSAIN, Intelligent Media Laboratory, Department of Software, Sejong University, Seoul 143-747, South Korea

JAVIER DEL SER, TECNALIA, Basque Research Technology Alliance (BRTA), 48160 Derio, Spain; and the University of the Basque Country (UPV/EHU), 48013 Bilbao, Spain

NEERAJ KUMAR, Thapar Institute of Engineering and Technology, Deemed to be University, Patiala 147004, Punjab,, India

MOHAMMAD TANVEER, Discipline of Mathematics, Indian Institute of Technology Indore, Simrol, Indore, 453552, India

FAIYAZ DOCTOR, Centre for Computational Intelligence, School of Computer Science and Electronic Engineering, University of Essex, Wivenhoe Park, Colchester, Essex, CO4 3SQ, United Kingdom

CCTV cameras installed for continuous surveillance generate enormous amounts of data daily, forging the term "Big Video Data" (BVD). The active practice of BVD includes intelligent surveillance and activity recognition, among other challenging tasks. To efficiently address these tasks, the computer vision research community has provided monitoring systems, activity recognition methods, and many other computationally complex solutions for the purposeful usage of BVD. Unfortunately, the limited capabilities of these methods, higher computational complexity, and stringent installation requirements hinder their practical implementation in real-world scenarios, which still demand human operators sitting in front of cameras to monitor activities or make actionable decisions based on BVD. The usage of human-like logic, known as fuzzy logic, has been employed emerging for various data science applications such as control systems, image processing, decision making, routing, and advanced safety-critical systems. This is due to its ability to handle various sources of real world domain and data uncertainties, generating easily adaptable and explainable data-based models. Fuzzy logic can be effectively used for surveillance as a complementary for huge-sized artificial intelligence models and tiresome training procedures. In this paper, we draw researchers' attention towards the usage of fuzzy logic for surveillance in the context of BVD. We carry out a comprehensive literature survey of methods for vision sensory data analytics that resort to fuzzy logic concepts. Our overview highlights the advantages, downsides, and challenges in existing video analysis methods based on fuzzy logic for surveillance applications. We enumerate and discuss the datasets used by these methods, and finally provide an outlook towards future research directions derived from our critical assessment of the efforts invested so far in this exciting field.

*Corresponding Authors: Khan Muhammad and Mohammad S. Obaidat (khanmuhammad@sju.ac.kr, msobaidat@gmail.com)

Manuscript submitted to ACM

CCS Concepts: • **Applied computing → Surveillance mechanisms**; • **Computing methodologies → Vagueness and fuzzy logic**.

Additional Key Words and Phrases: Video Surveillance, Fuzzy Logic, Neural Networks, Soft Computing Techniques, Big Data, Big Video Data, Fuzzy Logic Survey, Fuzzy Tutorial, Video Summarization, Video Surveillance Survey

ACM Reference Format:
Khan Muhammad, Mohammad S. Obaidat, Tanveer Hussain, Javier Del Ser, Neeraj Kumar, Mohammad Tanveer, and Faiyaz Doctor. 2020. Fuzzy Logic in Surveillance Big Video Data Analysis: Comprehensive Review, Challenges, and Research Directions. In *Proceedings of ACM Computing Surveys*. ACM, New York, NY, USA, 27 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

The worldwide growth of surveillance cameras installations is raising concerns for computer vision experts and Big Data analysts [1] due to its importance for observation and monitoring purposes. The video surveillance domain comprises several application areas including anomaly detection [2], violence recognition [3], as well as in general global security [4], and better and transparent urban monitoring. In addition, contextual information sharing and fusion related to road traffic, crowd density at shopping malls, healthcare centers, and many other useful locations can enhance video surveillance capabilities. For instance, capturing information about the traffic density can ease the daily life of smart cities' inhabitants by providing information on congested hot spots and suitable non-congested paths towards their destination [5]. This is possible by employing image processing techniques along with fuzzy logic-based quick and accurate decisions from surveillance BVD. Despite the enormous applications of surveillance through BVD, achieving them via computationally intelligent techniques poses challenges from precision time complexity perspective, given the different sources of real-world uncertainties these systems have to cope with. Mainstream available data for Machine Learning models and image processing algorithms have lowered generalization abilities and reduced adaptability towards real-world surveillance scenarios. As such, the trained models show limited performance in complex smart cities surveillance applications [6]. For improved utilization of surveillance BVD, researchers are investigating several image processing and machine learning algorithms [7].

These approaches require sufficient training data to generate models which can perform regression or classification tasks satisfactorily [8]. This can be difficult in real world surveillance settings with limited ground truth data available. These modelling paradigms have some limitations in their flexibility to adapt to short term and gradual changes and uncertainties in real time characteristics of the data streams in a self-supervised lifelong learning mode. For instance, a video skim generation model is presented by Hussain et al. to recognize activities inside an office environment for video summarization [6]. Their trained model has limited performance for industrial indoor environments and similarly outdoor scenarios without any prior training for these specific situations. There are other existing machine learning approaches that generate black-box models where the internal reasoning process or learned functional mappings are obscure and cannot be understood by end users, specially if they lack any technical background of machine learning. There is a growing need for creating explainable 'glass box' models which can provide accurate and human understandable modelling decisions. In addition, vision-based manual monitoring systems waste human resources, where a person or a group of individuals deeply observe an array of live cameras. Although human monitoring has major advantages such as operative monitoring, real-time response, and instant reporting, it still features several limitations. It is a tedious job and human operators often get frustrated when sitting in front of screens for lengthy periods, yielding a poor performance and deficiency in their surveillance potentials. In these scenarios the element of human subjectivity and variability may also comes into play in their ability to reach consistent decisions. Fuzzy logic, in contrast, enables human-like decisions in computer programs that can be implemented effectively for the aforementioned surveillance applications while handling human subjectivity and data uncertainties. [9].

Table 1. Structure of the overall survey.

Main heading	**Sub-headings/paragraphs/Tables**
1. Introduction	Introduction and motivation Applications of surveillance BVD Focus of our survey paper Main contributions
2. Background concepts of fuzzy logic	What is fuzzy logic? Basic pipeline of fuzzy systems
3. Representative surveys in fuzzy logic and our survey	Survey articles in fuzzy logic domain/ Table 2 Coverage of our survey/ Table 2 Discussion on our survey
4. Literature review	Fuzzy logic related works/ Table 5 Fuzzy logic in surveillance BVD Objects detection via fuzzy logic Objects tracking through fuzzy logic Fuzzy logic for traffic management Generic application domains of fuzzy logic
5. Performance evaluation of fuzzy logic methods for surveillance BVD	Evaluations methods used in fuzzy logic domain/ Table 4 Performance evaluation of fuzzy logic methods in surveillance domain Evaluation metrics utilized in fuzzy logic methods
6. Applying fuzzy logic: why, when, and where?	Background of CNNs and their limitations in surveillance domain Solutions to the mentioned problems using fuzzy logic How to apply the given solutions using fuzzy logic? CNN or fuzzy logic? Where to use which option?
7. Challenges and future research directions	Applications-wise future endeavors in fuzzy surveillance domain/Table 6 Edge intelligence and fuzzy logic Adaptive fuzzy logic for non-stationary environments Public availability of research implementation/ Table 7 Time complexity and computational resources analysis Proposals for hybrid techniques Explainability in fuzzy video data analysis
8. Concluding remarks	Surveillance BVD and fuzzy logic Key findings of our research Motivational reasons for further exploring fuzzy logic and its variants for surveillance BVD

The main focus of this survey is to provide an overall review of the application of fuzzy logic systems to video analysis in a comprehensive manner, with surveillance Big Data as a case study. Fuzzy logic in other domains are widely used due to their ability to provide reasoning and modelling techniques that are robust to uncertainties and imprecision in data sources [10]. The contributions from researchers and experts have had some focus on utilizing fuzzy logic for video analysis methods. However, there has been limited research on problems like action and activity recognition, anomaly detection, and video summarization [11], etc. that are the key application areas of surveillance systems. The highlighted challenges to surveillance BVD analysis using fuzzy logic and their possible future insights are covered in this review article. Finally, to motivate scientists towards this domain and focus their research efforts in video analytics literature from fuzzy perspective, we present this review article with the following major contributions.

- To the best of our knowledge, there is no previous survey on the topic of surveillance BVD processing based on fuzzy logic. Hence, we contribute to the fuzzy logic literature by presenting the first comprehensive survey on the topic of Big Data generated from vision sensors.

- Big Data generated from surveillance cameras requires image fuzzification, membership values modification, and de-fuzzification techniques for effective and efficient usage. The current literature of fuzzy logic lacks the focus on surveillance BVD. Therefore, we cover the existing literature in the domain of fuzzy logic to present the concepts that can possibly be integrated with surveillance domain for effective utilization of visual Big Data. Further, we discuss the baseline techniques and overview the representative works on the aforementioned topic that helps recognizing the open challenges in this domain.
- Another major contribution of our survey is the prescription of future research guidelines for surveillance BVD, with supported references to motivate scientists in conducting valuable research in this domain. Here, there are several possible directions for integration of fuzzy logic with other soft computing techniques, such as neural networks and spiking neural networks for fruitful results and sensitive yet important applications. We also highlight the major challenges and provide detailed discussion about the possible research tracks in the video analytics domain using fuzzy logic.

The rest of the paper contains several sections, whose details are provided in Table 1.

2 BACKGROUND CONCEPTS OF FUZZY LOGIC

Fuzzy Logic is a soft computing methodology providing an approach for approximate reasoning and modelling of data that uses words and phrases instead of numbers to model the real world systems similar to the way humans think and make decisions [12]. Fuzzy logic consists of two important components: fuzzy sets and fuzzy data structures. A fuzzy set, also known as an uncertain set, is a mathematical model that contains elements with varying degrees of membership such as member, non member, and partial membership. Fuzzy sets were introduced by L. A. Zadeh in [13] as an extension to classical sets. Fuzzy data structures such as relational rules produce outputs by processing the linguistic values predefined by fuzzy sets.

Similarly, in other domains [14], fuzzy sets can be used to partition attribute spaces associated with video features and quality indicators into linguistic variables such as *very low*, *low*, and *high*, which provide meaningful abstracted representations of these attributes [15]. Unlike crisp sets and partitions, the boundaries of fuzzy sets are not based on binary two-valued logic (0 or 1). Instead they use many valued logics that facilitate graduated degrees of belongingness of data points to a set or partition. Fuzzy sets can be represented using different types of mathematical membership functions that compute membership values of data points in the attribute spaces they partition. Since membership values are between 0 and 1, this allows data points to have partial memberships to one or more overlapping fuzzy sets where the boundaries between partitions are uncertain and cannot be precisely specified in the real-world. For instance, in a set of consecutive surveillance video frames, some of them can be highly informative and significant when compared to others that are of lower informative value or relevance with respect to detecting suspicious behaviour or anomalies. This can help reduce the number of frames which need to be processed for real-time edge based embedded surveillance devices or transmission over wireless sensors networks. This powerful feature facilitates data abstraction and approximate reasoning through specifying or learning interpretable structures such as If-Then rules, graphs classes or cluster-based representations [16]. These structures can be used to model functional mappings, causal dependencies, and relationships between the derived fuzzy partitions across different domain specific attributes in a similar way that other machine learning techniques learn or discover functional approximations or groupings between data points. In particular fuzzy rule based inference systems have been most commonly used for decision making and control applications, [17, 18], while indoor video monitoring and other video analytics tasks are also accomplished using fuzzy logic systems [19, 20].

The basic pipeline of a rule based fuzzy inference system includes data fuzzification where input values intersect with the antecedent fuzzy set. An inference mechanism then combines activated rules by employing intersection and union operations for modifying the membership values or weights of the aggregated output fuzzy sets [21]. The generated output is not necessarily a single number, instead the fuzzy set consists of a range of possible outcomes [22]. Therefore, to make it sensible to humans, it needs to be defuzzified to obtain a single output value [21]. The most commonly used defuzzification method is centroid defuzzification. The available fuzzy systems follow either type-1 or type-n fuzzy framework [21]. Type-1 Fuzzy Sets are only able to compute a crisp membership value with respect to the degree of membership of a data point to that set. A type-2 fuzzy set is characterized by a fuzzy membership function, where the computed membership value for a data point is itself a fuzzy set in [0, 1] represented by a secondary membership function with secondary membership grades projected in a separate dimension [18, 23]. This enables the fuzzy sets to have additional design degrees of freedom that can capture rich information and handle higher orders of uncertainties associated with the data point being processed. There are some restrictions when implementing type-2 fuzzy set such as time-varying data and non-stationary measurement noise. Readers are referred to [24] for detailed information about the implementation of type-1 fuzzy set systems.

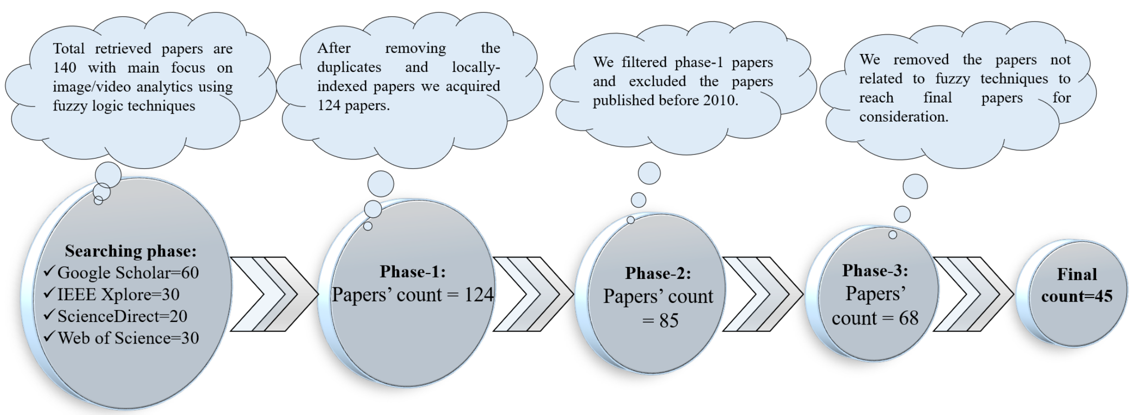

Fig. 1. Schematic diagram showing the process followed for searching, retrieving, and screening to acquire the finally selected articles critically reviewed in our survey. The inclusion and exclusion strategies are given in the hints alongside each phase. A few sample queries used during the research process are "fuzzy logic in surveillance videos", "fuzzy systems for surveillance big data", "fuzzy logic in CCTV videos", "fuzzy logic for smart vision", and "fuzzy inference systems in surveillance".

3 REPRESENTATIVE SURVEYS IN FUZZY LOGIC AND OUR SURVEY

The fuzzy logic arena has several review articles with a major focus on medicines and diagnosis [30, 31]. Since there is no existing survey on the specific problem of surveillance BVD analysis in the fuzzy logic literature, therefore, a baseline for survey comparison in this domain is absent. To provide readers a broader level of information about fuzzy logic, we review the existing representative surveys on fuzzy logic application domains in this section. Alcalá-Fernández and Alonso [32] present a survey with an overview, research trends, taxonomy, and various prospects of fuzzy systems

Table 2. Detailed descriptions of some representative surveys in fuzzy logic literature, along with their possible flexibility to surveillance domain.

Ref.	Coverage	Relevance to surveillance	Domain	Reviewed papers/Surveys	Main Theme
[17]	2007 ~2013	Dynamic parameter optimization can be utilized in surveillance methods	General, parameters optimization algorithms review using fuzzy theory	16/No coverage for existing surveys	Review of fuzzy logic based and nature inspired optimization techniques for dynamic parameters adaptation
[25]	1996 ~2014	Adaptation can be made in surveillance domain to solve complex non-linear problems	Fuzzy-based adaptive controllers under observation	35/Lacks the discussion of existing surveys	Survey of adaptive fuzzy controllers. Major focus on non-linear controllers and fuzzy inference systems
[26]	1994 ~2014	Gesture recognition and activity recognition can be effectively used in surveillance	Fuzzy set oriented techniques for human motion analysis	22/No coverage of existing surveys	Fuzzy methods for human motion analysis. First survey aiming at this problem using fuzzy literature
[27]	2005 ~2017	Purely related to disease diagnostics but the main fuzzy concepts are explained well and can be utilized for different purposes	Disease diagnostics	46/Lack of existing surveys' review	Diagnosis systems through fuzzy logic with proper literature coverage. Experimental results are given to show effectiveness of fuzzy methods in disease diagnosis
[28]	2007 ~2018	Fuzzy min-max neural networks can be used in many pattern recognition and video classification tasks in surveillance	Fuzzy neural networks	54/No coverage of survey papers	Fuzzy min-max models for pattern classification task and its meaningful division. Detailed discussion about future trends
[29]	2007 ~2018	No relevancy with surveillance because it provides only the coverage of the given domain	Fuzzy logic for chronic diseases	26/Yes, it has discussion about previous surveys	A review of disease diagnosis systems through fuzzy logic with proper literature coverage, articles, and year-wise frequency
[30]	2005 ~2019	No specific contingency	Infectious disease diagnosis using fuzzy logic	40/No discussion about previous survey papers	A systematic review of infectious disease diagnosis via fuzzy logic. Significant future research directions in the mentioned domain
Ours	2010 ~2020	Broader coverage of video analytics with focus on surveillance BVD	Surveillance BVD	45/7 existing surveys are covered and investigated	A comprehensive survey with broader overview of fuzzy logic methods. Future tracks on the basis of derived conclusions and current needs of the surveillance domain

software. A survey focusing on research works related to adaptive fuzzy controllers and the advancements made in non-linear systems is presented in [25]. Ahmadi et al. present a systematic and meta-analysis review of fuzzy logic methods for diseases' diagnosis [27]. The results and conclusions of this study show the effectiveness of fuzzy logic methods and their applications in this area. A review of FL applications in the field of medicine is studied in [29] with a recent editorial on applications to neural engineering in [33], providing current research and future directions. The closest survey to our topic is presented in [26], where the techniques of human motion analysis using fuzzy theories are reviewed. This work has a broader coverage of applied fuzzy techniques for the given topic with insights and suggestions for future research. A brief overview of some representative surveys with their key findings, coverage of their articles, and their possible relevancy (extension) to the surveillance domain is given in Table 2. The above discussion along with this table can be used as a reference to ascertain the existing contributions of researchers in the surveyed domain.

Our survey covers a diverse set of papers including reputed conferences, journals, and workshops. The main repositories used are ScienceDirect, Google Scholar, IEEE Xplore, ACM, and Springer.

The related papers are retrieved from these repositories with different queries based on the combination of a number of keywords such as "Fuzzy logic", "Fuzzy theory", and "Fuzzy inference system". The complete screening process is given in Figure 1. The overall data on the filtered papers with comprehensive description, dataset availability,

Table 3. Supporting table linking each method to its relevant citation from Figure 2.

Method	Ref.	Method	Ref.	Method	Ref.
M1	[34]	M2	[35]	M3	[36]
M4	[37]	M5	[38]	M6	[39]
M7	[40]	M8	[41]	M9	[42]
M10	[43]	M11	[44]	M12	[45]
M13	[46]	M14	[26]	M15	[47]
M16	[48]	M17	[49]	M18	[50]
M19	[51]	M20	[52]		

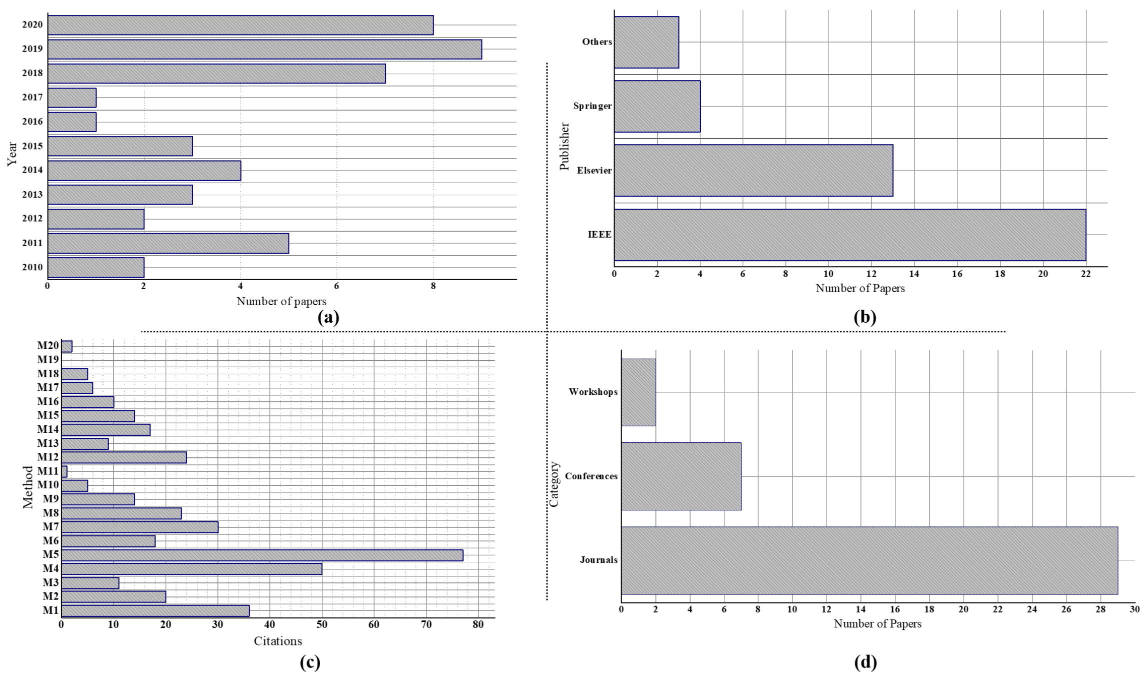

Fig. 2. The overall distribution of research papers with focused topic of surveillance BVD analytics using fuzzy logic. (a) Number of published papers versus year of publication. (b) Distribution of papers among different publishers. (c) Citations of the reviewed methods in the literature, where references are marked as in Table 3. Information about citations of each paper helps novice researchers select the best paper for the reviewed topic. (d) Scattered information about the nature of the publication, categorized as conference, journals, or workshop.

application domain, adapted strategy, and the utilized tools are given in Table 4, where we show the overall literature reviews of surveillance BVD analytics using fuzzy approaches. Furthermore, the distribution of the discussed research articles across various publishers, yearly publication information, their citation counts (till October 6, 2020), and the categorization of these papers are illustrated in Figure 2.

The literature survey presented in this paper is subject to some limitations. Our first limitation is that the targeted domain for reviewed papers in this survey is comparatively narrow, i.e., surveillance BVD. A broader version can be the complete video analytics domain, covering action and activity recognition [60], video summarization, [61], video retrieval [7], healthcare [62], objects detection and tracking [63, 64], etc. The specific focus of our research is to conduct

Table 4. Performance evaluation of reviewed techniques with dataset description, availability information, and the used evaluation metrics alongside the obtained score.

Method	Dataset/Available?	Description	Evaluation metrics and score
[40]	Two outdoor and one indoor videos were used / No	Surveillance video with two actions: leaving object and talking to someone	Visual results
[35]	[53] / No	Data collected from healthcare centers with different varieties, velocity, and volume	Classification time, average response time, accuracy, and false positive rate
[37]	[54] / No	Two surveillance videos are used: one for rolling a ball and second contains a moving car and a pedestrian	Visual representation of trajectories
[38]	[55, 56] / Yes	Fifteen different surveillance videos are used for the detection of moving objects in dynamic backgrounds	F1, precision, recall, and similarity
[39]	CAVIAR [57] / Yes	Public place surveillance video, containing different actions involved such as fighting, entering and exiting shops, window shopping, meetings, and walking alone	Visually represent multiple people activities
[34]	Private recorded data via Logitech webcam / No	Two minute's test videos with moving subjects in four scenarios	Visual results are given to show alarm level for the dataset videos without any objective or subjective evaluation
[58]	Private videos / No	Selected some videos from benchmark video dataset, originally prepared and recorded in Gdansk University of Technology, Gdansk, Poland	False positive and false negative rate
[40]	Surveillance traffic videos / No	Chien-Kuo Bridge in the Taipei City in the daytime and nighttime using camera (19) and Mu-Cha Tunnel on Highway 3 using camera (27)	Accuracy, recall, and precision
[41]	80 videos, each with duration of 20 seconds are recorded using Canon PowerShot SX150 / No	Total 80 videos: first four videos include human and vehicles, while the remaining videos contain human and animals	Accuracy
[42]	Private videos / No	Two sample videos: one is indoor and another is outdoor	Visual results
[43]	Private videos / No	Two types of surveillance videos for indoor and outdoor scenarios	Visual results
[44]	Ten different surveillance videos / No	Surveillance videos are used for skin based human detection	Accuracy over different classes.
[59]	Private videos / No	The dataset includes human, animals, and moving vehicles	Accuracy; human near recognition accuracy, and human far recognition accuracy
[45]	Private videos / No	On-board mounted experimental camera capturing videos in various bad weather conditions	Absolute categorical rating (ACR) and histogram
[46]	Outdoor surveillance video data / No	Two different test-bed scenarios:scenario-1: 10 OpenFlow, 24 links. Scenario-2: 28 OpenFlow, 50 links	Peak signal to noise ratio, average end-to-end delay, and packet loss ratio
[48]	TUD-Crossing, PETS09-S2L2, ETH-Jelmoli, and AVG-TownCentre as testing set and PETS09-S2L1 and TUD-Stadtmitte datasets as training sets / No	Surveillance video with crowded scenario	Multi-object tracking accuracy, tracked trajectories, lost trajectories, false positive, false negative, identify switches, and fragments
[49]	SNA2014-Nomal / No	Traffic video sequence with different normal traffic, retrograde, cross the road to the left, and cross the road to the right	Accuracy rate and false detection rate

an in-depth review of fuzzy methods applied to the generic video analysis domain, towards deriving a proper taxonomy of the applied fuzzy techniques.

4 LITERATURE REVIEW

The literature on fuzzy logic theory and applications is very rich, with research contributions in image/video processing, medical diagnosis, and control systems [65]. Researchers from the entertainment domain i.e., sports video classification have also employed fuzzy logic for soccer events detection and classification [66, 67]. In this section, we only discuss fuzzy logic based techniques that are either applicable to surveillance video analysis, or that can be extended to this domain. The concepts of transfer and online learning are widely used in many real-world problems including surveillance BVD due to their resourceful utilization and knowledge sharing abilities from existing models. Fuzzy transfer learning is a better option due to the uncertainties, that traditional transfer learning methods are unable to deal with [68]. However, fuzzy transfer learning poses the problems of appropriate domain selection and labeled data selection for the target domain. This is the reason why it is currently not used in many surveillance video analysis techniques. These problems are solved by [69] with the integration of infinite Gaussian mixture model and active learning, enhancing the generalizability of the constructed model. Therefore, it can be proved as an effective solution for different surveillance video analytics domain, particularly the areas dealing with image and video classification tasks.

Clustering techniques are widely used in many surveillance applications. However, feature selection for clustering has different levels of difficulties, depending on the nature of the data. For instance, a comprehensive review is presented in [70] to assist the surveillance experts in the selection of features for clustering, where the strategy is adaptable to complex scenes through online learning abilities. The clustering technique utilized in this research is fuzzy c-means, which is applicable to many surveillance applications such as similar frames clustering or differentiating among different shots or activities. Similar fuzzy logic-based emerging techniques are available in the literature, such as those in [71] for noise filtering, in [72] for features selection of large-scale classification problems, and in [73] for optimum-path forest classification. These approaches can be easily transformed to the surveillance domain for useful video analysis tasks.

The video analytics domain, particularly when dealing with surveillance data via fuzzy logic, is comparatively scarce and not investigated deeply to date. The tasks accomplished using fuzzy logic in surveillance BVD domain include road traffic anomaly detection, foreground object detection, multi-object tracking, and risk assessment. For instance, a fuzzy logic based multi-object tracker is presented by Liang-qun et al. [49], where a knowledge-based fuzzy inference system is designed via a set of fuzzy if-then rules known beforehand to improve the performance of multi-object tracking. Li et al. [50] considered fuzzy theory to deal with road traffic anomaly detection. A risk assessment analysis system using surveillance videos is proposed in [47], where fuzzy cognitive maps are used to report on risky situations. The idea of utilizing different fuzzy-based concepts for surveillance applications is therefore valuable, as can be inferred from the aforementioned research works. Detailed discussion about usage of fuzzy logic in surveillance BVD is explained in the next subsection 4.1

4.1 Fuzzy logic based methods for surveillance BVD

Herein, we cover the literature of fuzzy logic approaches applied to surveillance BVD domain, where some methods utilize these concepts for diverse problems including object detection, tracking, motion tracking, determining events, traffic surveillance, and human detection in outdoor scenarios [42]. The details of these approaches with their respective domain are covered in the subsequent paragraphs.

The problem of objects detection/tracking [74] with primary focus on human, single, and multi-objects tracking has gained significant attention of the researchers. Object detection has a vital role in many surveillance applications. In fact, it is considered as a preprocessing step for some interesting domains such as action and activity recognition, security (person identification and re-identification), and tracking, among others. For instance, an adaptive neural-fuzzy method for object detection is presented in [38] with the main motivation of tackling the dynamic background problem via the integration of a self-organizing map and a fuzzy inference system. The self-organizing map deals with dynamic background challenges for object detection while eliminating shadows. The fuzzy inference system is used to determine the human behaviors and adjust the self-organizing map parameters automatically for the detection task. This integration makes the overall system independent of the given scenario, thus showing significant improvements when compared to similar methods in the object detection literature [75]. In [42], fuzzy logic is used to detect foreground objects followed by distinct features extraction from the contours of detected objects. A unique aggregation strategy is used to produce a single feature vector from three feature vectors using a fuzzy inference system. The final feature vectors' size is reduced by using vector quantization to minimize the computation effort towards final human contour detection.

Followed by the literature of object detection using fuzzy logic concepts, the object tracking domain likewise has some remarkable research contributions. For instance, a motion tracking mechanism via fuzzification techniques is presented in [37]. This research work introduced a moving objects segmentation and tracking strategy, where motion-based algorithms acquire the shapes of dynamic objects in consecutive video sequences. The shapes acquisition is initiated with the detection of a change between two consecutive frames, computed through permanency values. The segmentation module applies fuzzy bi-dimensional rectangular regions that assist in capturing the similarities among the detected objects. The final tracking module performs the association between fuzzy regions over time. Segmentation, tracking, and analysis modules are highly influenced by the usage of fuzzy logic techniques for handling uncertainties in permanency values caused by image noise inherent to computer vision. Fuzzy logic data association algorithm is implemented in [49] for online multiple object tracking. There are several modules in this algorithm, where prominently a knowledge-based fuzzy inference system is designed to incorporate expert experience with data association for performance improvement in multi-objects tracking. Fuzzy if-then rules using parameters related to error and change of motion error, shape, and appearance of model in last prediction are utilized to determine the fuzzy membership degrees and substitute the association probabilities between detected objects and responses (objects and measurements). The fragmented trajectories that occur due to long-term occlusion are handled with track-to-track association approach based on a fuzzy synthetic function. This has the capability to precisely stitch together the track fragments. The authors of this work show improved results of their method when compared to state-of-art approaches, and the effectiveness of their technique in minimizing the number of fragment tracks.

Alongside object detection, tracking, and surveillance, video data can be effectively used in the management of abnormal traffic situation handling and assistance in routing, among many other applications. There are several contributions on the effective usage of traffic surveillance using fuzzy logic. For instance, Wu et al. [41] presented a fuzzy hybrid information inference mechanism "FHIIM" to determine tracked vehicles in live surveillance videos. FHIIM uses color similarity and area consistency for tracking assessment. The fuzzy rules input the degrees of color and the area for comparison as linguistic variables such as *low*, *medium*, and *high*. There are five membership functions, which process the linguistic variables to generate a meaningful output. Another research in a similar domain has focused on anomaly detection in road traffic scenarios using fuzzy theory [50]. The traffic flow, density, and the targets' motion state are designed on the basis of virtual detection lines, pixel statistics, and vehicle trajectory using fuzzy logic, correspondingly, which are fused together for optimal output. The final step of traffic anomaly detection method utilizes the above-mentioned parameters along with fuzzy control rules for road anomaly detection.

Besides the role of fuzzy logic in objects detection/tracking and traffic surveillance, there are other domains of surveillance where these concepts and implementations are applied. These domains include diverse applications such as healthcare [76, 77] particularly for elderly people [34], fusion of images (infrared and visible regions) [35], and events determination [40]. Further research contributions in the surveillance domain include static and moving objects in surveillance [44], activity modeling [9], video enhancement [46, 78], risk assessment [47], and walk directions estimations [52, 79]. As an example, a recent work has employed fuzzy logic for open-set single-sample face recognition in real-world surveillance scenarios [80]. This method is based on fuzzy adaptive resonance theory neural network [81] and is adoptable to various illumination and facial expression conditions. A three-level privacy preserving video encryption system is presented by Shifa et al. [4], where three parallel fuzzy inference systems assist to classify the threat to the live streaming video. In another recent research [82], a fuzzy system is used to mimic security personal decision-making skills to identify suspicious activity by using an embedded edge computing node. The video features used for suspicious activity identification are extracted using Deep Learning models. The mentioned research works have much influence on surveillance applications, and the usage of fuzzy logic makes them robust and applicable in real-world scenarios. For instance, in the latter work [82], considering the requirements collected from law enforcement services, a number of features are selected and fuzzified to handle various uncertainties that exist in officers decision-making procedure. However, potential applications related to activity recognition, anomaly detection, and video summarization used in practical surveillance environments are scarce in the fuzzy logic literature, needing researchers' attention.

5 PERFORMANCE EVALUATION OF FUZZY BASED SURVEILLANCE BVD ANALYTICS

The evaluation of each fuzzy method in the reviewed literature varies depending on the application domain of the implemented algorithm. Some fuzzy methods provide only visual confirmation (input data and output results) of their implemented algorithm without any state-of-the-art comparison with limited use of ground truth datasets. F-measure, accuracy, precision, recall, and sensitivity are used for people walking, change detection, human detection, traffic analysis, etc. The datasets provided in Table 5 can be observed and used in different ways as per the problem under consideration. There is no single pair of research methods in this domain sharing a common dataset with similar comparison metrics. Similarly, the data mentioned in many contributions is private, and some links provided in the relevant articles are mentioned without providing any further information. This information is also given in the second column of Table 4.

Fuzzy logic applications involving surveillance BVD are lacking enough evaluation standards, or benchmarks against which improvements in accuracy or a reduction in computational complexity can be measured. Mainstream methods rely only on graphical results, visualizing the sample outputs of their implemented techniques. Assessing results by visual inspection without any further objective evaluation or comparison is unsatisfactory and unreliable in the computer vision domain. For instance, the work in [44] only presented visual results of various trajectories occupied by a pedestrian, without a more grounded comparison with state-of-the-art methods dealing with similar problems. The comparison using objective evaluation is straightforward in this exemplifying case, and can be achieved by simply measuring the difference between the predicted person's trajectories and the ones that are given in the ground truth.

Despite the predicted outputs visualization of some fuzzy logic based surveillance related methods, in [49] researchers utilized the commonly used metrics in trajectories detection related literature and evaluated their method over benchmark datasets and scored new state-of-the-art results. Approaches relying only on visual results are very common in the fuzzy logic surveillance BVD domain. For instance, Munch et al. [39] attempted to recognize alert situation in surveillance environments using fuzzy metric temporal logic, where they justified their experiments using only visual results of multiple people activities. Similarly, a fuzzy logic based system by Yi et al. only provided visual results for the alarm level in surveillance environments, detected by their system [35]. On top of this, they utilized privately recorded videos for evaluation, thereby leaving no space for fair comparison in future research works.

Notwithstanding the downsides of evaluation standards of fuzzy logic-based surveillance BVD analytics methods, there are some optimistic outlooks in the related literature. The commonly utilized metrics in computer vision domain including precision, recall, F1-score, accuracy, false positives and negatives, peak signal to noise ratio, accuracy rate, and false detection rate, among others, are also employed by some existing algorithms. For instance, the authors in [38, 40, 41], implemented accuracy, precision, recall, and F1 measures to justify their output results in various surveillance domains, including human detection and their motion information computation, as given in Table 4. Thus, with these methods, it is possible to evaluate and validate the performance of fuzzy logic in surveillance domains when compared to other approaches employing machine learning and traditional image processing techniques.

Some of the assessment metrics in the fuzzy logic domain from a surveillance perspective are common with other artificial intelligence problem evaluation metrics like accuracy, time, response time, and false positive rate. For instance, the accuracy presented in [44] calculates the quantity of correct predictions declared as a proportion of the total predictions made. It is most commonly used and the best fit for data having an equal number of samples for positive and negative classes however is not effective for imbalance data modeling. Similarly, the false positive rate [58], also known as *fall-out*, calculates the proportion of negative samples incorrectly classified as positive samples. It is mostly utilized to check the false alarm rates of an AI model [83]. The above discussion reveals that there is a lack of common metrics for assessing fuzzy methods , where a set of benchmark evaluation strategies can be introduced for fair comparison and evaluation. Interested researchers are referred to [84] and [85] for different evaluation metric proposals.

6 APPLYING FUZZY LOGIC: WHY, WHEN, AND WHERE?

The recent success of convolutional neural networks (CNNs) in the video analysis [86] domain is commendable and has replaced statistical image processing, providing automated activity recognition [87, 88], data prioritization [89], and many other useful tasks. The most effective methods for video surveillance are based on CNNs or their variants to classify abnormal actions/activities. However, these methods mostly suffer from false alarm rates when exposed to challenging real-world environments. For instance, a fire detection method with a computationally complex CNN baseline achieves 9.34% false alarm rate for fire detection [90]. A false alarm rate of 27.2% has been found in research using activity recognition datasets [91]. In data prioritization approaches, there exists redundancy even after the final output generation [6]. Decision-making opportunities for anomalous events (fire, smoke, fight, violence, etc.) detection using CNNs with end-to-end architectures, that are intelligent enough to discriminate between a true and a false alarm, are yet to be explored. Due to direct affect of these methods over human lives and properties, they demand human-like decisions that are trustworthy when exposed to real-world scenarios.

Fuzzy logic is a suitable solution to address the aforementioned problems. For instance, the false alarm rate for anomalous events (fire, violence, and many others [92]) can be marginally reduced when handled through fuzzy inference systems. A possible direction, but not limited to the anomalous events and false alarm rate generation, is to keep the history of the anomalous events and generate alarms when the fuzzy inference system confirms its alarming nature by processing the previous data patterns. Similarly, the redundancy that can be observed while generating prioritized data can be handled effectively by using fuzzy image processing techniques. Using fuzzy sets/rules and membership values modification accordingly guarantees enhanced redundancy removal with reduced computational complexity [19, 67]. There are an abundance of image processing techniques with a fuzzy logic baseline approach that are used in many applications, ranging from image enhancement/interpretation/segmentation to law-enforcement.

Fuzzy logic-based image processing comprises image fuzzification, modification of membership values, and finally image defuzzification. These techniques contain grayness ambiguity, geometrical fuzziness, and vague knowledge that are referred to as low-level (preprocessing), intermediate-level (segmentation, representation, description), and high-level (analysis, interpretation, recognition) processing. The final output results are generated after an image is passed through theses phases. Some exemplary techniques are histogram-based gray-level fuzzification (histogram fuzzification) used to control brightness for image enhancement [93, 94]. Other techniques include local fuzzification used for edge detection, and feature fuzzification employed to analyze scenes and recognize various types of objects. On top of this, fuzzy image processing offers image information measurement (e.g. entropy, correlation), clustering, hybrid approaches for better performance (including neuro-fuzzy and genetic fuzzy systems), and image filtering opportunities.

Although the fuzzy image processing tools and techniques perform well for certain problems, their accuracy over complex classification/segmentation/object detection tasks lags behind CNNs. The major problem with mainstream CNN based techniques is their deployment over embedded hardware circuits and resource-constrained devices. Significant improvements have been made to optimize the models for deployment on resource-constrained devices. An example of this is described in our recent research in [88], where we employed optimization strategies to squeeze the model size and run over a resource-constrained device for video summarization and activity recognition. Achieving minimum/negligible accuracy loss with highest compression ratio of Deep Learning models after optimization is a dream for computer vision researchers and several approaches have achieved convincing results [95]. However, it is still challenging to run a highly precise model over edge devices for on-the-spot decisions to ensure secure surveillance. Another promising solution towards edge computing and decision making for continuous automated surveillance is to leverage advances in 5G and 6G technologies for data transfer to cloud analysis centers and receiving responses in real-time. Despite these solutions, mainstream fuzzy techniques are well suited for controllers and effective hardware that are functional over the edge and have real-time decision-making potential. Therefore, the usage of CNN or fuzzy logic still depends on the requirements of the users dealing with surveillance BVD. In real-world scenarios requiring timely decisions and instant explainable reporting, surveillance cameras and their hardware controllers can be re-designed and endowed with fuzzy logic techniques on board towards achieving such desired objectives. On the other hand, detailed analysis of surveillance BVD can be handled accurately by means of more complex CNN architectures functional at cloud analysis centers. The future is likely to see both approaches to be complementary for achieving distributed edge AI solutions.

The following edge computing applications using fuzzy logic, fuzzy clustering algorithms can be effectively used for surveillance BVD analysis to segment the videos or group them into similar classes [96], as proposed in [97] for sports videos. Surveillance BVD can be effectively monitored by applying fuzzy feature extraction strategies or hybrid mechanisms [98] with the assistance of Deep Learning architectures, as presented recently in [99]. Since fuzzy logic processes better linguistic data, crowd behaviors/activity predicted using Deep Learning models could be effectively analyzed from surveillance BVD using fuzzy logic and the statistics could be reported accordingly to corresponding authorities [100]. Consider an example of civil disturbance in an online video stream predicted by a Deep Learning model. Here the underlying event can be analyzed and compared with the previous history using fuzzy logic.

This rationale and advocation for continued research in the intersection between surveillance BVD and fuzzy logic stimulates several challenges and future research directions, which are explained in the next section.

7 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

A huge number of research methods in the fuzzy logic domain have been presented since the last decade and particularly over the last 5 years. These methods are split over diverse categories with applications in medical [101], security [102, 103], and surveillance [104], to mention a few.

However, in the fuzzy logic literature, there is a deficiency of research contributions related to disaster management [105], surveillance video summarization [96], embedded vision applications [62], action and activity recognition [106] with major focus on violence detection [3], and the Internet of Things (IoT) [107]. Similarly, hybrid systems proposed from the integration of simple or complex structured Deep Learning architectures and fuzzy theories are very limited and only just emerging [108]. The employed techniques lack focus on high potentials of CNNs and other emerging types of deep neural networks such as SNNs, and graph neural networks integrated with fuzzy rules to generate accurate results. There are also a limited number of contributions in the fuzzy logic literature focusing on the broader coverage of smart cities and converged to IoT and edge intelligence.

The need for such systems with possible research tracks in these specified domains are explained in the subsequent sections and comprehensively summarized in Table 6.

7.1 Application-wise Future Endeavors in the Fuzzy Surveillance Domain

As for future research in the fuzzy logic from these applications' perspective, there are various tracks that are discussed in this section. These tracks include disaster management [105], video summarization [147], actions and activities recognition [106], and intelligent decision systems using fuzzy logic.

Disaster management is a hybrid area of research that has attracted scientists from various domains, including computer and environmental sciences and engineering. Several reporting systems have been developed by using different sensor data and computer vision techniques to identify various types of disasters in their early stages. Natural disasters include wildfire, earthquake, floods, and storms, where their early detection and identification can help saving human lives and properties. For example, fire detection using data from various sensors such as smoke detection sensors, alarm generators or vision sensors with intelligent fire detection mechanisms help identify fire at its early stages. Fire detection sensors (heat and smoke sensors) for dense forests are difficult to install and have limited coverage. Vision sensors, in contrast, can perform well for instant reporting after smoke or flame detection [83].

The usage of fuzzy theory in disaster management can lead us to satisfying results due to its human like reasoning and decision methodology. In particular for fire detection using vision sensors in wild scenes, fuzzy logic can be used to handle false alarms, variable weather conditions, and other sources of uncertainty associated to the video scenes. Some early fuzzy-based methods [112, 148, 149] for fire detection with lower accuracy and high false alarm rates exist that can be used as references for future research in this arena. Here the use of type-2 fuzzy systems or tunable fuzzy systems could improve performance in these domains.

As like in disaster management, fuzzy logic systems are not greatly explored in video summarization literature, where there is an extreme need for human-like rules for representative content selection from lengthy videos. Video summarization aims at the condensation and summarization of videos, generated from live surveillance video or any other input depending upon the application [150]. This is a trending research topic due to its importance in saving resources of huge amount of video data that is generated on a daily basis. video summarization methods are split into two sub-domains, i.e., single and multi-view video summarization on the basis of vision sensors used to generate video data. Single-view video summarization [96] provides a summary with limited coverage, while multi-view video summarization [61] gives a proper reporting from different angles and thus creates a diverse and representative summary. To the best of our knowledge, there are only countable number of research studies [19, 104] that use fuzzy logic (even as a prerequisite step) to assist an algorithm in generating a video summary. This field of research should be considered in the future to realize an effective usage of fuzzy logic for useful surveillance video summarization. Here, fuzzy logic can generate summaries that are closer to human perception.

In contrast to video summarization using fuzzy theories, the domain of action recognition [106] with sub-domains of violence detection [3] and gesture recognition [151] has relatively dense research and application contributions. Activity recognition is an active domain of research providing services in automated surveillance and playing a vital role in ensuring public safety. Representative activity recognition methods from fuzzy logic literature include [152] and [153], where they used fuzzy clustering, fuzzy self-organizing map, and fuzzy inference systems to predict human activity. Unfortunately, the recent fuzzy literature is still limited on the coverage of these topics from real-world implementation and accuracy perspectives. Therefore, human activity recognition using fuzzy theories is still an open research area for dealing with video data for effective activity recognition.

7.2 Edge Intelligence and Fuzzy Logic

Fuzzy systems have comparatively lower computational complexity than other modeling approaches [154], and can be easily transformed for their use at the edge of networks that support the generation and distributed analysis of data [155, 156] at the point of its creation. Visual sensors in surveillance IoT networks can be made intelligent enough to analyze online streams efficiently, and eventually report on abnormal situation. These intelligent vision sensors can be used with a resource-constrained device having limited computational capabilities, or the hardware of the input camera might be made smarter with several functionalities such as automated objects analysis, events detection, and recognition. As fuzzy logic performs well over controllers and hardware devices [155], embedded programming can be employed to make surveillance cameras intelligent with various functionalities, as exemplified previously.

Transforming these capabilities into the edge has several advantages with primary benefits of effective resource usage and instant reporting. Edge intelligence ensures real-time responsive actions with instant decision making capabilities [62]. For instance, readers can refer to [5], where authors utilized a resource-constrained device for suspicious objects detection, followed by video summarization. A similar case is reported in [62], which aims at intelligently using a resource-restricted device for smart healthcare centers. In another research work [157], a Raspberry Pi is utilized for facial expression recognition to provide smart law-enforcement services. Thus, bringing fuzzy logic to the edge of networks [158] can play a significant role [159] in the effective analysis of generated surveillance BVD.

7.3 Adaptive Fuzzy Logic for Non-Stationary Environments

Non-stationary environments refer to scenarios where new data is produced continuously subject to exogenous factors that make the knowledge captured by data-based models vary over time [160]. Therefore, the rules or inference systems pre-defined for a certain scenario are limited to such environment without any adaptability for new scenes or events. This is an emerging issue, particularly for vision data generated from surveillance cameras, where the environment changes from time to time, and unexpected situations can be encountered at anytime. Decisions made by fuzzy logic are safe for data with high-level of uncertainties and variation. Therefore, the problem of non-stationary surveillance environments can be effectively tackled by virtue of adaptive fuzzy logic systems.

An adaptive fuzzy system can perform well over the new distribution of data and overcome the deficiency of confined decisions. This track of future research is very important for effective decision making in surveillance scenarios. Researchers in the fuzzy logic domain should be highly motivated to contribute to this direction of research. In this line of reasoning we refer them to the study in [109], where surveillance of live streams with non-stationary environments are handled for precise action recognition. In a similar approach towards non-stationary data handling, Jesus L et al. [161] utilized recently evolved SNNs to provide an active adaptation for drift detection problems.

On a closing note, as fuzzy rules are based on continuous values they can be effectively utilized in non-stationary environments to represent and generalize a situation in the learning stage of an algorithm or a hybrid model.

7.4 Public Availability of Research Implementation

The majority of the fuzzy based research works do not provide a public release of the implementation of their proposals, nor do they made the utilized datasets public for the community.The primary concern of private resources is that comparison of their techniques with the state of the art methods becomes tough in cases where the authors have not made their implementation publicly accessible. Possible content that should be attached to prospective works should contain the codes, datasets, and supplementary materials, along with clear instructions and scripts to replicate the results discussed in the publication of reference. When made available, codes and datasets can be harnessed by other researchers working in different fuzzy domains towards better outcomes. Therefore, researchers should be encouraged to release codes and necessary supporting material in Github or other open repositories for future usage of the research community. In this regard, Table 7 shows a list of some fuzzy logic software frameworks and tools that can be utilized for new implementations in prospective studies.

7.5 Time Complexity and Computational Resources Analysis

The generic trend in the research community for measurement of novel acceptable contributions compared to the state-of-the-art includes F1 score, accuracy, preciseness, or increase in efficiency. Most of the research articles are racing for higher accuracy without any focus on computational complexity. Similarly, the employed methods lack focus on the size of the final hybrid model or method to use, its feasibility for installation, deployment conditions, CPU or GPU inter-adoptability, extension of any algorithm from GPU to CPU, and in turn into embedded devices. For instance, time computational complexity analysis can be observed in the study reported in [88], where authors exposed time comparison and other issues related to the adoptability of their framework. In other research proposed by Hussain et al. [5], a detailed analysis is made about their systems' response time, individual algorithms comparison, experiments over different videos resolutions, and varying frame rates. Such detailed experiments open up new directions for further research. A possible future research avenue can be unleashed by introducing the computational complexity of fuzzy methods, where researchers can optionally focus on reducing time complexity or increasing the precision of their methods.

7.6 Proposals of Hybrid Techniques

Recently, different flavors of neural networks and efficient architectures have been introduced that convincingly succeeded in imitating many functions of the human brain. These networks include SNNs [165], which have the potential to model the human brain, and work well for pattern learning tasks such as human motion for abnormal activity recognition. As an example, an audiovisual information processing system was implemented by [166] with convincing results compared to state-of-the-art approaches. A derived version of SNNs with so-called *super spikes* is proposed by Zenke and Ganguli [167] to open a new trend in SNNs research. Chandhok et al. solved the problem of image clustering using SNNs [168]. Other trending neural network techniques are GNNs [169], which have been proven to yield better solutions to complex tasks such as action recognition [170]. As an example, it is interesting to observe the semantic segmentation results achieved by 3D graph neural networks [171]. Another research work [172] has resorted to graph neural networks to rank web pages with promising results. These techniques can compete with human-level accuracy, however research in regard to such hybrid models endowed with fuzzy logic capabilities has yet to be explored for complex real-world problems.

7.7 Explainability in Fuzzy Video Data Analysis

Much attention has been lately paid to the interpretability of black-box Machine Learning models, mainly due to their noted significance in practical scenarios where they are used [173, 174]. In fact, it is widely acknowledged that in certain domains [175], a proper understanding of how decisions are furnished by these opaque models ease the acceptability and trust of the user who is making decisions on the basis of their output [176]. Surveillance is not an exception to this noted need for explainability, particularly for the identification and accountability of the reasons why the model detected a given event. Explainability (XAI) techniques can help the user discriminate these reasons, analyze them, and ultimately design countermeasures to minimize their recurrence over time.

Fuzzy logic can be an efficient interface for explaining the knowledge contained in the model to its end user. For instance, evolutionary fuzzy rule-based systems can complement black-box models (e.g. Deep Learning) for their understanding by an audience without in Machine Learning [177]. However, the provision of explanations over non-stationary data (Subsection 7.3) still remains an open challenge, particularly in regards to how model changes resulting from this lack of stationarity propagate to the produced explanations, and how these varying explanatory information can be consumed by the audience.

Another challenge emerges when matching the cognitive skills of the user for which explainability is sought with the complexity of explanations elicited by XAI techniques [178]. This issue becomes even more involved when explanations are produced over both space and time domains, including natural language stories about the sequence of frames that triggered the output of the model at hand [85]. Some baseline research is carried out in this direction towards the explainable type-2 fuzzy logic systems for gesture recognition [20]. We foresee vast research opportunities to address these aspects in coming years [108].

8 CONCLUDING REMARKS

Surveillance cameras are one of the most common sources responsible for generation of huge amount of video data, requiring effective analysis methods for their significant usage. There exists a variety of methods undertaking this raw video data and transforming it into useful information via machine learning, Deep Learning, image processing, and pattern recognition techniques. Fuzzy methods such as fuzzy inference, fuzzy clustering, and extensions to type-1 fuzzy systems mimic human cognitive abilities to process any type of data. These methods can achieve video analytics tasks by transforming input video data into useful information while having the ability to handle different sources of contextual uncertainties. At the same time, as fuzzy logic and its generated system is based on perceived assumptions, it may show limited performance for some complex pattern recognition tasks when compared to classical image processing and machine learning algorithms. Fuzzy systems excel in their ability to proved explainable, flexible and robust knowledge representation and reasoning solutions. However, using them on their own may show poor performance for video analysis tasks (activity classification, anomaly recognition, etc.). Therefore, in the majority of these cases, fuzzy inference techniques are widely used in combination with neural networks for precise output predictions in several domains.

Fuzzy logics's usage in surveillance BVD is comparatively scarce. This review paper addresses this research niche by highlighting the need for surveying the use of fuzzy techniques in this challenging and increasing relevant domain. The studies reviewed in Section 4 confirm that fuzzy methods are able to outperform traditional methods in many complex problems related to security [179], sentiment analysis [180], data classification [181], and natural language processing tasks [182], among others. However, the literature still receives rare contributions from the perspective of surveillance applications. There are approximately 20 methods performing object detection, tracking human actions, or dealing with surveillance BVD using a variety of fuzzy systems. In this review paper, we have first introduced the topic, along with its motivation and applications of interest. Next, we have explained the basic working procedure of fuzzy methods, followed by an introduction of video analytics via fuzzy logic. Following this, we have introduced possible challenges and a motivational rationale for the review article directed towards our major contributions. In Section 3, we have presented and discussed existing surveys in the fuzzy logic domain to familiarize readers with previous and ongoing works in this realm. Furthermore, we have provided a wide literature coverage of our survey followed by different surveillance methods utilizing BVD for various applications. Most importantly, Section 7 has exposed future research directions in terms of applications leveraging this synergy of technologies, as well as possible areas of research in machine learning that align closely with the needs of fuzzy logic BVD analytics.

Fuzzy logic is a hot topic of research and development with major focus on disease diagnosis, control systems, semantic similarity controllers, and pattern classification problems. The effectiveness of fuzzy logic is not properly utilized for inspection and reporting of surveillance BVD, leading to the possibility of developing robust and representative solutions. Through this survey, we encourage scientists to develop novel applications or improvements to previous research applying fuzzy methods utilized for surveillance applications. A lack of research focus on the domain will leave fuzzy techniques for surveillance as deserted, and surveillance BVD analytics will be deprived from the full potential of fuzzy logic. This overview has provided baseline material and outlined valuable research directions for this area to blossom in the years to come.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. 2019R1A2B5B01070067). Javier Del Ser would like to thank the Basque Government for its funding support through the EMAITEK program. He also receives funding support from the Consolidated Research Group MATHMODE (IT1294-19) granted by the Department of Education of the same institution. This work is also supported in part by PR of China Ministry of Education Distinguished Possessor Grant given to Prof. Obaidat under number MS2017BJKJ003.

REFERENCES

[1] Zhihan Lv, Houbing Song, Pablo Basanta-Val, Anthony Steed, and Minho Jo. Next-generation big data analytics: State of the art, challenges, and future research topics. *IEEE Transactions on Industrial Informatics*, 13(4):1891–1899, 2017.

[2] Waseem Ullah, Amin Ullah, Ijaz Ul Haq, Khan Muhammad, Muhammad Sajjad, and Sung Wook Baik. Cnn features with bi-directional lstm for real-time anomaly detection in surveillance networks. *Multimedia Tools and Applications*, pages 1–17, 2020.

[3] Fath U Min Ullah, Amin Ullah, Khan Muhammad, Ijaz Ul Haq, and Sung Wook Baik. *Sensors*, 19(11):2472, 2019.

[4] Amna Shifa, Mamoona Naveed Asghar, Adeel Ahmed, and Martin Fleury. Fuzzy-logic threat classification for multi-level selective encryption over real-time video streams. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–29, 2020.

[5] Tanveer Hussain, Khan Muhammad, Javier Del Ser, Sung Wook Baik, and Victor Hugo C de Albuquerque. Intelligent embedded vision for summarization of multiview videos in iiot. *IEEE Transactions on Industrial Informatics*, 16(4):2592–2602, 2019.

[6] Tanveer Hussain, Khan Muhammad, Amin Ullah, Zehong Cao, Sung Wook Baik, and Victor Hugo C de Albuquerque. Cloud-assisted multiview video summarization using cnn and bidirectional lstm. *IEEE Transactions on Industrial Informatics*, 16(1):77–86, 2019.

[7] A. Ullah, K. Muhammad, T. Hussain, S. W. Baik, and V. H. C. De Albuquerque. Event-oriented 3d convolutional features selection and hash codes generation using pca for video retrieval. *IEEE Access*, 8:196529–196540, 2020.

[8] Amritpal Singh, Sahil Garg, Ravneet Kaur, Shalini Batra, Neeraj Kumar, and Albert Y Zomaya. Probabilistic data structures for big data analytics: A comprehensive review. *Knowledge-Based Systems*, 188:104987, 2020.

[9] Derek Anderson, Robert H Luke, James M Keller, Marjorie Skubic, Marilyn J Rantz, and Myra A Aud. Modeling human activity from voxel person using fuzzy logic. *IEEE Transactions on Fuzzy Systems*, 17(1):39–49, 2008.

[10] Rangan Das, Sagnik Sen, and Ujjwal Maulik. A survey on fuzzy deep neural networks. *ACM Computing Surveys (CSUR)*, 53(3):1–25, 2020.

[11] Song Wei and Hani Hagras. A hybrid fuzzy football scenes classification system for big video data. In *Multimodal Analytics for Next-Generation Big Data Technologies and Applications*, pages 299–318. Springer, 2019.

[12] Farman Ali, Shaker El-Sappagh, and Daehan Kwak. Fuzzy ontology and lstm-based text mining: A transportation network monitoring system for assisting travel. *Sensors*, 19(2):234, 2019.

[13] Lotfi A Zadeh. Fuzzy sets. *Information and control*, 8(3):338–353, 1965.

[14] Harish Garg and Gagandeep Kaur. Quantifying gesture information in brain hemorrhage patients using probabilistic dual hesitant fuzzy sets with unknown probability information. *Computers & Industrial Engineering*, 140:106211, 2020.

[15] Qilian Liang and Jerry M Mendel. Mpeg vbr video traffic modeling and classification using fuzzy technique. *IEEE Transactions on Fuzzy systems*, 9(1):183–193, 2001.

[16] Eduard Puerto, José Aguilar, C Lopez, and Danilo Chávez. Using multilayer fuzzy cognitive maps to diagnose autism spectrum disorder. *Applied soft computing*, 75:58–71, 2019.

[17] Javier Navarro, Faiyaz Doctor, Víctor Zamudio, Rahat Iqbal, Arun Kumar Sangaiah, and Carlos Lino. Fuzzy adaptive cognitive stimulation therapy generation for alzheimer's sufferers: Towards a pervasive dementia care monitoring platform. *Future Generation Computer Systems*, 88:479–490, 2018.

[18] Zi-Xiao Wei, Faiyaz Doctor, Yan-Xin Liu, Shou-Zen Fan, and Jiann-Shing Shieh. An optimized type-2 self-organizing fuzzy logic controller applied in anesthesia for propofol dosing to regulate bis. *IEEE Transactions on Fuzzy Systems*, 28(6):1062–1072, 2020.

[19] B. Yao, H. Hagras, D. Alghazzawi, and M. J. Alhaddad. A type-2 fuzzy logic based system for linguistic summarization of video monitoring in indoor intelligent environments. In *2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 825–833, 2014.

[20] J. Rožman, H. Hagras, J. A. Perez, D. Clarke, B. Müller, and S. F. Data. Privacy-preserving gesture recognition with explainable type-2 fuzzy logic based systems. In *2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–8, 2020.

[21] Woei Wan Tan and Teck Wee Chua. Uncertain rule-based fuzzy logic systems: introduction and new directions (mendel, jm; 2001)[book review]. *IEEE Computational Intelligence Magazine*, 2(1):72–73, 2007.

[22] Yanpeng Qu, Qilin Fu, Changjing Shang, Ansheng Deng, Reyer Zwiggelaar, Minu George, and Qiang Shen. Fuzzy-rough assisted refinement of image processing procedure for mammographic risk assessment. *Applied Soft Computing*, page 106230, 2020.

[23] Jerry M Mendel and RI Bob John. Type-2 fuzzy sets made simple. *IEEE Transactions on fuzzy systems*, 10(2):117–127, 2002.

[24] Ahmad Taher Azar. Overview of type-2 fuzzy logic systems. *International Journal of Fuzzy System Applications (IJFSA)*, 2(4):1–28, 2012.

[25] Meng Joo Er and Sayantan Mandal. A survey of adaptive fuzzy controllers: Nonlinearities and classifications. *IEEE Transactions on Fuzzy Systems*, 24(5):1095–1107, 2015.

[26] Chern Hong Lim, Ekta Vats, and Chee Seng Chan. Fuzzy human motion analysis: A review. *Pattern Recognition*, 48(5):1773–1796, 2015.

[27] Hossein Ahmadi, Marsa Gholamzadeh, Leila Shahmoradi, Mehrbakhsh Nilashi, and Pooria Rashvand. Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review. *Computer Methods and Programs in Biomedicine*, 161:145–172, 2018.

[28] Osama Nayel Al Sayaydeh, Mohammed Falah Mohammed, and Chee Peng Lim. Survey of fuzzy min–max neural network for pattern classification variants and applications. *IEEE transactions on fuzzy systems*, 27(4):635–645, 2018.

[29] Sunny Thukral and Vijay Rana. Versatility of fuzzy logic in chronic diseases: A review. *Medical Hypotheses*, 122:150–156, 2019.

[30] Goli Arji, Hossein Ahmadi, Mehrbakhsh Nilashi, Tarik A Rashid, Omed Hassan Ahmed, Nahla Aljojo, and Azida Zainol. Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature and classification. *Biocybernetics and Biomedical Engineering*, 39(4):937–955, 2019.

[31] Kamran Munir, Alberto de Ramón-Fernández, Sohail Iqbal, and Nadeem Javaid. Neuroscience patient identification using big data and fuzzy logic–an alzheimer's disease case study. *Expert Systems with Applications*, 136:410–425, 2019.

[32] Jesús Alcalá-Fdez and Jose M Alonso. A survey of fuzzy systems software: Taxonomy, current research trends, and prospects. *IEEE Transactions on Fuzzy Systems*, 24(1):40–56, 2015.

[33] Javier Andreu-Perez. Fuzzy learning and its applications in neural-engineering. *Neurocomputing*, 389:196–197, 2020.

[34] Marwa Elbouz, Alfalou Ayman, and Christian Brosseau. Fuzzy logic and optical correlation-based face recognition method for patient monitoring application in home video surveillance. *Optical Engineering*, 50(6):067003, 2011.

[35] Yi Zheng and Ping Zheng. Multisensor image fusion using fuzzy logic for surveillance systems. In *2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, volume 2, pages 588–592. IEEE, 2010.

[36] R Badaoui and Adel Al-Jumaily. Fuzzy logic based human detection for cctv recording application. In *2010 6th International Conference on Advanced Information Management and Service (IMS)*, 2010.

[37] Juan Moreno-Garcia, Luis Rodriguez-Benitez, Antonio Fernández-Caballero, and María T López. Video sequence motion tracking by fuzzification techniques. *Applied Soft Computing*, 10(1):318–331, 2010.

[38] Mario I Chacon-Murguia and Sergio Gonzalez-Duarte. An adaptive neural-fuzzy approach for object detection in dynamic backgrounds for surveillance systems. *IEEE Transactions on Industrial Electronics*, 59(8):3286–3298, 2011.

[39] David Münch, Joris IJsselmuiden, Michael Arens, and Rainer Stiefelhagen. High-level situation recognition using fuzzy metric temporal logic, case studies in surveillance and smart environments. In *2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops)*, pages 882–889. IEEE, 2011.

[40] Carles Fernández, Pau Baiget, F Xavier Roca, and Jordi Gonzàlez. Determining the best suited semantic events for cognitive surveillance. *Expert Systems with Applications*, 38(4):4068–4079, 2011.

[41] Bing-Fei Wu, Chih-Chung Kao, Jhy-Hong Juang, and Yi-Shiun Huang. A new approach to video-based traffic surveillance using fuzzy hybrid information inference mechanism. *IEEE Transactions on Intelligent Transportation Systems*, 14(1):485–491, 2012.

[42] Ansuman Mahapatra, Tusar Kanti Mishra, Pankaj K Sa, and Banshidhar Majhi. Background subtraction and human detection in outdoor videos using fuzzy logic. In *2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–7. IEEE, 2013.

[43] Auday AH Mohamad and Mohammed Osman. Adaptive median filter background subtractions technique using fuzzy logic. In *2013 INTERNATIONAL CONFERENCE ON COMPUTING, ELECTRICAL AND ELECTRONIC ENGINEERING (ICCEEE)*, pages 115–120. IEEE, 2013.

[44] R Revathi and M Hemalatha. Moving and immovable object in video processing using intuitionistic fuzzy logic. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)*, pages 1–6. IEEE, 2013.

[45] Ansuman Mahapatra, Tusar Kanti Mishra, Pankaj K Sa, and Banshidhar Majhi. Human recognition system for outdoor videos using hidden markov model. *AEU-International Journal of Electronics and Communications*, 68(3):227–236, 2014.

[46] Ahmad Alajarmeh, Rosalina Abdul Salam, Mohd Fadzli Marhusin, and Khairi Abdulrahim. Real-time video enhancement for various weather conditions using dark channel and fuzzy logic. In *2014 International Conference on Computer and Information Sciences (ICCOINS)*, pages 1–6. IEEE, 2014.

[47] Piotr Szwed, Pawel Skrzynski, and Wojciech Chmiel. Risk assessment for a video surveillance system based on fuzzy cognitive maps. *Multimedia Tools and Applications*, 75(17):10667–10690, 2016.

[48] Reza Mohammadi and Reza Javidan. An adaptive type-2 fuzzy traffic engineering method for video surveillance systems over software defined networks. *Multimedia Tools and Applications*, 76(22):23627–23642, 2017.

[49] Li Liang-qun, Zhan Xi-yang, Liu Zong-xiang, and Xie Wei-xin. Fuzzy logic approach to visual multi-object tracking. *Neurocomputing*, 281:139–151, 2018.

[50] Yanshan Li, Tianyu Guo, Rongjie Xia, and Weixin Xie. Road traffic anomaly detection based on fuzzy theory. *IEEE Access*, 6:40281–40288, 2018.

[51] Miguel A Molina-Cabello, Ezequiel López-Rubio, Rafael M Luque-Baena, Enrique Domínguez, and Esteban J Palomo. Foreground object detection for video surveillance by fuzzy logic based estimation of pixel illumination states. *Logic Journal of the IGPL*, 26(6):593–604, 2018.

[52] Rahul Raman, Larbi Boubchir, Pankaj Kumar Sa, Banshidhar Majhi, and Sambit Bakshi. Beyond estimating discrete directions of walk: a fuzzy approach. *Machine Vision and Applications*, 30(5):901–917, 2019.

[53] Healthcare dataset. Last accessed 1 November 2019 (http://cvprlab.uniparthenope.it).

[54] Moving cars and pedestrain data. Last accessed 1 November 2019 (http://www.imagefusion.org/images/toet2).

[55] Surveillance videos. Last accessed 1 November 2019 (http://www.imagefusion.org/images/toet2).

[56] Surveillance videos. Last accessed 1 November 2019 (www.research.ibm.com/peoplevision/videoprivacy.htm), url = www.research.ibm.com/peoplevision/videoprivacy.htm.

[57] James L Crowley, Patrick Reignier, and Sebastien Pesnel. Context aware vision using image-based active recognition. 2004.

[58] Maciej Szczodrak, Jozef Kotus, Krzysztof Kopaczewski, Kuba Lopatka, Andrzej Czyzewski, and Henryk Krawczyk. Behavior analysis and dynamic crowd management in video surveillance system. In *2011 22nd International Workshop on Database and Expert Systems Applications*, pages 371–375. IEEE, 2011.

[59] Arnav Chowdhury and Sanjaya Shankar Tripathy. Detection of human presence in a surveillance video using fuzzy approach. In *2014 International Conference on Signal Processing and Integrated Networks (SPIN)*, pages 216–219. IEEE, 2014.

[60] Amin Ullah, Khan Muhammad, Tanveer Hussain, Miyoung Lee, and Sung Wook Baik. 5 deep lstm-based sequence learning approaches for action and activity recognition. *Deep Learning in Computer Vision: Principles and Applications*, page 127, 2020.

[61] Tanveer Hussain, Khan Muhammad, Weiping Ding, Jaime Lloret, Sung Wook Baik, and Victor Hugo C de Albuquerque. A comprehensive survey of multi-view video summarization. *Pattern Recognition*, 109:107567, 2020.

[62] Tanveer Hussain, Khan Muhammad, Salman Khan, Amin Ullah, Mi Young Lee, and Sung Wook Baik. Intelligent baby behavior monitoring using embedded vision in iot for smart healthcare centers. *Journal of Artificial Intelligence and Systems. J. Artif. Intell. Syst*, 1(15):2019, 2019.

[63] Alper Yilmaz, Omar Javed, and Mubarak Shah. Object tracking: A survey. *Acm computing surveys (CSUR)*, 38(4):13–es, 2006.

[64] Dingwen Zhang, Junwei Han, Guangyu Guo, and Long Zhao. Learning object detectors with semi-annotated weak labels. *IEEE Transactions on Circuits and Systems for Video Technology*, 29(12):3622–3635, 2018.

[65] Anh-Tu Nguyen, Tadanari Taniguchi, Luka Eciolaza, Victor Campos, Reinaldo Palhares, and Michio Sugeno. Fuzzy control systems: Past, present and future. *IEEE Computational Intelligence Magazine*, 14(1):56–68, 2019.

[66] Wei Song and Hani Hagras. A big-bang big-crunch fuzzy logic based system for sports video scene classification. In *2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 642–649. IEEE, 2016.

[67] Wei Song and Hani Hagras. A type-2 fuzzy logic system for event detection in soccer videos. In *2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–6. IEEE, 2017.

[68] Jethro Shell and Simon Coupland. Fuzzy transfer learning: methodology and application. *Information Sciences*, 293:59–79, 2015.

[69] Hua Zuo, Jie Lu, Guangquan Zhang, and Feng Liu. Fuzzy transfer learning using an infinite gaussian mixture model and active learning. *IEEE Transactions on Fuzzy Systems*, 27(2):291–303, 2018.

[70] Thanh Minh Nguyen and QM Jonathan Wu. Online feature selection based on fuzzy clustering and its applications. *IEEE Transactions on Fuzzy Systems*, 24(6):1294–1306, 2015.

[71] Vikas Singh, Raghav Dev, Narendra K Dhar, Pooja Agrawal, and Nishchal K Verma. Adaptive type-2 fuzzy approach for filtering salt and pepper noise in grayscale images. *IEEE Transactions on Fuzzy Systems*, 26(5):3170–3176, 2018.

[72] Hong Zhao, Ping Wang, Qinghua Hu, and Pengfei Zhu. Fuzzy rough set based feature selection for large-scale hierarchical classification. *IEEE Transactions on Fuzzy Systems*, 27(10):1891–1903, 2019.

[73] Renato WR De Souza, João Vitor Chaves De Oliveira, Leandro A Passos, Weiping Ding, João P Papa, and Victor Albuquerque. A novel approach for optimum-path forest classification using fuzzy logic. *IEEE Transactions on Fuzzy Systems*, 2019.

[74] Dingwen Zhang, Junwei Han, Long Zhao, and Deyu Meng. Leveraging prior-knowledge for weakly supervised object detection under a collaborative self-paced curriculum learning framework. *International Journal of Computer Vision*, 127(4):363–380, 2019.

[75] Dingwen Zhang, Junwei Han, Long Zhao, and Tao Zhao. From discriminant to complete: Reinforcement searching-agent learning for weakly supervised object detection. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.
[76] Charlie J Daniels and Ferdia A Gallagher. Unsupervised segmentation of 5d hyperpolarized carbon-13 mri data using a fuzzy markov random field model. *IEEE transactions on medical imaging*, 37(4):840–850, 2017.
[77] Kup-Sze Choi, Xue-Jian He, Vico CL Chiang, Zhaohong Deng, and Jing Qin. A heuristic force model for haptic simulation of nasogastric tube insertion using fuzzy logic. *IEEE transactions on haptics*, 9(3):295–310, 2016.
[78] Anil Singh Parihar, Om Prakash Verma, and Chintan Khanna. Fuzzy-contextual contrast enhancement. *IEEE Transactions on Image Processing*, 26(4):1810–1819, 2017.
[79] Chang Ho Kang, Chan Gook Park, and Jin Woo Song. An adaptive complementary kalman filter using fuzzy logic for a hybrid head tracker system. *IEEE Transactions on Instrumentation and Measurement*, 65(9):2163–2173, 2016.
[80] Wasseem N Ibrahem Al-Obaydy and Shahrel Azmin Suandi. Open-set single-sample face recognition in video surveillance using fuzzy artmap. *Neural Computing and Applications*, 32(5):1405–1412, 2020.
[81] Gail A Carpenter, Stephen Grossberg, Natalya Markuzon, John H Reynolds, David B Rosen, et al. Fuzzy artmap: A neural network architecture for incremental supervised learning of analog multidimensional maps. *IEEE Transactions on neural networks*, 3(5):698–713, 1992.
[82] Seyed Yahya Nikouei, Yu Chen, Alexander Aved, Erik Blasch, and Timothy R Faughnan. I-safe: Instant suspicious activity identification at the edge using fuzzy decision making. In *Proceedings of the 4th ACM/IEEE Symposium on Edge Computing*, pages 101–112, 2019.
[83] Salman Khan, Khan Muhammad, Shahid Mumtaz, Sung Wook Baik, and Victor Hugo C de Albuquerque. Energy-efficient deep cnn for smoke detection in foggy iot environment. *IEEE Internet of Things Journal*, 6(6):9237–9245, 2019.
[84] Sandra Eliza Fontes De Avila, Ana Paula Brandão Lopes, Antonio da Luz Jr, and Arnaldo de Albuquerque Araújo. Vsumm: A mechanism designed to produce static video summaries and a novel evaluation method. *Pattern Recognition Letters*, 32(1):56–68, 2011.
[85] Nayyer Aafaq, Ajmal Mian, Wei Liu, Syed Zulqarnain Gilani, and Mubarak Shah. Video description: A survey of methods, datasets, and evaluation metrics. *ACM Computing Surveys (CSUR)*, 52(6):1–37, 2019.
[86] Dingwen Zhang, Junwei Han, Le Yang, and Dong Xu. Spftn: a joint learning framework for localizing and segmenting objects in weakly labeled videos. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2018.
[87] Le Yang, Houwen Peng, Dingwen Zhang, Jianlong Fu, and Junwei Han. Revisiting anchor mechanisms for temporal action localization. *IEEE Transactions on Image Processing*, 29:8535–8548, 2020.
[88] Tanveer Hussain, Khan Muhammad, Amin Ullah, Javier Del Ser, Amir H Gandomi, Muhammad Sajjad, Sung Wook Baik, and Victor Hugo C de Albuquerque. Multi-view summarization and activity recognition meet edge computing in iot environments. *IEEE Internet of Things Journal*, 2020.
[89] Yujia Zhang, Xiaodan Liang, Dingwen Zhang, Min Tan, and Eric P Xing. Unsupervised object-level video summarization with online motion auto-encoder. *Pattern Recognition Letters*, 130:376–385, 2020.
[90] Khan Muhammad, Salman Khan, Mohamed Elhoseny, Syed Hassan Ahmed, and Sung Wook Baik. Efficient fire detection for uncertain surveillance environment. *IEEE Transactions on Industrial Informatics*, 15(5):3113–3122, 2019.
[91] Mahmudul Hasan, Jonghyun Choi, Jan Neumann, Amit K Roy-Chowdhury, and Larry S Davis. Learning temporal regularity in video sequences. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 733–742, 2016.
[92] Kelton AP da Costa, João P Papa, Leandro A Passos, Danilo Colombo, Javier Del Ser, Khan Muhammad, and Victor Hugo C de Albuquerque. A critical literature survey and prospects on tampering and anomaly detection in image data. *Applied Soft Computing*, page 106727, 2020.
[93] Ming Liu, Zhiqian Zhou, Penghui Shang, and Dong Xu. Fuzzified image enhancement for deep learning in iris recognition. *IEEE Transactions on Fuzzy Systems*, 28(1):92–99, 2019.
[94] Bharath Subramani and Magudeeswaran Veluchamy. Fuzzy gray level difference histogram equalization for medical image enhancement. *Journal of Medical Systems*, 44:1–10, 2020.
[95] Shupeng Gui, Haotao N Wang, Haichuan Yang, Chen Yu, Zhangyang Wang, and Ji Liu. Model compression with adversarial robustness: A unified optimization framework. In *Advances in Neural Information Processing Systems*, pages 1285–1296, 2019.
[96] Khan Muhammad, Tanveer Hussain, and Sung Wook Baik. Efficient cnn based summarization of surveillance videos for resource-constrained devices. *Pattern Recognition Letters*, 130:370–375, 2020.
[97] Wu-Yeh Chang. Research on sports video image based on fuzzy algorithms. *Journal of Visual Communication and Image Representation*, 61:105–111, 2019.
[98] Zulfiqar Ahmad Khan, Tanveer Hussain, Amin Ullah, Seungmin Rho, Miyoung Lee, and Sung Wook Baik. Towards efficient electricity forecasting in residential and commercial buildings: A novel hybrid cnn with a lstm-ae based framework. *Sensors*, 20(5):1399, 2020.
[99] Jing-Jing Wang. Intelligent recognition method of fuzzy features of surveillance video image based on big data. In *2019 International Conference on Virtual Reality and Intelligent Systems (ICVRIS)*, pages 105–108. IEEE, 2019.
[100] Elizabeth Varghese, Sabu M Thampi, and Stefano Berretti. A psychologically inspired fuzzy cognitive deep learning framework to predict crowd behavior. *IEEE Transactions on Affective Computing*, 2020.
[101] Weisheng Li, Jiao Du, Zhengmin Zhao, and Jinyi Long. Fusion of medical sensors using adaptive cloud model in local laplacian pyramid domain. *IEEE Transactions on Biomedical Engineering*, 66(4):1172–1183, 2018.

[102] FengJi Luo, ZhaoYang Dong, Guo Chen, Yan Xu, Ke Meng, YingYing Chen, and KitPo Wong. Advanced pattern discovery-based fuzzy classification method for power system dynamic security assessment. *IEEE Transactions on Industrial Informatics*, 11(2):416–426, 2015.

[103] Mohamed Hamdy, Sameh Abd-Elhaleem, and MA Fkirin. Time-varying delay compensation for a class of nonlinear control systems over network via H_∞ adaptive fuzzy controller. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(8):2114–2124, 2016.

[104] Bo Yao, Hani Hagras, Daniyal Alghazzawi, and Mohammed J Alhaddad. A big bang–big crunch type-2 fuzzy logic system for machine-vision-based event detection and summarization in real-world ambient-assisted living. *IEEE Transactions on Fuzzy Systems*, 24(6):1307–1319, 2016.

[105] Khan Muhammad, Jamil Ahmad, and Sung Wook Baik. Early fire detection using convolutional neural networks during surveillance for effective disaster management. *Neurocomputing*, 288:30–42, 2018.

[106] Amin Ullah, Khan Muhammad, Javier Del Ser, Sung Wook Baik, and Victor Hugo C de Albuquerque. Activity recognition using temporal optical flow convolutional features and multilayer lstm. *IEEE Transactions on Industrial Electronics*, 66(12):9692–9702, 2018.

[107] Iker Sobron, Javier Del Ser, Iñaki Eizmendi, and Manuel Vélez. Device-free people counting in iot environments: New insights, results, and open challenges. *IEEE Internet of Things Journal*, 5(6):4396–4408, 2018.

[108] R. Chimatapu, H. Hagras, M. Kern, and G. Owusu. Hybrid deep learning type-2 fuzzy logic systems for explainable ai. In *2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–6, 2020.

[109] Amin Ullah, Khan Muhammad, Ijaz Ul Haq, and Sung Wook Baik. Action recognition using optimized deep autoencoder and cnn for surveillance data streams of non-stationary environments. *Future Generation Computer Systems*, 96:386–397, 2019.

[110] Iker Sobron, Javier Del Ser, Iñaki Eizmendi, and Manuel Velez. A deep learning approach to device-free people counting from wifi signals. In *International Symposium on Intelligent and Distributed Computing*, pages 275–286. Springer, 2018.

[111] Ijaz Ul Haq, Khan Muhammad, Tanveer Hussain, Soonil Kwon, Maleerat Sodanil, Sung Wook Baik, and Mi Young Lee. Movie scene segmentation using object detection and set theory. *International Journal of Distributed Sensor Networks*, 15(6):1550147719845277, 2019.

[112] Simon Y Foo. A fuzzy logic approach to fire detection in aircraft dry bays and engine compartments. *IEEE Transactions on Industrial Electronics*, 47(5):1161–1171, 2000.

[113] Paulo Vinicius Koerich Borges and Ebroul Izquierdo. A probabilistic approach for vision-based fire detection in videos. *IEEE transactions on circuits and systems for video technology*, 20(5):721–731, 2010.

[114] Olivia Mendoza, Patricia Melín, and Oscar Castillo. Interval type-2 fuzzy logic and modular neural networks for face recognition applications. *Applied soft computing*, 9(4):1377–1387, 2009.

[115] Pramit Roy, Sudipta Bhattacharjee, Soumalya Ghosh, Sudip Misra, and Mohammad S Obaidat. Fire monitoring in coal mines using wireless sensor networks. In *2011 International Symposium on Performance Evaluation of Computer & Telecommunication Systems*, pages 16–21. IEEE, 2011.

[116] Mestan Tekin, Daniel Hissel, Marie-Ccile Pera, and Jean Marie Kauffmann. Energy-management strategy for embedded fuel-cell systems using fuzzy logic. *IEEE Transactions on Industrial Electronics*, 54(1):595–603, 2007.

[117] Faiyaz Doctor, Hani Hagras, and Victor Callaghan. A fuzzy embedded agent-based approach for realizing ambient intelligence in intelligent inhabited environments. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 35(1):55–65, 2004.

[118] Ala Mhalla, Thierry Chateau, Sami Gazzah, and Najoua Essoukri Ben Amara. An embedded computer-vision system for multi-object detection in traffic surveillance. *IEEE Transactions on Intelligent Transportation Systems*, 20(11):4006–4018, 2018.

[119] Chen Zhao, Wu Gao, and Feiping Nie. A memory-efficient hardware architecture for connected component labeling in embedded system. *IEEE Transactions on Circuits and Systems for Video Technology*, 2019.

[120] Xiaomin Chang, Wei Li, Jin Ma, Ting Yang, and Albert Y Zomaya. Interpretable machine learning in sustainable edge computing: A case study of short-term photovoltaic power output prediction. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 8981–8985. IEEE, 2020.

[121] Yan-Jun Liu, Mingzhe Gong, Shaocheng Tong, CL Philip Chen, and Dong-Juan Li. Adaptive fuzzy output feedback control for a class of nonlinear systems with full state constraints. *IEEE Transactions on Fuzzy Systems*, 26(5):2607–2617, 2018.

[122] Liheng Chen, Shasha Fu, Yuxin Zhao, Ming Liu, and Jianbin Qiu. State and fault observer design for switched systems via an adaptive fuzzy approach. *IEEE Transactions on Fuzzy Systems*, 2019.

[123] Dapeng Li, Lei Liu, Yan-Jun Liu, Shaocheng Tong, and CL Philip Chen. Fuzzy approximation-based adaptive control of nonlinear uncertain state constrained systems with time-varying delays. *IEEE Transactions on Fuzzy Systems*, 2019.

[124] Shiqi Zheng, Peng Shi, Shuoyu Wang, and Yan Shi. Event triggered adaptive fuzzy consensus for interconnected switched multiagent systems. *IEEE Transactions on Fuzzy Systems*, 27(1):144–158, 2018.

[125] Yiming Zhou, Cong Shen, and Mihaela van der Schaar. A non-stationary online learning approach to mobility management. *IEEE Transactions on Wireless Communications*, 18(2):1434–1446, 2019.

[126] Alireza Borhani and Matthias Pätzold. A non-stationary channel model for the development of non-wearable radio fall detection systems. *IEEE Transactions on Wireless Communications*, 17(11):7718–7730, 2018.

[127] Luigi Vigneri, Thrasyvoulos Spyropoulos, and Chadi Barakat. Low cost video streaming through mobile edge caching: Modelling and optimization. *IEEE Transactions on Mobile Computing*, 18(6):1302–1315, 2018.

[128] Chern Hong Lim, Anhar Risnumawan, and Chee Seng Chan. A scene image is nonmutually exclusive—a fuzzy qualitative scene understanding. *IEEE transactions on fuzzy systems*, 22(6):1541–1556, 2014.

[129] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.

[130] Peter Kok Keong Loh and Deepak Subramanian. Fuzzy classification metrics for scanner assessment and vulnerability reporting. *IEEE Transactions on Information Forensics and security*, 5(4):613–624, 2010.

[131] Mengran Gou, Ziyan Wu, Angels Rates-Borras, Octavia Camps, Richard J Radke, et al. A systematic evaluation and benchmark for person re-identification: Features, metrics, and datasets. *IEEE transactions on pattern analysis and machine intelligence*, 41(3):523–536, 2018.

[132] Peter Howarth and Stefan Rüger. Evaluation of texture features for content-based image retrieval. In *International conference on image and video retrieval*, pages 326–334. Springer, 2004.

[133] Ammara Anjum Khan, Mehran Abolhasan, Wei Ni, Justin Lipman, and Abbas Jamalipour. A hybrid-fuzzy logic guided genetic algorithm (h-flga) approach for resource optimization in 5g vanets. *IEEE Transactions on Vehicular Technology*, 68(7):6964–6974, 2019.

[134] Prakash K Ray, Shiba R Paital, Asit Mohanty, YS Eddy Foo, Ashok Krishnan, Hoay Beng Gooi, and Gehan AJ Amaratunga. A hybrid firefly-swarm optimized fractional order interval type-2 fuzzy pid-pss for transient stability improvement. *IEEE Transactions on Industry Applications*, 55(6):6486–6498, 2019.

[135] Shouyi Yin, Shibin Tang, Xinhan Lin, Peng Ouyang, Fengbin Tu, Leibo Liu, and Shaojun Wei. A high throughput acceleration for hybrid neural networks with efficient resource management on fpga. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 38(4):678–691, 2018.

[136] Imo Eyoh, Robert John, Geert De Maere, and Erdal Kayacan. Hybrid learning for interval type-2 intuitionistic fuzzy logic systems as applied to identification and prediction problems. *IEEE Transactions on Fuzzy Systems*, 26(5):2672–2685, 2018.

[137] Dalibor Krleža and Krešimir Fertalj. Graph matching using hierarchical fuzzy graph neural networks. *IEEE Transactions on Fuzzy Systems*, 25(4):892–904, 2016.

[138] Balint Petro, Nikola Kasabov, and Rita M Kiss. Selection and optimization of temporal spike encoding methods for spiking neural networks. *IEEE transactions on neural networks and learning systems*, 31(2):358–370, 2019.

[139] Shuangming Yang, Jiang Wang, Bin Deng, Chen Liu, Huiyan Li, Chris Fietkiewicz, and Kenneth A Loparo. Real-time neuromorphic system for large-scale conductance-based spiking neural networks. *IEEE transactions on cybernetics*, 49(7):2490–2503, 2018.

[140] Elena Mocanu, Decebal Constantin Mocanu, Phuong H Nguyen, Antonio Liotta, Michael E Webber, Madeleine Gibescu, and Johannes G Slootweg. On-line building energy optimization using deep reinforcement learning. *IEEE transactions on smart grid*, 10(4):3698–3708, 2018.

[141] Harshita Patel and Ghanshyam Singh Thakur. Classification of imbalanced data using a modified fuzzy-neighbor weighted approach. *International Journal of Intelligent Engineering and Systems*, 10(1):56–64, 2017.

[142] Alberto Fernández, María José del Jesus, and Francisco Herrera. On the influence of an adaptive inference system in fuzzy rule based classification systems for imbalanced data-sets. *Expert Systems with Applications*, 36(6):9805–9812, 2009.

[143] Yunlong Lu, Xiaohong Huang, Yueyue Dai, Sabita Maharjan, and Yan Zhang. Differentially private asynchronous federated learning for mobile edge computing in urban informatics. *IEEE Transactions on Industrial Informatics*, 16(3):2134–2143, 2019.

[144] Khan Muhammad, Salman Khan, Javier Del Ser, and Victor Hugo C de Albuquerque. Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.

[145] Muhammad Aminul Islam, Derek T Anderson, Anthony Pinar, Timothy Craig Havens, Grant Scott, and James M Keller. Enabling explainable fusion in deep learning with fuzzy integral neural networks. *IEEE Transactions on Fuzzy Systems*, 2019.

[146] Thilo Spinner, Udo Schlegel, Hanna Schäfer, and Mennatallah El-Assady. explainer: A visual analytics framework for interactive and explainable machine learning. *IEEE transactions on visualization and computer graphics*, 26(1):1064–1074, 2019.

[147] Khan Muhammad, Tanveer Hussain, Javier Del Ser, Vasile Palade, and Victor Hugo C De Albuquerque. Deepres: A deep learning-based video summarization strategy for resource-constrained industrial surveillance scenarios. *IEEE Transactions on Industrial Informatics*, 16(9):5938–5947, 2019.

[148] Turgay Celik, Huseyin Ozkaramanlt, and Hasan Demirel. Fire pixel classification using fuzzy logic and statistical color model. In *2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP'07*, volume 1, pages I–1205. IEEE, 2007.

[149] Santiago Garcia-Jimenez, Aranzazu Jurio, Miguel Pagola, Laura De Miguel, Edurne Barrenechea, and Humberto Bustince. Forest fire detection: A fuzzy system approach based on overlap indices. *Applied Soft Computing*, 52:834–842, 2017.

[150] Ijaz Ul Haq, Amin Ullah, Khan Muhammad, Mi Young Lee, and Sung Wook Baik. Personalized movie summarization using deep cnn-assisted facial expression recognition. *Complexity*, 2019, 2019.

[151] Juan C Nunez, Raul Cabido, Juan J Pantrigo, Antonio S Montemayor, and Jose F Velez. Convolutional neural networks and long short-term memory for skeleton-based human activity and hand gesture recognition. *Pattern Recognition*, 76:80–94, 2018.

[152] T. Banerjee, J. M. Keller, M. Skubic, and E. Stone. Day or night activity recognition from video using fuzzy clustering techniques. *IEEE Transactions on Fuzzy Systems*, 22(3):483–493, 2014.

[153] Weiming Hu, D. Xie, Tieniu Tan, and S. Maybank. Learning activity patterns using fuzzy self-organizing neural network. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 34(3):1618–1626, 2004.

[154] Jiehao Li, Junzheng Wang, Hui Peng, Longbin Zhang, Yingbai Hu, and Hang Su. Neural fuzzy approximation enhanced autonomous tracking control of the wheel-legged robot under uncertain physical interaction. *Neurocomputing*, 410:342–353, 2020.

[155] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin. Edge intelligence in the cognitive internet of things: Improving sensitivity and interactivity. *IEEE Network*, 33(3):58–64, 2019.

[156] T. Han, K. Muhammad, T. Hussain, J. Lloret, and S. W. Baik. An efficient deep learning framework for intelligent energy management in iot networks. *IEEE Internet of Things Journal*, pages 1–1, 2020.

[157] Muhammad Sajjad, Mansoor Nasir, Fath U Min Ullah, Khan Muhammad, Arun Kumar Sangaiah, and Sung Wook Baik. Raspberry pi assisted facial expression recognition framework for smart security in law-enforcement services. *Information Sciences*, 479:416 – 431, 2019.

[158] Thang Le Duc, Rafael García Leiva, Paolo Casari, and Per-Olov Östberg. Machine learning methods for reliable resource provisioning in edge-cloud computing: A survey. *ACM Comput. Surv.*, 52(5), September 2019.

[159] C. Sonmez, A. Ozgovde, and C. Ersoy. Fuzzy workload orchestration for edge computing. *IEEE Transactions on Network and Service Management*, 16(2):769–782, 2019.

[160] Gregory Ditzler, Manuel Roveri, Cesare Alippi, and Robi Polikar. Learning in nonstationary environments: A survey. *IEEE Computational Intelligence Magazine*, 10(4):12–25, 2015.

[161] Jesus L Lobo, Javier Del Ser, Ibai Laña, Miren Nekane Bilbao, and Nikola Kasabov. Drift detection over non-stationary data streams using evolving spiking neural networks. In *International symposium on intelligent and distributed computing*, pages 82–94. Springer, 2018.

[162] G Nhivekar, S Nirmale, and R Mudholkar. A survey of fuzzy logic tools for fuzzy–based system design. *vol. ICRTITCS*, (9):25–28, 2013.

[163] Christian Wagner. Juzzy-a java based toolkit for type-2 fuzzy logic. In *2013 IEEE Symposium on Advances in Type-2 Fuzzy Logic Systems (T2FUZZ)*, pages 45–52. IEEE, 2013.

[164] Josie McCulloch. Fuzzycreator: A python-based toolkit for automatically generating and analysing data-driven fuzzy sets. In *2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–6. IEEE, 2017.

[165] Jesus L Lobo, Javier Del Ser, Albert Bifet, and Nikola Kasabov. Spiking neural networks and online learning: An overview and perspectives. *Neural Networks*, 121:88–100, 2020.

[166] Simei Gomes Wysoski, Lubica Benuskova, and Nikola Kasabov. Evolving spiking neural networks for audiovisual information processing. *Neural Networks*, 23(7):819–835, 2010.

[167] Friedemann Zenke and Surya Ganguli. Superspike: Supervised learning in multilayer spiking neural networks. *Neural computation*, 30(6):1514–1541, 2018.

[168] Chinki Chandhok and Soni Chaturvedi. Adaptation of spiking neural networks for image clustering. *Int J Video Image Proces Netw Secur IJVIPNS-IJENS*, 12(03):8–13, 2012.

[169] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.

[170] Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Skeleton-based action recognition with directed graph neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7912–7921, 2019.

[171] Xiaojuan Qi, Renjie Liao, Jiaya Jia, Sanja Fidler, and Raquel Urtasun. 3d graph neural networks for rgbd semantic segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 5199–5208, 2017.

[172] Franco Scarselli, Sweah Liang Yong, Marco Gori, Markus Hagenbuchner, Ah Chung Tsoi, and Marco Maggini. Graph neural networks for ranking web pages. In *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI'05)*, pages 666–672. IEEE, 2005.

[173] Amina Adadi and Mohammed Berrada. Peeking inside the black-box: A survey on explainable artificial intelligence (xai). *IEEE Access*, 6:52138–52160, 2018.

[174] Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, Richard Benjamins, et al. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, 58:82–115, 2020.

[175] M Shamim Hossain, Ghulam Muhammad, and Nadra Guizani. Explainable ai and mass surveillance system-based healthcare framework to combat covid-i9 like pandemics. *IEEE Network*, 34(4):126–132, 2020.

[176] J. Adams and H. Hagras. A type-2 fuzzy logic approach to explainable ai for regulatory compliance, fair customer outcomes and market stability in the global financial sector. In *2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 1–8, 2020.

[177] Alberto Fernandez, Francisco Herrera, Oscar Cordon, Maria Jose del Jesus, and Francesco Marcelloni. Evolutionary fuzzy systems for explainable artificial intelligence: why, when, what for, and where to? *IEEE Computational Intelligence Magazine*, 14(1):69–81, 2019.

[178] David Leslie. Understanding artificial intelligence ethics and safety. *arXiv preprint arXiv:1906.05684*, 2019.

[179] Kavitha Bharathi Shanmugam and S Vengataasalam. Fuzzy-based trusted security for mobile grid systems. *International Journal of Networking and Virtual Organisations*, 18(3):211–226, 2018.

[180] Iti Chaturvedi, Ranjan Satapathy, Sandro Cavallari, and Erik Cambria. Fuzzy commonsense reasoning for multimodal sentiment analysis. *Pattern Recognition Letters*, 125:264–270, 2019.

[181] Shweta Taneja, Bhawna Suri, Sachin Gupta, Himanshu Narwal, Anchit Jain, and Akshay Kathuria. A fuzzy logic based approach for data classification. In *Data engineering and intelligent computing*, pages 605–616. Springer, 2018.

[182] Charu Gupta, Amita Jain, and Nisheeth Joshi. Fuzzy logic in natural language processing–a closer view. *Procedia computer science*, 132:1375–1384, 2018.

Table 5. A detailed analysis of the reviewed literature in surveillance domain along with their description, application domain, adapted strategy, and used tools for the implementation of the proposed method (s).

Ref	Description	Domain	Strategy	Tool/Output results
[35]	A fuzzy logic approach is used to fuse images from different sensors in order to enhance visualization for surveillance.	Visible and infrared image fusion	Fuzzy if-then rules and Mamdani-type fuzzy with several membership functions	Simulation results
[37]	Fuzzy logic for locating moving objects in a video sequence with segmentation, tracking, and analysis phase	Motion tracking	Fuzzy bi-dimensional is used for objects matching. Trapezoidal fuzzy sets are also used to describe the movement over each dimension	Not available
[34]	Posture based events detection with fuzzy logic to determine the subject's behavior	Face recognition	FuzzyAND and fuzzyOR with sigmoid membership function	MATLAB
[38]	Dynamic neural fuzzy approach is used for segmentation of moving objects in dynamic backgrounds.	Object detection with dynamic backgrounds	Neural-fuzzy model based on one-to-one self-organizing map architecture. Fuzzy inference Sugeno system to mimic human behavior	Not available
[39]	A hierarchical approach to focus on modeling expert knowledge via fuzzy metric temporal Logic and Situation Graph Trees	Recognize moving objects, bag packing etc.	Fuzzy metric temporal logic rules dictionary for guiding the operator's attention in surveillance video and automatic report generation	Simulation results
[40]	An ontology-based method for identification, modeling, and generalization of the most relevant events to a specific domain	Semantic events detection	Top-down general knowledge is built based on end-user descriptions of events, followed by automatic video indexing via bottom-up approach.	Natural language generation and understanding
[41]	Video-based traffic surveillance approach using a fuzzy hybrid information inference mechanism	Object detection and tracking	Three major steps: background updating, vehicle detection with block-based segmentation, and tracking	Not available
[42]	An efficient fuzzy logic background modeling method for human detection	Human detection	Fuzzy logic assisted moving human detection, feature extraction and aggregation, and contour detection	Simulation results
[45]	Five different phases for foreground objects detection i.e., humans	Human recognition	A robust background modeling algorithm using fuzzy logic is used to detect foreground objects.	MATLAB
[46]	A fast yet robust technique to enhance the visibility of video frames using the dark channel with fuzzy logic	Video enhancement for foggy, hazy, and rainy weather scenarios	Fuzzy logic-based technique produces high quality haze-free images in real-time	Java
[47]	Risk assessment method, risk calculation is based on fuzzy cognitive maps for a complex automated video surveillance system.	Risk assessment	Fuzzy cognitive maps are used to capture dependencies between assets and fuzzy cognitive maps-based reasoning is applied to aggregate risks assigned to lower-level assets	Not available
[48]	An adaptive traffic engineering method based on type-2 fuzzy logic for video surveillance system over SDN	Video surveillance	Type-2 fuzzy system to assign network links costs based on quality of experience; and adaptive traffic engineering calculates the best routes to guarantee quality of service in a video surveillance system	Java
[49]	A fuzzy logic data association algorithm for online visual multi-object tracking	Multi-object tracking	By incorporating fuzzy logic into multi-object tracking system, the association probabilities are allowed to be adjusted dynamically based on the conclusions of a set of fuzzy rules.	MATLAB and C++
[50]	Fuzzy theory to handle the complex issues in traffic video surveillance and a traffic anomaly detection algorithm	Road traffic anomaly	Fuzzy traffic flow, density, and fuzzy motion state are input to relevant membership functions for an anomalous state evaluation	Not available
[51]	Probabilistic self-organizing map and fuzzy logic-based model for foreground object detection in video sequences	Foreground object detection	Probabilistic self-organising maps based model to incorporate a suitable choice of pixel features and a featured foreground self organizing map is combined with a fuzzy rule-based system for final detection.	Python, MATLAB, and Java
[52]	A type-1 fuzzy approach over apposite inter and intra-frame locomotion feature of pedestrian to yield precise walks direction	Walk directions estimation	Inter and intra-frame motion features of pedestrians are extracted to finally predict their walk directions via fuzzy rules and membership functions.	Simulation results

Table 6. Challenges on the basis of surveyed literature of fuzzy theories in surveillance domain, including solutions, baseline papers, and possible follow-up citations.

Ref.	Problems and their solutions	Baseline papers	Future works
7.1	Fuzzy logic is underrated in lots of emerging computer vision domains including disaster management [105], video summarization [96], action and activity recognition [109], healthcare [62], communication [110], violence detection [3], and entertainment [111].	[61], [28], [80]	[112], [113], [114], [115], [116]
7.2	Providing services at the edge of the network using efficient fuzzy logic-based techniques are missing from the current literature in surveillance BVD.	[117], [116]	[118], [119], [120]
7.3	There are limited adaptive methods in fuzzy logic literature. Although surveillance BVD encounters distinct patterns in real-world scenarios every day and focusing on such data is missing in the current fuzzy logic literature. The irregular patterns encountered in everyday surveillance instigate the need of malleable fuzzy based techniques functional in stationary as well as non-stationary environments.	[121], [122], [123], [124]	[125], [126], [127]
7.4	The implementation of majority of the fuzzy methods is not reported or publicized, which could help other researchers to fine-tune the available methods for other purposes or use them to compare their results and notice the advancement or lag in their method.	[128]	Table 7
5, 7.5	The literature of fuzzy theories lacks some common evaluation metrics for a certain domain such as video analytics (video classification, retrieval), image processing (classification, clustering), etc. Common evaluation metrics for a certain area of fuzzy theories can hold the researchers at one mutual point, seeking some quality results and methods. Similar intuition can be obtained from image classification [129] and image retrieval domains.	[130]	[131], [84], [132]
7.6	There are plenty of hybrid methods in overall fuzzy literature integrated with neural networks, machine learning strategies heading towards a common output solution. This aspect seems inadequately covered in surveillance BVD literature. Hybrid techniques are highly encouraged to have quality results.	[133], [134]	[135], [136]
7.1	There is an appealing advancement in neural networks and learning strategies, where new trending practices pose higher precisions and computationally efficient solutions to complex real-world problems. These networks include SNNs, graph neural networks, and learning strategies such as reinforcement learning, etc. It is a challenging phenomenon to integrate these networks with fuzzy logic theories and explore the intermediate layers for possible entrance of fuzzy rules to provide effective and computationally intelligent solutions to different real-world complications.	[137]	[138], [139], [140]
7.3, 7.4	Medical image data and its related processing to assist humans in diagnostic procedures and many other applications is delicate in nature. Such data is not always publicly available where similar concepts as federated learning should be adopted by fuzzy methods to introduce effective solutions in data scarce situations and propose precise and accurate solutions.	[141, 142]	[143], [144]
7.7	Recently, non-experts of computer science are taking interest in AI-based solutions to the problems they encounter in their respective domains. Explainable AI (XAI) has simple decision making process that is understandable for an average person. Introducing such fuzzy rules, predicate logic, or inference systems etc. that are understandable for average person can lead the technology of dealing BVD effectively to its best level.	[145]	[146]

Table 7. List of main fuzzy logic software frameworks. For more information and details about other related tools, refer to [162].

Tools	Provider	Remarks
Fuzzy Logic Toolbox for MATLAB	MathWorks https://www.mathworks.com/help/fuzzy/ (Accessed on 23 November 2020)	Fuzzy Logic Toolbox has different functions for fuzzy based design, analysis, and simulations. It is licensed under Fuzzy Logic Toolbox by MathWorks.
LabVIEW PID and Fuzzy Logic Toolkit	NATIONAL INSTRUMENTS https://knowledge.ni.com/KnowledgeArticleDetails?id=kA00Z0000019RTlSAM (Accessed on November 23, 2020)	Suitable for fuzzy system designs and control systems with multiple applications integration capabilities. It is licensed under National Instruments Patent Notice at ni.com/patents.
fuzzyTECH	INFORM GmbH and Inform Software Corporation https://www.fuzzytech.com/ (Accessed on November 23, 2020)	Software development kit for fuzzy logic and neural-fuzzy problems. Open source, editions can be made at https://fuzzytech.com/e/fteo.html.
sciFLT	SCILab (ATOMS) https://atoms.scilab.org/toolboxes/sciFLT/0.4.7 (Accessed on November 23, 2020)	Supports fuzzy logic simulations and final code generation. Open source under Free Software Foundation
Scikit-Fuzzy	SciKit (Python) https://github.com/scikit-fuzzy/scikit-fuzzy (Accessed on November 23, 2020)	It contains a lot of fuzzy logic algorithms implemented in Python language. Open source, redistribution under licence by Copyright (C) 2011, the scikit-image team
Juzzy	[163] http://juzzy.wagnerweb.net/ (Accessed on November 23, 2020)	"A Java based toolkit for type-1, interval type-2, general type-2 fuzzy logic, and fuzzy logic systems" Free to use and cite the reference.
Fuzzycreator	[164] https://bitbucket.org/JosieMcCulloch/fuzzycreator/src/master/ (Accessed on November 23, 2020)	"A python-based toolkit for automatically generating and analysing data-driven fuzzy sets" Free to use and redistribution reserved by Copyright (C) 2016 Josie McCulloch.