Table 2. The selected papers with their references

Research ID	Author	Publisher
R01	(Rajavel *et al.*, 2021)	Springer
R02	(Jiang *et al.*, 2021)	IEEE
R03	(Shivappriya *et al.*, 2021)	MDPI
R04	(Xie *et al.*, 2021)	Elsevier
R05	(Alahakoon *et al.*, 2020)	Springer
R06	(Gao, 2020)	Springer
R07	(Gao *et al.*, 2020)	IEEE
R08	(Chandrasekar and Geeth, 2020)	Elsevier
R09	(Ray and Chakraborty, 2019)	Elsevier
R10	(Xu *et al.*, 2019)	Springer
R11	(Shamsolmoali *et al.*, 2019)	Springer
R12	(Gao *et al.*, 2018)	IEEE
R13	(Xie *et al.*, 2019)	Springer
R14	(Kajo *et al.*, 2018)	Springer
R15	(Shami *et al.*, 2018)	IEEE
R16	(Liu *et al.*, 2018)	IEEE
R17	(Li, 2018)	IEEE
R18	(Pradhan *et al.*, 2017)	IEEE
R19	(Shao *et al.*, 2017)	IEEE
R20	(**?**)	IEEE
R21	(Mondal *et al.*, 2017)	Springer
R22	(Chuang *et al.*, 2017)	IEEE

The results in the target column show that 54% of the selected papers were used for individual surveillance in the videos, while the remaining 46% was applied to observe the crowd as a single unit. Moreover, information extracted from Table 3 indicates that 63% of the selected papers use real-time processing, and 37% of them use batch processing. The real-time processing means that administrators deal with video surveillance data immediately, while in batch processing, data analysis can be deferred to another time (Subudhi *et al.*, 2019). Lastly, the results in Column 5 revealed that 90% of the selected papers did not provide any cloud computing on the surveillance methods they applied.

Another results extracted from the analysis of the selected papers are presented in Table 4. It is the methodology used in each surveillance technique. It can be seen in Table 4 that different methodology for intelligent monitoring has been implemented by researchers. In R01, R03, R10, R11, R18, R20, and R21, the convolutional neural network algorithm was used. It is a deep learning technology that extracts an image from a video, allocates important features of different objects in each frame, and then distinguishes one from the other. Much less preprocessing is required in the convolutional neural network algorithm compared to other related technologies, such as training and learning (Pradhan *et al.*, 2017). R02 used three-phase flow field analysis, which is a framework consisting of a series of unordered and uncoordinated point clouds to detect and extract a moving object in a video (Jiang *et al.*, 2021). In R04, K-mean clustering is proposed which is an unsupervised segmentation algorithm that can identify clusters in an image based on the similarity of data within the same group (Xie *et al.*, 2021).

The other methodology used is the machine learning algorithms in R05, R12, and R13. They are algorithms that can identify important features from raw data, learn from them without human intervention, and then update their work from experience (Xie *et al.*, 2019). R06, R08, and R16 use image filters with or without the original. A filter is a software procedure that has the ability to modify the pixel values of images. These values relate to the color, appearance, brightness, and contrast of the image (Gao, 2020). Some methodologies combine two or more techniques to produce a hybrid method, such as R08, R14, and R15. The last important methodology is the Spatio-temporal algorithms, which are used

Table 3. Video surveillance purpose, target, processing type, and computing type

ID	Purpose	Target	Processing	Computing
R01	Patient and elderly people tracking	Individual	Real-time	Cloud
R02	Detecting moving objects	Individual	Real-time	Local
R03	Cascade object detection	Crowd	Batch	Local
R04	Automatic vehicles obstacle detection	Individual	Real-time	Local
R05	Capture human activity	Individual	Real-time	Cloud
R06	Vehicles detection and classification	Individual	Real-time	Local
R07	Vehicle detection	Individual	Real-time	Local
R08	Multiple vehicles tracking	Crowd	Real-time	Local
R09	Moving objects	Individual	Real-time	Local
R10	Crowd anomaly detection	Crowd	Real-time	Local
R11	Human detection	Individual	Batch	Local
R12	Human action recognition	Individual	Batch	Local
R13	Crowd anomaly detection	Crowd	Real-time	Local
R14	Crowd motion detection	Crowd	Real-time	Local
R15	People counting	Crowd	Batch	Local
R16	Object tracking	Individual	Real-time	Local
R17	Understanding crowd behavior	Crowd	Batch	Local
R18	Estimate of tropical cyclone intensity	Individual	Batch	Local
R19	Abnormal events detection	Crowd	Real-time	Local
R20	Crowd counting	Crowd	Batch	Local
R21	Camouflaged object detection	Individual	Batch	Local
R22	Fish stock tracking	Crowd	Real-time	Local

in R07, R09, R17 and R19. They are a set of algorithms that detect objects within a video using similar behavioral features, and then classify the objects using those features as groups. It is widely used to identify abnormal behavior of an individual or crowd and then send alarms to administrators (Li, 2018). This research focuses on the important methodologies given in Table 4, for more details about others that are not explained, it can return to references in this table.

Other results extracted from the analysis of the selected papers are presented in Table 5. They are the strengths and weaknesses of the surveillance methods and future directions for improving the current methods. Evaluation of the surveillance methods is a key factor in finding strengths. An evaluation process using standardized metrics to determine the best among the comparative methods. Table 5 shows that the metrics used as a comparison of surveillance methods are accuracy, processing time, computational cost, big data self-processing, alignment, and similarity.

From Table 5, it can be seen that most of the papers (85%) included in this research used the accuracy metric. In contrast, processing time or computational cost had the lowest percentage value with an average of 27%. In general, each study uses accuracy to measure a different target. For example, in R01, accuracy was used to detect elderly fall behavior while in R02, it was used to track small and large moving objects. Moreover, in R03, it was used to identify things of various sizes: small, medium, and huge in the video while in R04, it was used to detect obstacles in the movement of agricultural machinery. This indicates that the objectives of surveillance methods are diverse and their applications in our lives are many.

Table 5 also shows a set of weaknesses in the surveillance methods that can be seen as challenges for researchers and graduate students to find the gaps faster and to overcome the drawbacks in those methods using complex scenarios. One of these weaknesses that has received less attention from most researchers is the processing time and computational cost of monitoring methods. It's an estimate of how long time your method will take to implement in a real-time environment (Subudhi *et al.*, 2019). Implementation of intelligent surveillance method under big data often requires huge computational cost which causes

Table 4. The methodology used in each surveillance method

ID	Used methodology
R01	A remote monitoring of patients using deep convolution neural network algorithms.
R02	Detecting and extracting a moving object using three-phase flow field analysis technique.
R03	Detecting small objects using additive activation analysis with neural network.
R04	Detecting obstacles around agricultural machinery using K means clustering algorithm.
R05	Capturing human activity in smart cities using machine learning algorithms.
R06	Detect and classify vehicles in wide area videos using image filters.
R07	Detection of vehicles in videos using spatio-temporal algorithms with post-processing.
R08	Tracking vehicles using subtraction algorithm, image filters, and LSTM classifier.
R09	Track objects based on a motion camera without sensors using spatio-temporal filters.
R10	Detection of abnormal behaviour of crowds using a neural network.
R11	A convolutional neural network is used to identify an object in low-resolution images.
R12	Recognize actions using supervised and unsupervised cross-domain learning algorithms.
R13	Crowd abnormal behavior detection using machine learning algorithms.
R14	Crowd motion estimation using social force model and block-based algorithm.
R15	Count people using features-based classifier and distance-based weighted averaging.
R16	Object tracking in real-time scenarios using an improved correlation filter.
R17	Understanding crowd behavior using deep Spatio-temporal analysis.
R18	A convolutional neural network is used to determine the intensity of tropical cyclones.
R19	Abnormal events detection from video using temporal-spatial association method.
R20	Detecting and counting specific crowd using deep convolutional neural network.
R21	Camouflaged object detecting and tracking using probabilistic neural network.
R22	Fish stock tracking using a set of kernel movement with deformable configuration.

long processing time. This has become a major obstacle to the wide applications of this type of methods. To get around this drawback, some researchers are using cloud computing to process their big data. However, the financial cost of storing and processing large data in the cloud may be disproportionately high for a range of applications (Ahmad, 2022), such as personal text and video speech recognition (Habeeb *et al.*, 2020,?). Other weaknesses were briefly mentioned in Table 5 that researchers can benefit from them as future directions for developing their research on this Topic.

4. Conclusion

Prior to this research, the comparative study of intelligent observation with big data was not systematically explored in recent years. Hence, this research provides an appropriate and high-quality comparison with valuable information on this topic. Many studies have been investigated to highlight the current technologies and their description related to intelligent surveillance. In the investigation process, 8 key metrics have been explored, namely intelligent surveillance purpose, target, processing type, computing type, used methodology, strengths, weaknesses, and future directions. The comparative study found certain challenges and gaps resulting from using big data in intelligent surveillance which have been represented in tabular forms. This study is considered a useful guide for researchers in providing guidance and valuable information for future directions for improvement. In the future, this research will be expanded to improve some of the drawbacks of intelligent surveillance.

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Table 5. Strengths and weaknesses of the surveillance methods and future directions

ID	Strengths, weaknesses, and future directions
R01	Better accuracy of patient behavior. Requires a distributed monitoring infrastructure.
R02	Better accuracy of moving objects. Nonlinear motions have not been tested.
R03	Better accuracy of multi-size objects. Real-time environment has not been tested.
R04	Better accuracy and processing time. Inflection curves motion should be examined.
R05	Self-handle big data. Self-learning algorithms may lead to poor results in some cases.
R06	Better metrics of alignment and similarity. The real-time environment has not been tested.
R07	Better accuracy of vehicle detection. Vehicles in the crowd have not been tested.
R08	Better accuracy with less processing time. Vehicle's speed estimation has not been tested.
R09	Better accuracy. Presence of noise and complex background should be investigated.
R10	Better accuracy in detecting abnormal behavior. Large-scale crowd should be examined.
R11	Better accuracy for low-resolution videos. The processing time should be investigated.
R12	Works with various environmental cases. The crowded scenario has not been evaluated.
R13	Better accuracy for abnormal behavior. Real-time detection needs improvement.
R14	Better accuracy with less processing time. Large-scale crowd has not been investigated.
R15	Works well in a heavy crowd. Computational complexity needs to be investigated.
R16	Better accuracy with less processing time. Fog computing presents many challenges.
R17	Better accuracy. Design needs a structure to learn the dependencies of crowd movement.
R18	Better accuracy in detecting tropical cyclones. No testing in a real-time environment.
R19	Better solutions for storage and recovery of Big Data. The crowd has not been tested.
R20	Better accuracy. Crowd analysis has not been tested extensively.
R21	Better accuracy and processing time. No testing of the camouflaged object in the crowd.
R22	Better accuracy and processing time. No testing of the sudden change in the trajectory.

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