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Change Detection Based on Artificial Intelligence

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ABSTRACT:
Based on data from remote sensing (RS), change detection is a vital technique for identifying changes on Earth's surface. It finds extensive use in urban planning, environmental monitoring, agricultural research, disaster assessment, and map revision. Developing novel techniques for change detection has made integrated artificial intelligence (AI) technology a focus of research in recent years. It's not immediately clear how and to what extent artificial intelligence (AI) can enhance change detection effectiveness, despite some researchers' claims that AI-based systems beat traditional approaches. This review centers on the most recent developments, uses, and difficulties in artificial intelligence for change detection. In particular, the first step of the AI-based change detection implementation method is presented. Next, the accessible open datasets are mentioned together with the data from various sensors used for change detection, such as optical remote sensing (RS), synthetic aperture radar (SAR), street view photos, and merged heterogeneous data. The general frameworks of AI-based change detection techniques are examined and thoroughly examined, and an in-depth analysis is conducted on the unsupervised schemes employed in AI-based change detection. The frequently utilized networks in AI for change detection are then explained. The application domains of AI-based change detection techniques are categorized according to their practical suitability. The main issues surrounding AI for change detection are finally explored and outlined. These issues include (a) heterogeneous big data processing, (b) unsupervised AI, and (c) AI reliability. Researchers will find this review useful in comprehending this field.

KEYWORDS: Artificial intelligence; change detection; remote sensing; deep learning; neural network; unsupervised learning; SAR; hyperspectral; multispectral; street view.

1.INTRODUCTION:

The practice of detecting changes in an object's or phenomenon's condition by observing it at various intervals is known as change detection [1]. It has been the subject of much research in recent decades and is one of the main issues with earth observation. Multi-temporal remote sensing data, including satellite and aerial photos, can yield a wealth of information about changes in land use and land cover (LULC) across time in a particular area. This is critical for many applications, including catastrophe assessment, agricultural research, urban planning, environmental monitoring, and map modification. Large volumes of RS data with a high spectral-spatial-temporal resolution are now available due to the continued advancement of Earth observation techniques, which significantly advances the development of change detection systems and creates new challenges for them. Numerous change detection techniques are put forth in an effort to overcome the issues raised by higher spatial and spectral resolution images throughout the change detection process. They fall into two main categories here: those that significantly advance their development and those that use change detection techniques. Numerous change detection techniques are put forth in an effort to overcome the issues raised by higher spatial and spectral resolution images throughout the change detection process. They fall into two main types here: AI-based and traditional.

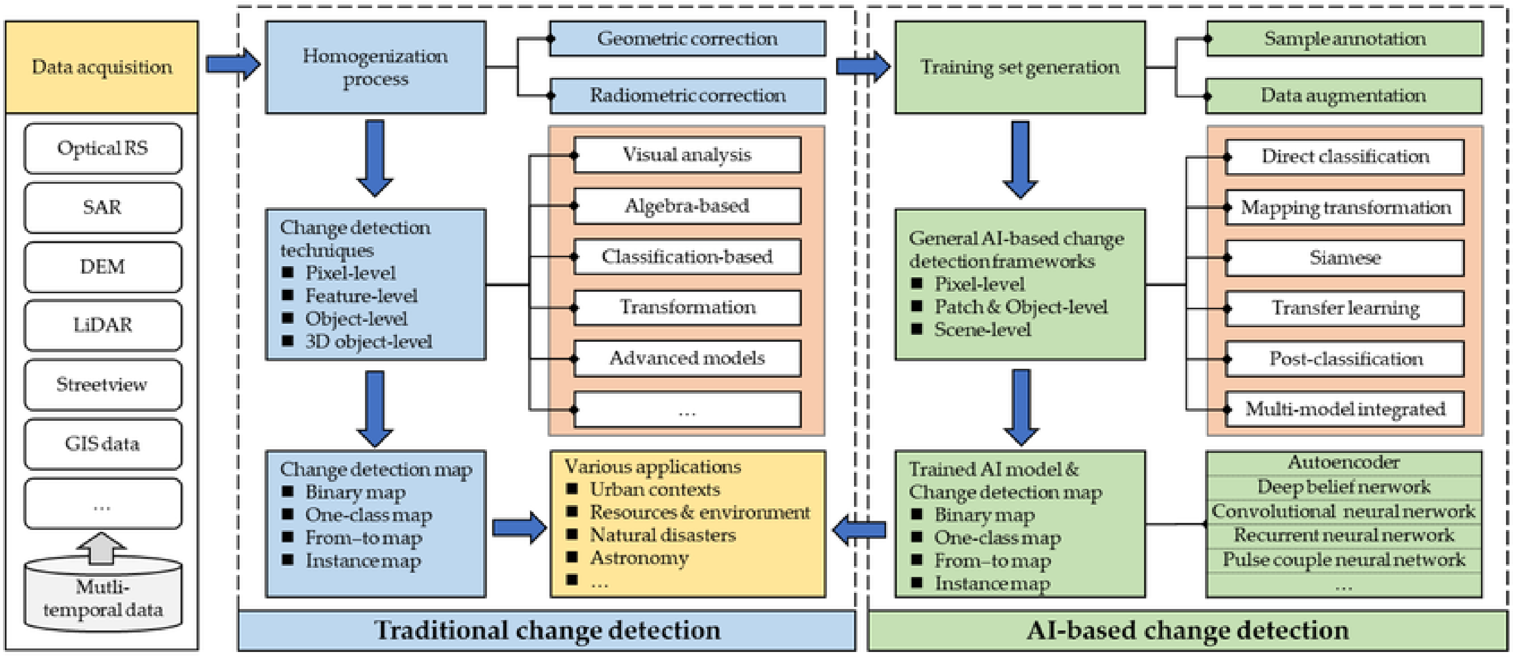


Fig.1. General schematic diagram of change detection.

The creation of change detection methods in high-spatial-resolution pictures and multi-temporal hyperspectral imaging (HSIs) has been the primary focus of previous reviews on change detection. The majority of the methods they examined are conventional change detection strategies, which can be broadly categorized into the following groups:

- Visual analysis: The change map is obtained through labor-intensive and time-consuming manual interpretation, which can yield highly trustworthy results based on specialist knowledge;
- Techniques based on algebra: the change map is produced by applying algebraic operations or transformations, such as image differencing, image regression, image ratioing, and change vector analysis (CVA), to multi-temporal data;
- Transformation: To reduce correlated information and highlight variation, data reduction techniques including principal component analysis (PCA), tasseled cap (KT), multivariate alteration detection (MAD), Gramm–Schmidt (GS), and Chi-Square are employed.
- Classification-based methods: utilizing a trained classifier to directly classify data from several periods (i.e., multidate classification or direct classification) or comparing multiple classification maps (i.e., post-classification comparison) are two ways to identify changes;
- Advanced models: To perform change analysis, the spectral reflectance values of multi-period data are converted into physically based parameters or fractions using advanced models like the Li-Strahler reflectance model, the spectral mixture model, and the biophysical parameter method. This process is more intuitive and has tangible implications, but it is also more complex and time-consuming;
- Other approaches: knowledge-based, spatial statistics-based, integrated GIS and RS methods, among others, are employed, along with hybrid approaches.

Artificial intelligence (AI), often known as machine intelligence, can perform better in a variety of data processing jobs. It is the capacity of a system to accurately understand outside input, to learn from that data, and to apply that learning to accomplish certain tasks and goals through adaptable change. The recent rise of deep learning techniques, novel network architectures, and intelligent machine learning approaches—all of which draw inspiration from biological systems—are the main topics of this paper's AI methodologies. Because of their comparatively low intelligence and prior studies, traditional machine learning techniques like decision trees and support vector machines have not been taken into consideration in this research.
Many new approaches integrating AI techniques have been developed to improve the accuracy as well as change detection automation. Numerous studies in RS have revealed that AI-based change detection techniques are superior to the traditional in terms of feature extraction. Due to the AI approaches with strong modeling and learning skills can model the relationship between the picture item and the closest possible real-world geographical feature, allowing for the detection of more accurate change data. They often use spatial-contextual data in multi-temporal data to develop high-level feature representations that are hierarchical, and these feature representations are more resilient and effective in tasks involving change detection. The majority of research on AI that has already been done is either a broad overview of the AI algorithm's progress or a thorough analysis of RS applications for a certain hot-field. The writers of concentrated on the deep learning theories, resources, and difficulties within the RS community. Put differently, the theory and implementation of AI approaches in RS provide the foundation of these review papers. An extensive assessment of AI techniques used with multi-source data is still lacking in the field of RS data change detection. An extensive analysis of the use of AI technologies in RS change detection processing is given in this research. It focuses on the most recent techniques, uses, and difficulties related to artificial intelligence (AI) for change detection in multi-temporal data.

1. We outline the steps involved in implementing AI-based change detection and provide a summary of typical implementation techniques to aid newcomers in understanding this area of study;
2. We detail the data from various sensors—primarily optical RS, SAR, street-view photos, and merged heterogeneous data—that were used for AI-based change detection. In a more practical sense, we enumerate the publicly accessible datasets that have annotations, serving as reference points for AI model training and assessment in upcoming change detection research;
3. We provide a useful summary of the main frameworks of AI-based change detection methods through a methodical evaluation and analysis of their processes, which might aid in the future design of change detection strategies. In addition, an analysis is conducted on the unsupervised techniques employed in AI-based change detection in order to help address the problem of lack of training samples in practical applications;
4. We outline the networks that are frequently used in AI to identify changes.
5. We offer the application of AI-based change detection in various fields and divide it into different data types, which helps those interested in these areas find relevant AI-based change detection approaches; Analyzing their applicability is helpful for the selection of AI models in practical applications;

6. We outline and explore the potential and difficulties of AI for change detection from three main angles: unsupervised AI, heterogeneous big data processing, and AI dependability. This serves as a helpful guide for further study.

2. IMPLEMENTATION PROCESS OF AI-BASED CHANGE DETECTION:

1. Homogenization: Multi-period data typically require homogenization prior to change detection because of variations in illumination and atmospheric conditions, seasons, and sensor attitudes at the time of acquisition. There are two popular techniques for correction: geometric and radiometric. The former uses co-registration or registration to achieve the geometric alignment of two or more provided pieces of data. Only when two period data are superimposed can equivalent positions be meaningfully compared.In order to lessen false alarms brought on by these radiation faults in change detection, the latter seeks to decrease radiance or reflectance differences created by the digitalization process of sensors and atmospheric attenuation distortion induced by absorption and scattering in the atmosphere.

2. Creation of training sets: In order to create an AI model, a sizable, superior training set is needed. This collection can aid algorithms in realizing that a particular question will result in a particular pattern or set of outcomes. Various strategies, such as manual annotation, pre-classification, and the usage of theme data, are used to label or annotate multi-period data in order to facilitate the AI model's ability to understand the properties of the altered objects. a two-period RS image and a matching ground truth labeled with building changes at the pixel level comprise an annotated example of building change detection. The AI model can be taught supervisedly using the ground truth, or past knowledge. In order to mitigate used, is a good strategy.

3. Model training: Depending on the quantity of samples or the region, the generated training set can typically be split into two datasets: a training set for AI model training and a test set for accuracy assessment during the training phase. Iteratively and alternatively, the testing and training procedures are carried out. A learning criterion, such as a loss function (such as softmax loss, contrastive loss, Euclidean loss, or cross-entropy loss) may be used to optimize the model during the training phase.
The AI model's convergence state can be determined by tracking the training procedure and test accuracy. This information can be used to modify the model's hyperparameters, such as the learning rate, and determine whether the model is performing as intended. has reached the best (i.e., termination) condition.

4. Model serving: Change maps can be produced more automatically and intelligently for useful applications by utilizing a trained AI model. Additionally, this can support the model's resilience and generalization, which is crucial for assessing the usefulness of the AI-based change detection method.

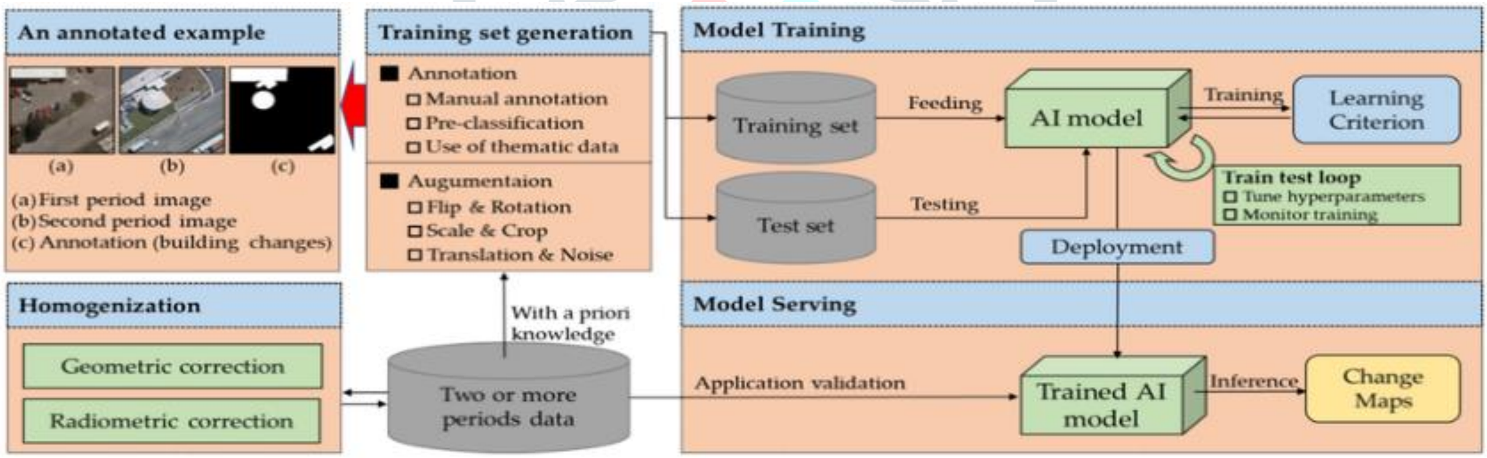
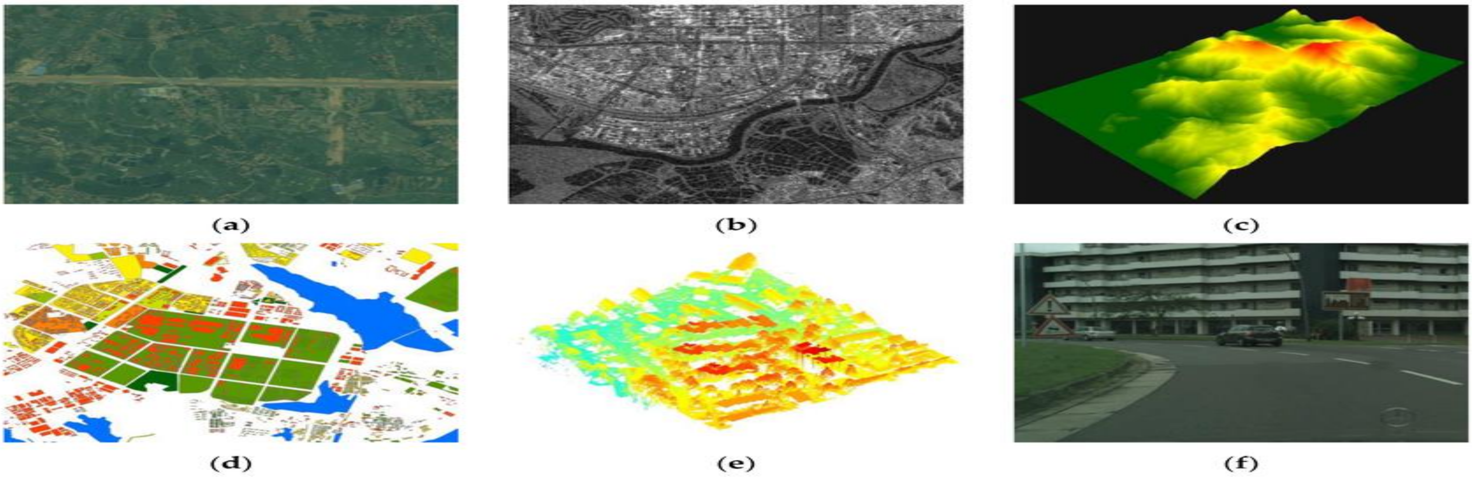


FIGURE: Implementation process of AI-based change detection (black arrows indicate workflow and red arrow indicates an example)

The procedures listed above offer a broad approach for implementing AI-based change detection; however, the structure of the AI model is varied and must be carefully tailored to suit various application scenarios. It is important to note. The stages listed above provide a broad process for implementing AI-based change detection; however, the structure of the AI model is varied and must be carefully tailored to the various application scenarios and training data. It is important to note that researchers may more readily realize the design, training, and deployment of AI models with the aid of established frameworks like TensorFlow, Keras, Pytorch, and Coffee, whose development documentation offer thorough introductions. that well-established frameworks like TensorFlow, Keras, Pytorch, and Caffe make it easier for researchers to realize the design, training, and deployment of AI models, and their development documents provide detailed introduction.

3. DATA SOURCES FOR CHANGE DETECTION:

New application requirements for land change monitoring are brought out by the advancement of data gathering tools including satellites, drones, and ground survey vehicles, as well as the large multi-source RS data they provide. To lower the expense of manual interpretation, more automatic and reliable change detection techniques are especially needed for multi-sensor high-spatial and high-temporal resolution data. We may thoroughly examine the suitability of current change detection techniques for the data by describing the various data kinds that are utilized for change detection. The three categories of data utilized in this work for change detection are optical RS images, SAR photos, and street view photographs. It should be mentioned that street view photos are typically used as supplemental data rather as RS data. Different electromagnetic spectrum ranges are covered by passive and active sensors, respectively, in the collection of optical RS and SAR images. Additional data sources that can offer useful extra qualities include point cloud, geographic information system (GIS), and digital elevation models (DEMs). Large spatial areas can be covered by overhead remote sensing, however its temporal resolution is not very high. At the street level, information can be obtained almost instantly from Street View photos.



Examples of different data sources for change detection: (a) Optical RS image (obtained by Quickbird); (b) SAR image (obtained by the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR)); (c) digital elevation model (DEM); (d) geographic Figure 3. Examples of different data sources for change detection: (a) Optical RS image (obtained by Quickbird); (b) SAR image (obtained by the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR)); (c) digital elevation model (DEM); (d) geographic information system (GIS) data (from OpenStreetMap); (e) Point cloud data (from International Society for Photogrammetry and Remote Sensing (ISPRS) benchmarks); (f) Street view image (from Cityscapes datasets.

4.GENERAL AI-BASED CHANGED DETECTION FRAMEWORK:

The change detection job receives multi-temporal data as input, which can be either homogeneous or heterogeneous over two or more time periods .Based on the learning process of latent feature representation or deep feature extraction from bi-temporal data, artificial intelligence-based change detection frameworks can be divided into three categories: integrated multi-model, single-stream, and double-stream systems. Furthermore, we further investigate the supervised schemes within these frameworks, a highly significant and difficult area of AI research.

1. One-Stream Structure:
   For AI-based change detection, there are two primary kinds of single-stream framework structures shown in below figure: direct classification structures and mapping transformation-based structures. They can be considered single-stream structures because they typically just require a core AI model to accomplish change detection.

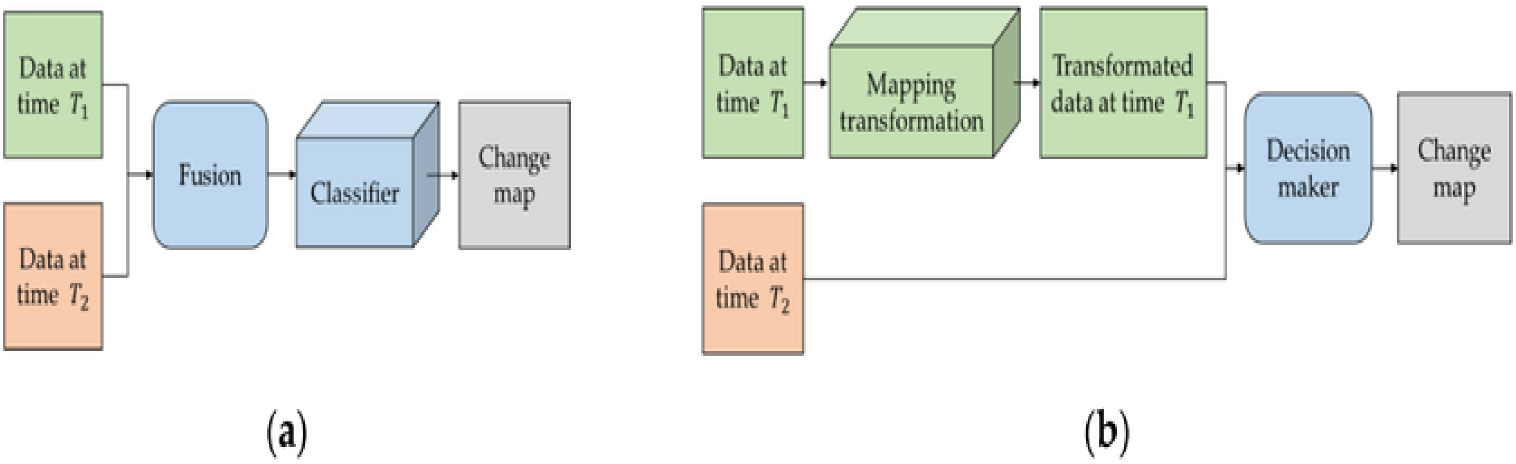


Figure: Schematic diagram of single-stream framework structures of AI-based change detection: (a)the direct classification structure;(b) The mapping transformation-based structure.

2.DOUBLE STREAM FRAMEWORK: As illustrated in Figure, a Siamese structure typically consists of two identically structured sub-networks, or feature extractors, which create feature maps from the incoming two-period data. Ultimately, change analysis is used to create the change map (i.e., decision maker). This structure's primary benefit lies in its two sub-networks, which receive simultaneous direct training to acquire deep features from the input two-period data. As illustrated in Figure, a Siamese structure typically consists of two identically structured sub-networks, or feature extractors, which create feature maps from the incoming two-period data. Ultimately, change analysis is used to create the change map (i.e., decision maker). This structure's primary benefit lies in its two sub-networks, which receive simultaneous direct training to acquire deep features from the input two-period data. The pure-Siamese structure and the pseudo-Siamese structure can be distinguished based on whether the weights of the sub-networks are shared. The primary distinction is that by sharing weights, the former sub-network retrieves the shared characteristics of the two-period data. The last sub-network increases the amount of trainable parameters and complexity while maintaining flexibility by extracting features from related input data. In a similar vein, for change detection, the authors of created a triple network made up of three sub-networks that shared weights.

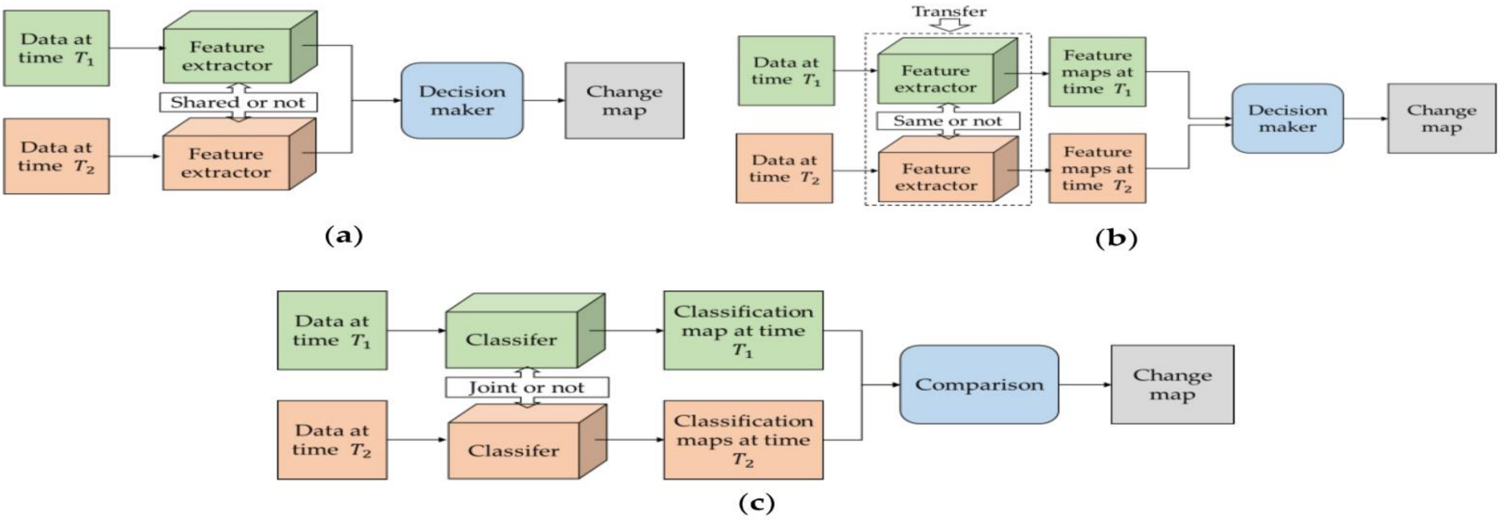


Figure: Schematic diagram of double-stream framework structure of AI-based change detection: (a) the Siamese structure; (b) the transfer-learning-based structure; (c) the post-classification structure.

The Siamese Framework:
Unsupervised training is more difficult, even though this structure allows the feature extractor to directly learn deep features through supervised training with labeled examples. Training feature extractors separately and without supervision is a popular approach. The feature maps, or latent representation of the original data, are provided by these pre-trained feature extractors for additional As illustrated in Figure, a Siamese structure typically consists of two identically structured sub-networks, or feature extractors, which create feature maps from the incoming two-period data. Ultimately, change analysis is used to produce the change map. This structure's primary benefit is that it simultaneously trains both of its sub-networks to learn the deep features of the input two-period data detection of changes. To The resulting feature maps from the two periods can either be used directly for change mapping by concatenating the channels, or they can be used to create difference maps by applying a specific distance metric, which can then be utilized for additional change analysis. Feature maps at several levels can be concatenated for change detection, which effectively retains multi-scale change information.

3. Integrated Structure with Multiple Models:
Several studies have combined several AI models to enhance the effectiveness of change detection techniques. Only a representative structure is summarized because of the enormous number and intricate structure, as seen in Figure

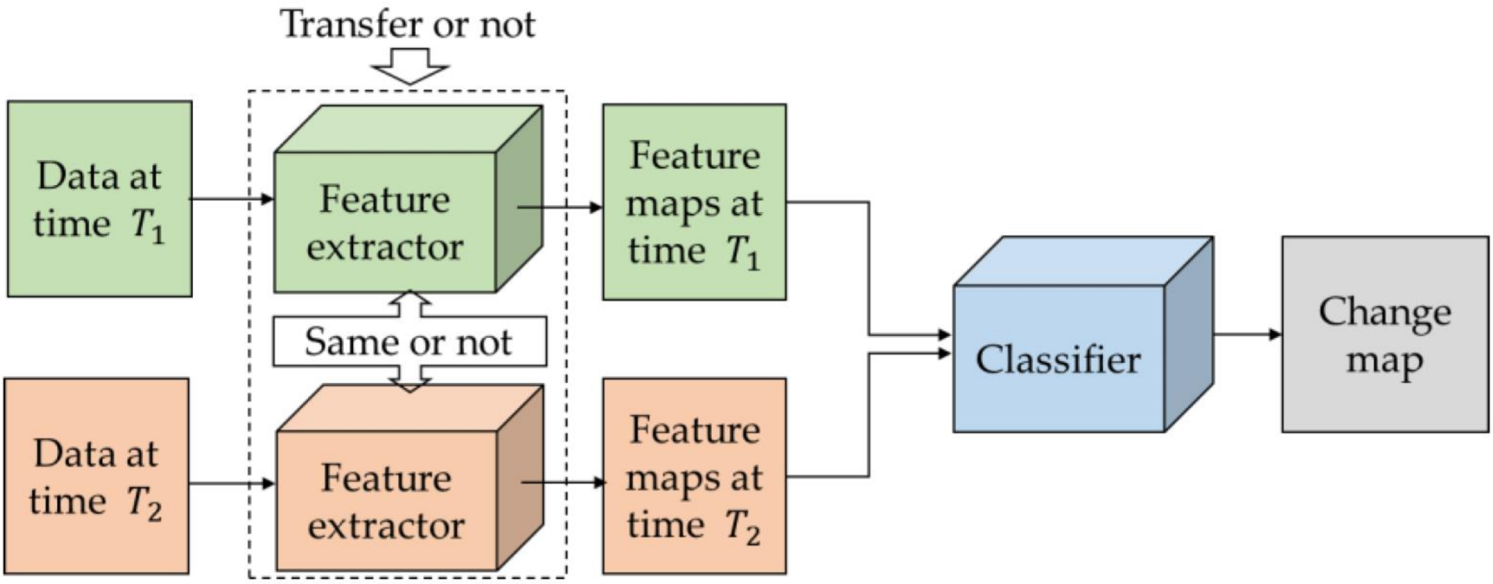


Figure: Schematic diagram of multi-model integrated structure of AI-based change detection.

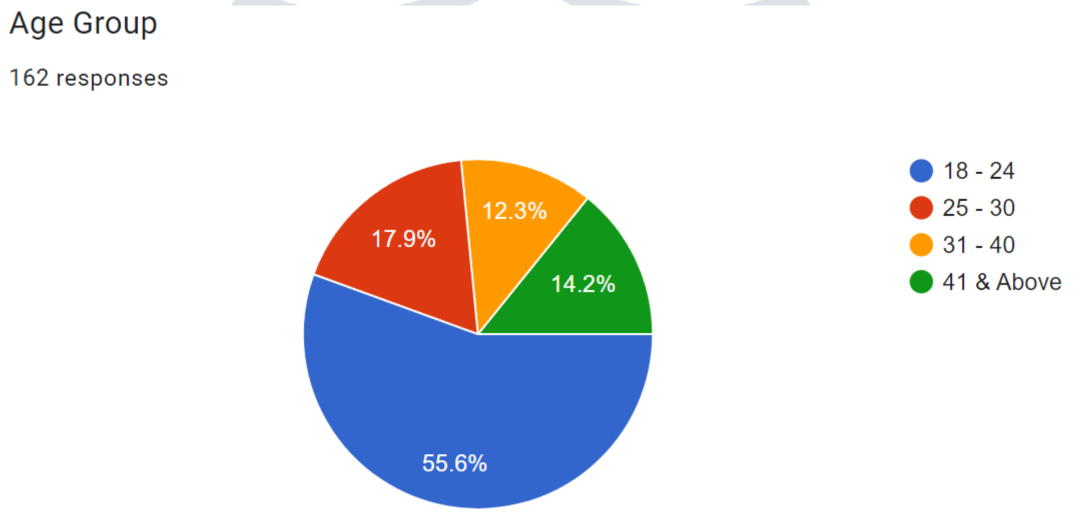
Similar to the double stream structure, the multi-model integrated framework is a hybrid structure that can be taught in phases and has access to a wider variety of AI models. Obtaining the spatial-spectral data allows for the spatiotemporal study of change detection. Similar to the double stream structure, the multi-model integrated framework is a hybrid structure that can be taught in phases and has access to a wider variety of AI models. Change detection is a spatiotemporal analysis that is accomplished by first modeling the temporal dependency using an AI-based classifier as a temporal module, and then obtaining the spatial-spectral characteristics through an AI-based feature extractor as a spectral-spatial module. Additionally, this hybrid structure is expertly used to unattended change both object-level change detection and detection. This improves performance but increases the complexity of the entire change detection process.

5. APPLICATIONS:
1. Urban contexts: building change detection, public space management, and urban expansion;
2. Resources and environment: monitoring of forests, sea ice, surface water, hydro-environmental changes caused by humans, and surface water;
3. Natural disasters: damage assessment and mapping of landslides;
4. Planetary surfaces in astronomy.

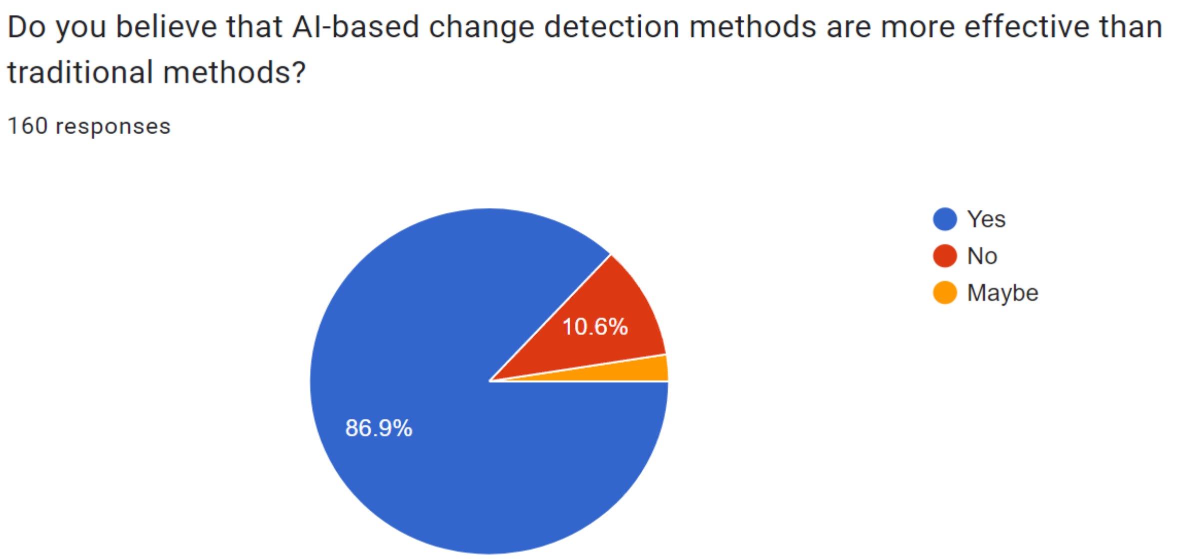
One major factor altering the land surface is urbanization. As a result of population growth, natural land cover is being transformed into urban amenities for people through the expansion of urbanization. The authors put forth a novel framework for change detection and urban area extraction that is based on transfer learning and an RNN. Around 96% of the single-year urban maps in the four target cities—Beijing, New York, Melbourne, and Munich—are accurate overall. Urban alterations were achieved by calculating the difference in the anticipated urban distribution maps using a CNN or a genetic algorithm-evolved ANN. Change detection based on street view photos is an effective method for public space management to detect the invasion of private areas.
In the VL-CMU-CD dataset, a CNN using Siamese structure and transfer learning obtained 98.3% pixel accuracy.

SCREENSHOTS OF SURVEY:

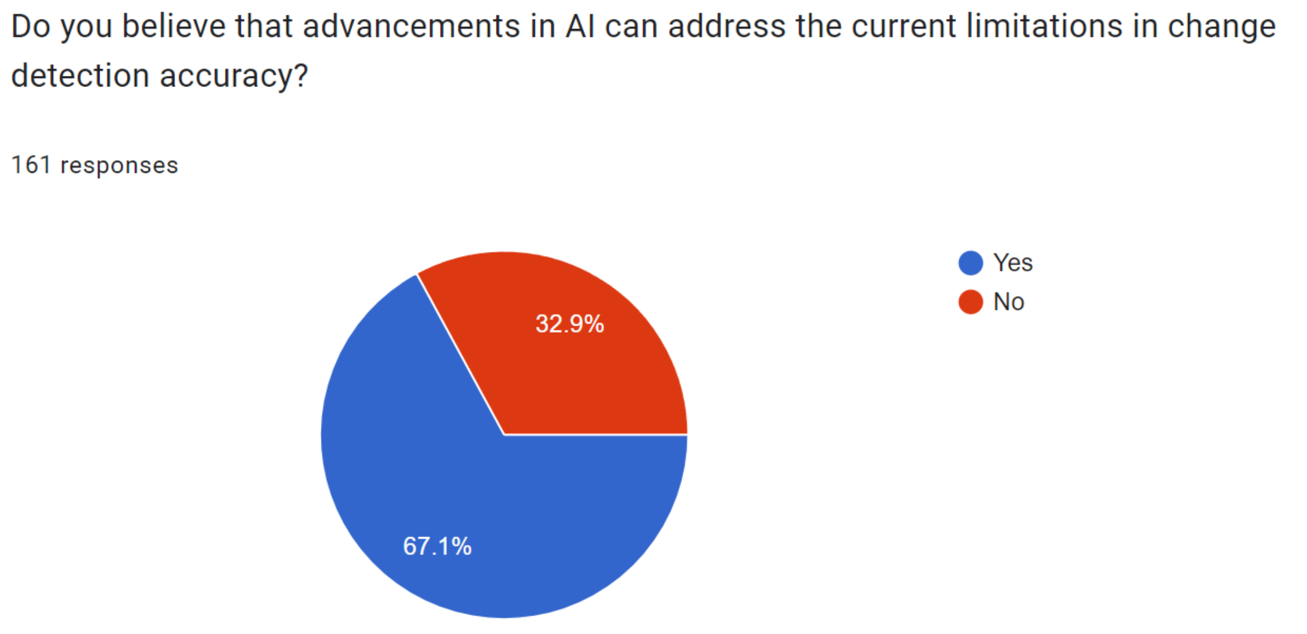
1. **Age Group**



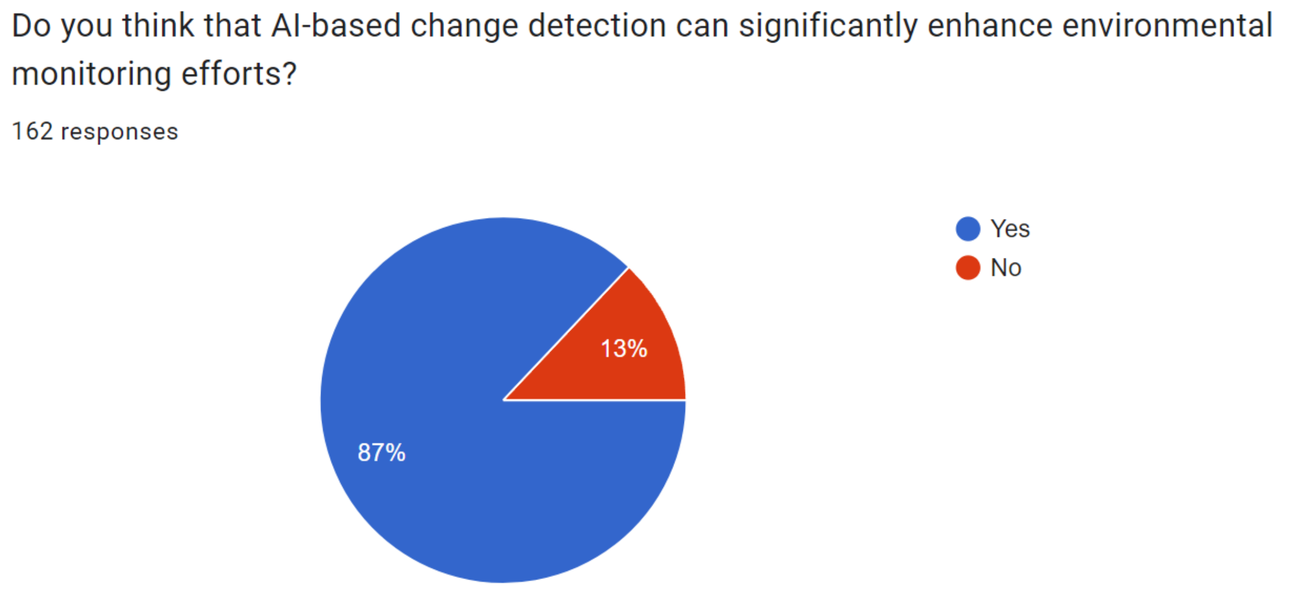
2. **Do you believe that AI-based change detection methods are more effective than traditional methods?**



3. Do you believe that advancements in AI can address the current limitations in change detection accuracy?



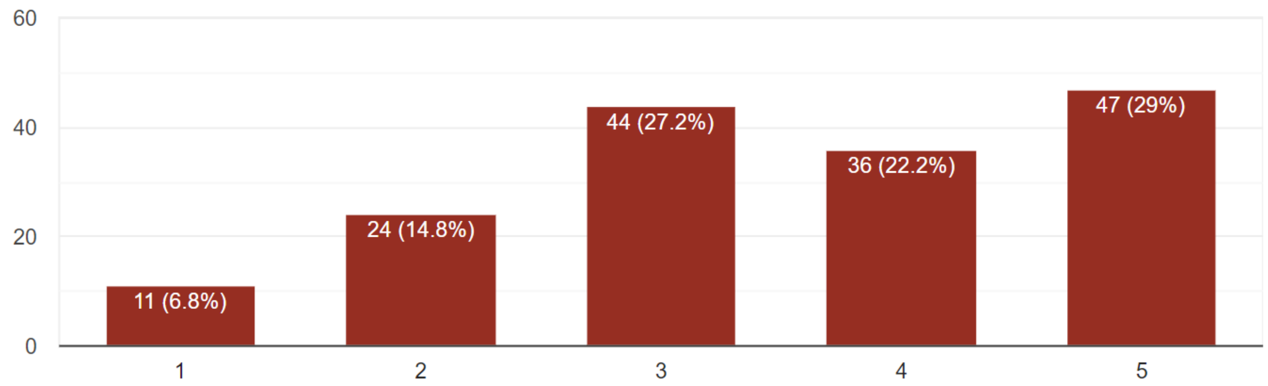
4. Do you think that AI-based change detection can significantly enhance environmental monitoring efforts?



5. How would you rate current effectiveness of AI-based change detection methods compared to traditional methods?

How would you rate the current effectiveness of AI-based change detection methods compared to traditional methods?

162 responses



6. Are current AI-based change detection systems capable of handling the diverse range of real-world scenarios effectively?

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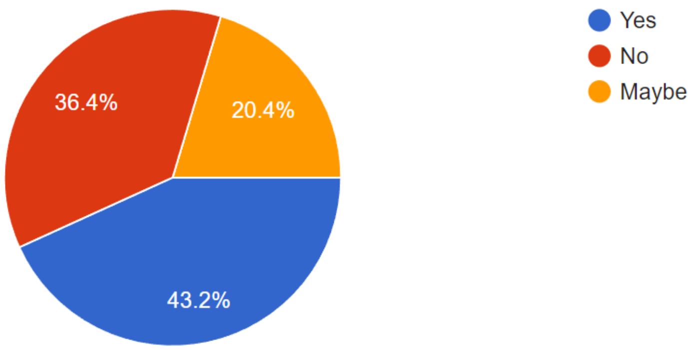
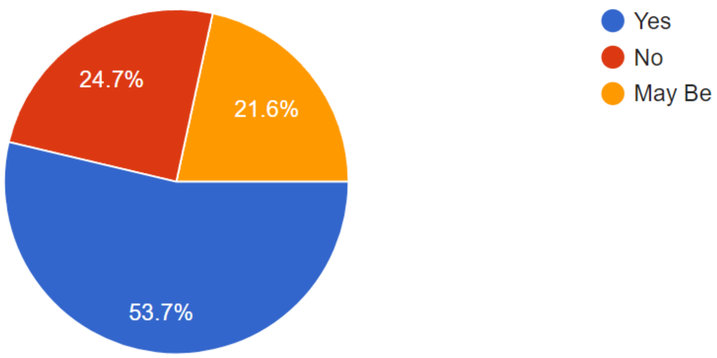
162 responses



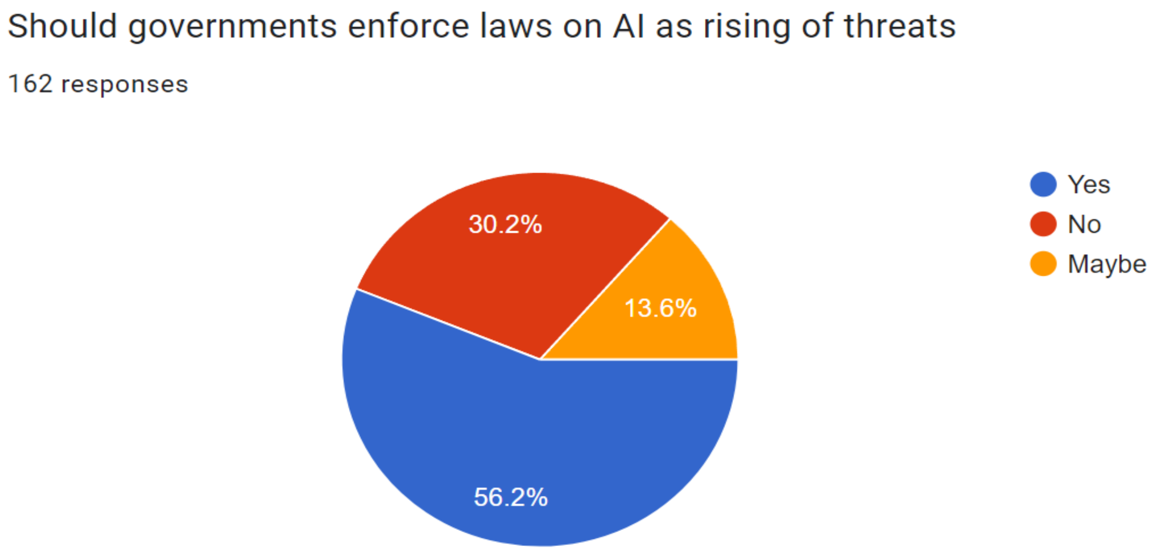
7. Do you think that AI-based change detection can significantly enhance environmental monitoring efforts?

Do you think that AI-based change detection can significantly enhance environmental monitoring efforts?

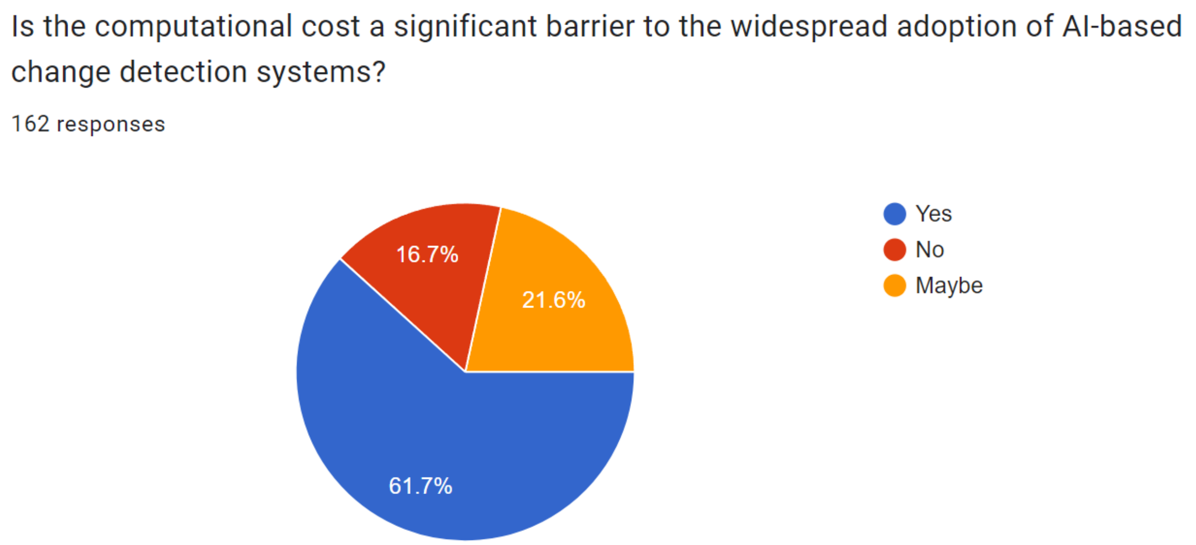
162 responses



8. Should government enforce laws on AI as rising of threats?



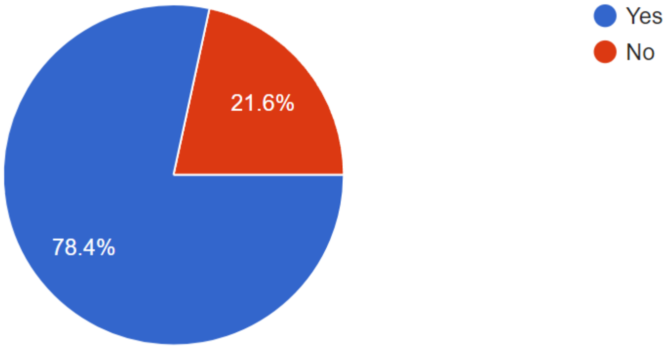
9. Is the computational cost a significant barrier to the widespread adaptation of AI-based change detection systems?



10. Are you concerned about ethical implications of using AI for change detection in surveillance?

Are you concerned about the ethical implications of using AI for change detection in surveillance?

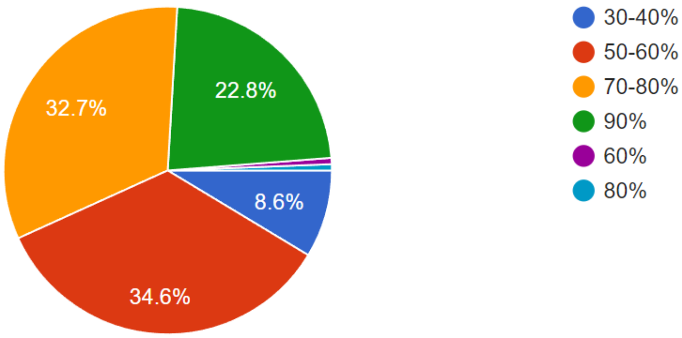
162 responses



11. **How concerned are you about the ethical implications of using of AI for change detection in areas like surveillance and privacy?**

How concerned are you about the ethical implications of using AI for change detection in areas like surveillance and privacy?

162 responses



DESCRIPTIVE STATISTICS:

1. **Do you believe that AI-based change detection methods are more effective than traditional methods?**

Mean	1.15625
Standard Error	0.033817484
Median	1
Mode	1
Standard Deviation	0.427761101
Sample Variance	0.18297956
Kurtosis	7.656270892
Skewness	2.82775072
Range	2
Minimum	1
Maximum	3
Sum	185
Count	160
Confidence Level(95.0%)	0.066789404

2. **Do you believe that advancements in AI can address the current limitations in change detection accuracy??**

Mean	1.329192547
Standard Error	0.037150439
Median	1
Mode	1
Standard Deviation	0.471386221
Sample Variance	0.222204969
Kurtosis	-1.480052814
Skewness	0.733818543
Range	1
Minimum	1
Maximum	2
Sum	214
Count	161

3. **Do you think that AI-based change detection can significantly enhance environmental monitoring efforts?**

Mean	1.12962963
Standard Error	0.026472274
Median	1
Mode	1
Standard Deviation	0.336937042
Sample Variance	0.11352657
Kurtosis	2.991569651
Skewness	2.225935137
Range	1
Minimum	1
Maximum	2
Sum	183
Count	162
Confidence Level(95.0%)	0.052277661

4. How would you rate current effectiveness of AI-based change detection methods compared to traditional methods?

Mean	3.518518519
Standard Error	0.097598737
Median	4
Mode	5
Standard Deviation	1.242229124
Sample Variance	1.543133195
Kurtosis	-0.886219359
Skewness	-0.357769765
Range	4
Minimum	1
Maximum	5
Sum	570
Count	162
Confidence Level(95.0%)	0.192738776

5. Are current AI-based change detection systems capable of handling the diverse range of real-world scenarios effectively?

Mean	1.771604938
Standard Error	0.060208652
Median	2
Mode	1
Standard Deviation	0.766331029
Sample Variance	0.587263247
Kurtosis	-1.185252117
Skewness	0.415221476
Range	2
Minimum	1
Maximum	3
Sum	287
Count	162
Confidence Level(95.0%)	0.118900533

6. Do you think that AI-based change detection can significantly enhance environmental monitoring efforts?

Mean	1.679012346
Standard Error	0.0635421
Median	1
Mode	1
Standard Deviation	0.808758891
Sample Variance	0.654090944
Kurtosis	-1.165634779
Skewness	0.651063434
Range	2
Minimum	1
Maximum	3
Sum	272
Count	162
Confidence Level(95.0%)	0.125483452

7. **Should government enforce laws on AI as rising of threats?**

Mean	1.574074074
Standard Error	0.056618916
Median	1
Mode	1
Standard Deviation	0.720641153
Sample Variance	0.519323671
Kurtosis	-0.607736808
Skewness	0.84614574
Range	2
Minimum	1
Maximum	3
Sum	255
Count	162
Confidence Level(95.0%)	0.111811494

8. **Is the computational cost a significant barrier to the widespread adaptation of AI-based change detection systems?**

Mean	1.598765432
Standard Error	0.06462237
Median	1
Mode	1
Standard Deviation	0.822508484
Sample Variance	0.676520206
Kurtosis	-0.965121241
Skewness	0.865395483
Range	2
Minimum	1
Maximum	3
Sum	259
Count	162
Confidence Level(95.0%)	0.127616778

9. **Are you concerned about ethical implications of using AI for change detection in surveillance?**

Mean	1.216049383
Standard Error	0.032434554
Median	1
Mode	1
Standard Deviation	0.412824475
Sample Variance	0.170424047
Kurtosis	-0.060891398
Skewness	1.392843774
Range	1
Minimum	1
Maximum	2
Sum	197
Count	162
Confidence Level(95.0%)	0.06405202

10. **How concerned are you about the ethical implications of using of AI for change detection in areas like surveillance and privacy?**

Mean	1.216049383
Standard Error	0.032434554
Median	1
Mode	1
Standard Deviation	0.412824475
Sample Variance	0.170424047
Kurtosis	-0.060891398
Skewness	1.392843774
Range	1
Minimum	1
Maximum	2
Sum	197
Count	162
Confidence Level(95.0%)	0.06405202

CONCLUSION AND FUTURE SCOPE:

The most recent approaches, uses, and difficulties with AI-based change detection algorithms are covered in this review. The AI-based change detection implementation process is explained for novices. The frequently used data sources and existing datasets used for change detection were thoroughly evaluated, given that one of the main issues is ensuring the authenticity of training data. Openly labeled datasets for change detection are still rare and inadequate, despite the fact that the number of public datasets available today has greatly expanded. This calls for the combined efforts of the RS community. There has been significant advancement in the use of AI for change detection, according to a systematic analysis of general network frameworks and frequently used networks. However, there are still many issues with change detection, including heterogeneous big data processing, unsupervised AI, and AI reliability. This indicates that more research must be conducted.

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