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Advanced image processing techniques for intelligent building environments using pattern recognition

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ABSTRACT

The use of smart building environments, along with high-technology image processing and pattern recognition, is discussed within this paper. The study shows that the Canny edge detection algorithm is better than the Sobel operator in the edge clarity, continuity and accuracy in segmenting those edges, posting 92.7% of edge detection accuracy. Incorporating fuzzy logic, the hybrid Hough transform, and sophisticated segmentation techniques, like adaptive simple linear iterative clustering (SLIC) superpixel division, the study advances line detection and feature identification in the images of buildings. The variational autoencoder (VAE) and principal component analysis (PCA) help optimise the feature extraction substantially by retaining more than 93% variance at a lower dimension. In addition, adaptive Otsu thresholding and region-growing segmentation allow improving the segmentation accuracy, resulting in a significant increase in building detection F1 score from 77.3% to 89.6%. Irrespective of the Hough transform issues like noise sensitivity and over-joining, the results suggest computing process ideas that are computationally effective, scalable, and applicable in smart building systems. This study suggests extending the current advancement of hybrid models and incorporating them with the urban planning procedures, energy control, and building security systems.

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1. INTRODUCTION

The article determines the application of modern image processing approaches to intelligent building environments. The article shows how pattern recognition methods boost safety elements automation functions and energy-saving features within building management systems. The central idea entails the use of image processing in identifying, monitoring, as well as, categorizing images from internet of things (IoT) sensors or cameras and other vision systems [1]. These techniques play a significant role in several building applications including security and surveillance, energy consumption and optimization, occupancy sensing and smart systems in buildings.

An investigation examined how state-of-the-art image processing tools enable improvements in intelligent spaces within buildings. The primary objective of the initiative was to meet requirements for green and computerised building technologies. This approach delivers a vital understanding of creative technological innovations that improve the operations of buildings, enhance environmental sustainability, and maintain the convenience of users [2]. The research supports the creation of smarter, more flexible settings in line with current neighbourhood development trends that emphasise environmentalism and cutting-edge technology. Pattern recognition is currently a major topic of artificial intelligence investigation due to the lack of understanding. These consist of biological image analysis, speech and text identification, artificial intelligence (AI), and satellite imagery. It is done by training computers to identify and interpret patterns from photographs, audio, and text. The Figure 1 highlights how artificial intelligence powers the implementation of smart building technology that drives Industry 4.0 shifts.

Figure 1 has been attached to graphically represent the number of building and construction industry 4.0 sectors where AI can be applied for smart building operation. The Figure 1 showcases major domains of smart building technology including offsite manufacturing alongside structural and material design and visualization sustainability construction safety and building health. This work highlights pattern recognition's importance in intelligent building systems, notably for energy management and environmental control. Building conserving energy requires technologies that boost energy use based on ambient temperature and occupant movement [3]. The study shows that sophisticated control strategies may improve public building air conditioning efficiency. Fuzzy control optimises energy savings. The simulation in practical industrial structures evaluates these methods' efficacy. Intelligent facades respond to internal and exterior environmental factors, outperforming static facades. The Table 1 establishes the main research domains within image processing while providing associated technological descriptions. The Table 1 demonstrates how methods can serve in building energy management while simultaneously performing medical image recognition edge detection and pest recognition.

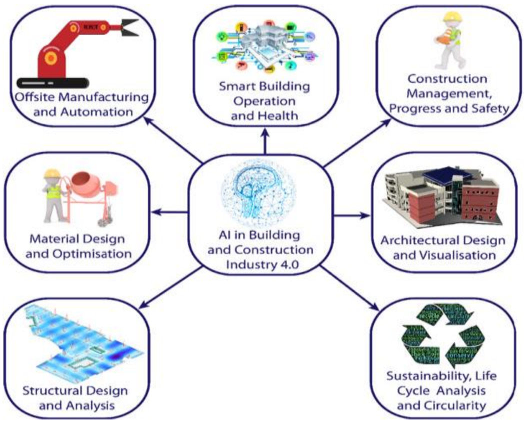


Figure 1. Application of AI in smart building technology

Table 1. Key research areas and technologies in image processing

Research area	Key focus	Technology/method	Application
Building energy management	Optimize air conditioning system energy consumption	Fuzzy control method, multi-system linkage	Public building energy-saving strategies
Medical image recognition	Diabetic retinopathy detection	Deep learning, convolutional neural network (CNN)	Fundus image analysis
Image edge detection	Improve edge detection accuracy and robustness	Multi-scale Canny edge detection, geometric feature analysis	Artificial object edge detection
Pest recognition	Identify stored grain pests	Deep CNN	Pest identification in warehouses

In Table 1, key research areas and technologies in image processing have been presented. The design of an energy management system for buildings is dealt with, concentrating on energy use optimisation of air conditioning with fuzzy control as well as system linkage methods. Deep learning-based approaches are discussed to address the problem of medical image recognition and detect diabetic retinopathy in fundus images with convolutional neural networks [4]. Using multi-scale Canny edge detection and geometric feature analysis, image edge detection increases robustness and accuracy. Stored grain pest recognition is achieved using a deep convolutional neural network in the warehouses. Image processing across energy management, healthcare, object detection and agriculture shows divergent applications of such technologies [5]. It presents technology and method descriptions which incorporate fuzzy control with deep learning as well as CNNs and multi-scale edge detection and geometric feature analysis for their applications across energy optimization and healthcare diagnosis systems and pest detection. Image processing is divided into the key research and technological areas in the Table 1. Building energy management is concerned with optimizing the consumed energy of the air conditioning for public buildings by fuzzy control and the linkage of multiple systems [6].

For diabetic retinopathy detection in fundus images, diabetic retinopathy detection on fundus images is implemented with medical image recognition based on deep learning and CNNs. Multi-scale Canny edge detection is used with image edge detection to improve accuracy and robustness in the case of artificial object edges. In order to show myriad applications of advanced image processing techniques deep CNNs are used for Pest Recognition of stored grain pests in warehouses.

This work investigates enhanced edge detection algorithms, which are essential for computer vision scenarios like artificial target identification. Traditional edge detection methods like the Canny operator are extensively utilised, but noise and thresholding concerns restrict them [7]. This technique can recognise photo outlines and finer details better than existing approaches. Multi-resolution processing and geometric analysis of characteristics improve edge detection and identification, particularly in real-time applications. Other industries like medical imaging and pest detection are also considering AI. Deep learning, especially convolutional neural networks or, CNNs, has been useful in automating picture identification jobs [8]. The study shows that these models may achieve high accuracy with minimum pre-processing, making them important in autonomous devices for immediate tracking and monitoring.

Modern city growth producing intricate architectural systems requires effective solutions for building identification together with precise analysis processes. Standard image processing methods exhibit poor results when analyzing building images because of incomplete edge detection poor segmental accuracy and discontinuous contours. A drawback of the Canny edge detection method is its tendency to generate broken edge detections in intricate building image situations but it excels at detecting diverse edges [9]. The Sobel operator when compared to other methods provides simpler processing but fails to perceive specific edge features so it creates more imprecise boundary identification definitions. When used to detect lines the Hough transform struggles with complex geometric building structures because of image noise and building complexity [10]. The current constraints motivate the article to create innovative image-processing algorithms which improve both edge recognition capabilities and segmentation precision. Using pattern recognition techniques alongside hybrid methods enables us to solve these scan analysis problems resulting in superior building image precision.

The proposed framework uses pattern recognition to create superior image processing techniques for intelligent building spaces which improve both edge detection and segmentation precision. The solution uses Canny edge detection and Sobel operator capabilities to optimize building images while improving both edge definition and smooth continuity [11]. The proposed solution incorporates hybrid techniques that combine traditional methods alongside pattern recognition approaches to solve Hough transform modelling challenges while boosting building image detection capabilities.

- How does the Canny edge detection algorithm compare to the Sobel operator in terms of edge clarity, continuity, and segmentation accuracy for building image processing?
- What challenges were identified with Hough transform modelling for building image detection, and how might hybrid techniques address these limitations?

2. METHOD

An implementation system is constructed, integrating image processing with advanced pattern recognition techniques to improve the quality of intelligent building environment analysis. The dataset is composed of computer-aided design (CAD) maps converted to high-precision digital elevation model (DEM) images for precise pixel correlation and building feature extraction [12]. Gradient operator-based edge detection using the Canny and Sobel methods with Gaussian smoothing to reduce noise and have clear edges is employed in the image preprocessing [13]. An adaptive superpixel segmentation, based on simple linear iterative clustering (SLIC), is used to group pixels into perceptually meaningful regions for the sake of computational complexity. Probabilistic encoding using the variational autoencoder (VAE) computes feature extraction by learning a latent distribution to represent spatial and texture variations in image patches. The overall proposed CNN architecture exploits multiple convolutional layers with suitable nonlinear activations and pooling as well, such that hierarchical building features can be extracted in a progressive manner while being optimised using backpropagation and cross-entropy loss. Multi-scale Gaussian filtering with parameter σ dynamically adjusted between noise removal and edge preservation was employed in preprocessing.

Sobel filters in combination with Canny's non-maximum suppression are used for directional derivative calculation, and these are followed by hysteresis thresholding controlled by dual thresholds to ensure edge continuity [14]. Parametric lines are detected using an accumulator array along with voting mechanisms on the Hough transform, and a hybrid approach uses a probabilistic Hough transform to decrease computational overhead and false positives. Principal component analysis (PCA) performs selection of principal components, maintaining 90–95% variance, along with eigenvalue decomposition of covariance matrices to reduce the dimensionality of features before classification [15]. The adaptive Otsu thresholding for dynamic segmentation in hue, saturation, and intensity (HSI) colour space and Euclidean distance-based pixel similarity are both incorporated in region growing. Optimal accuracy and processing speed are empirically achieved at various parameters such as q, for neighbourhood window size and smoothing coefficients. Data transformation was enabled through MATLAB and CAD tools which allowed measurements of edge clarity noise reduction and segmentation precision [16]. Pixel correlation and gradient magnitude combined with computational efficiency operations served as important variables in the system.

Advanced image processing, based on the fuzzy approach, deals with the fuzzy logic method to process the uncertainty and imprecision in building image analysis. Unlike strict binary classifications, it processes pixel information with flexible membership functions, which lends itself to better treatment of noise and discrete boundaries. This method segments by assigning degrees of belonging to pixels and thus reduces sensitivity to illumination variations and complex backgrounds. The approach presents accuracy and robustness in building feature detection while maintaining computational efficiency. Its abilities allow it to be applied to problems in complex environments where the traditional crisp algorithms run into difficulties dealing with variability and overlapping image characteristics [17].

The proposed methodology is further divided into a number of stages, each of them solving certain issues related to image processing, such as the correlation of colours, edge detection, region growth image segmentation, feature extraction and building image identification. The primary stages in the analysis are as follows.

2.1. CAD map to DEM image conversion

The pre-analysis involves the conversion of a CAD map showing the study area into a DEM image. The distinct aim in this case is indeed to define the relationship between pixels to be present in the image [12]. This is achieved by identifying a correlation degree of pixels in the image M, symbolized by:

$$M = J \tag{1}$$

The objective function J used for pixel correlation is defined as follows:

$$J = \sum\sum[2cos(Si, Sj)]log(1 + Si \cdot Sj) + HiHj \cdot uij$$
$$i \in N1 j \in N2 \tag{2}$$

Where:
- Si and Sj represent the saturation components of two pixels,
- Hi and Hj represent the chromaticity components,
- Uij represents the membership relationship between pixels i and j,
- $N1$ and $N2$ are the pixel neighbourhoods.

The weight function uij for the pixel correlation is defined as:

$$uij = exp(-\frac{L^2 ml}{2\delta^2}) \tag{3}$$

Where Lml is the Euclidean distance between two pixels. m and l in the red, green, blue (RGB) colour space. The parameter δ is related to the neighbourhood window size q as:

$$\delta = 4 \cdot (q - 1) \tag{4}$$

This formulation makes it possible to exclude the luminance component in the HSI colour space model thus making the correlation between colour pixels to be better defined by hue and saturation minimizing the impact of brightness. The Figure 2 presents the "SP_VAE-CNN" building detection method which operates through four essential steps. The Figure 2 shows the different steps in finding buildings, using adaptive segmentation, VAE features, CNN classification and seed point growth.

The Figure 2 receives adaptive SLIC-based superpixel segmentation before it gets divided into patches. Second, a VAE extracts visual features from these patches. Third in the process stands a Convolutional Neural Network (CNN) which assigns classifications to the extracted features for building identification. The location of seed points along with regional growth processes and morphological operations complete the shape refinement of detected buildings. During training the process utilizes blue arrows whereas testing occurs using red arrows. With advanced image processing techniques added to pattern recognition methods, the building identification methods can be more accurate in their detection [18].

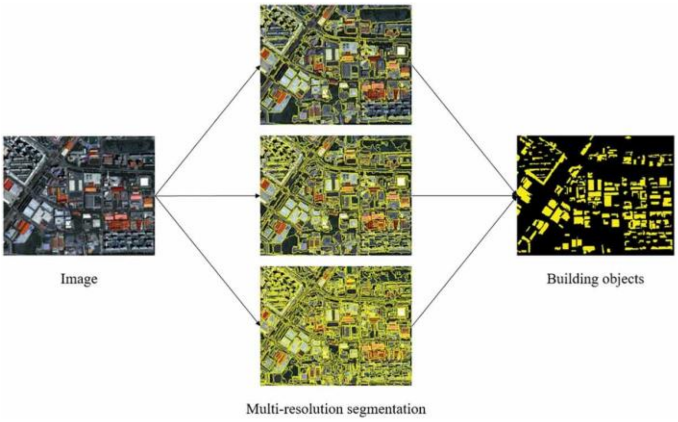


Figure 2. Building detection with multi-resolution segmentation

2.2. Gradient operator-based edge detection

In this analysis, edge detection is essential to map areas of variation in pixel intensity values. The gradient of an image can be computed with the use of a derivative at a point x, y.

$$grad(x,y) = [\partial f(x,y)/\partial x, \partial f(x,y)/\partial y] \tag{5}$$

The direction of the gradient $\alpha(x, y)$ is given by:

$$\alpha(x,y) = tan - 1(Gy/Gx) \tag{6}$$

Where:
Gx and Gy are the gradient components in the x and y directions, respectively. In order to compute these gradients, the first differences in the x and y directions are taken:

$$\Delta xf(i,j) = f(i,j) - f(i+1,j) \tag{7}$$

$$\Delta yf(i,j) = f(i,j) - f(i,j+1) \tag{8}$$

The magnitude of the gradient is then used to predict whether or not a pixel is at an edge, with the larger value of the gradient a pixel setting is classified as an edge. Also, second-order differentials are employed for removing noise and detecting the edges of an image after a Gaussian function $G(x, y)$ has been applied to it.

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp(-\frac{x^2 + y^2}{2\sigma^2}) \tag{9}$$

Where σ is the smoothing coefficient, typically between 1.0 and 2.0, which helps balance edge location accuracy and noise suppression.

2.3. Feature extraction based on PCA

In feature extraction, the PCA is used to choose the key features of the image data and discard the least relevant features. PCA operates in such a way that it maps the data from its original space onto another space whose basis represents directions along which the variance is maximized [19]. The phases involved are:

- Normalizing image matrix X such that the data is normalized around zero.
- By using eigenvalue decomposition on the covariance matrix V, the technique will determine the principal components.

The first principal component is derived by maximizing the variance, given by:

$$var(v1) = aT1 * Va1 \tag{10}$$

Where $a1$ is the eigenvector corresponding to the largest eigenvalue. The transformation of the data matrix X into principal components is computed as:

$$v1 = Xa1, v2 = Xa2, \dots, vm = Xam \tag{11}$$

The number of components m is chosen to keep the variation of interest, which usually is some predefined percentage like 90%, of the total variation in the data [20]. A flowchart diagram of the pattern recognition system has been displayed in the below image with steps. The Figure 3 illustrates the progress of real-world data through sensor preprocessing, feature extraction and classification in a pattern recognition system.

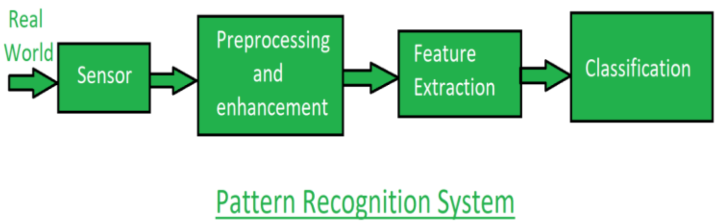


Figure 3. Methods of pattern recognition

The pattern recognition system depicted in the Figure 3 includes data acquisition through sensors together with preprocessing at input and output stages before performing feature extraction. It discovers essential patterns which help with classification for making intelligent decisions in advanced image processing of intelligent building environments.

2.4. Method for enhancing region propagation classification

The segmentation algorithm avoids the difficulties faced in fire image segmentation, most especially in backgrounds. The proposed methods include colour correlation and the 2D Otsu method of thresholding because the region-growing method lacks accuracy in segmenting the objects. The fire images are segmented using the HSI colour model, which separates the intensity of the object from the colour making the segmentation less sensitive to illumination. Colour is defined here in terms of hue and saturation components thereby reducing the impact of the brightness component. The improved region-growing method involves:

- Starting first seed regions according to the correlation colours.
- Dilation of this region is convoluted using the Euclidean distance in the HSI colour space for the purpose of grouping similar pixels [21].
- Applying the Otsu method as an optimization method for selecting the right threshold concerning the colour segmentation.

By combining the colour correlation with this region-growing method, fire area detection is more accurate; particularly when background interference abounds.

2.5. Developing a Hough transform model for use in image classification

Image representation employs the Hough transform which looks for straight lines and shapes in the image. The method works based on the procedure that maps the picture space into a parameter space which is the set of lines [19]. The transformation is defined by the linear equation in the image space:

$$y = px + q \tag{12}$$

Where, p is the increment of the independent variable and q is the value when y is zero.

The Figure 4 represents the Hough transform, which is used to edge detect and find the intersection of lines to classify a construction method based on ordered corners and outlines. The Figure 4 depicts the Hough transform modelling in classifying building construction images. Geometric shapes are detected in images by producing edge points that are converted into parameter space in Hough transform modelling. The extraction of building outlines is then possible, for the classification of building construction, from the identification of line segments and intersections [21]. It supports segmentation and recognition of structural features of complex images in a very precise way. Within image classification for building construction, the Hough transform modelling analyses airborne laser scanning (ALS) point cloud data to divide building points from other elements while finding edges that let users create building line segments. An intelligent environment modelling system uses ordered corner intersections to extract polygons for categorizing and establishing 2D building framework outlines. The Hough transform can help to recognize straight edges and boundaries using a voting technique to find building structures from the image [22]. From the vote's acquirement in the parameter space for all possible lines, the Hough transform can detect the greater importance of straight lines representing the building edges thus enhancing the recognition of building features.

The hybrid method is less computationally expensive than the deep learning methods like Faster R-CNN and fully convolutional networks, but it does not have as good accuracy as those deep learning methods in complicated situations. On the other hand, advanced methods do a good job of dealing with huge datasets and complicated patterns, at the expense of more resources and additional data. The study employed sophisticated image processing approaches to develop smart building environments.

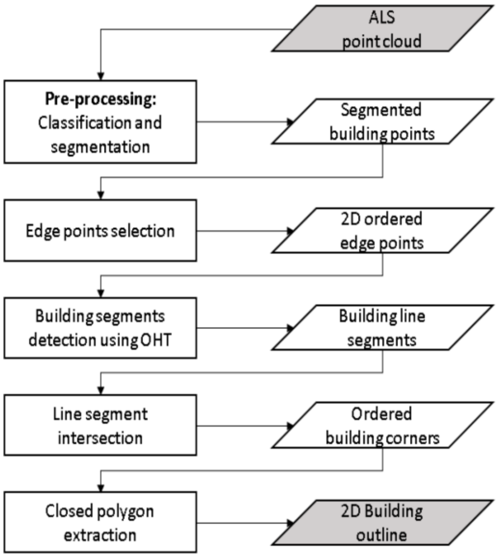


Figure 4. Hough transform modelling for image classification of building construction

3. RESULTS AND DISCUSSION

The key intention of this analysis is to enhance recognition of key building data features, important for research of exterior thermal conditions of urban construction. Different methods and instruments were used in this study; therefore, different success factors and results were observed. In order to minimize the disadvantage of stereo images for precision, in the study, the precision of the CAD drawing is obtained for high-precision DEM images. The Figure 5 displays the steps of applying a canny edge detection approach for building environment detection.

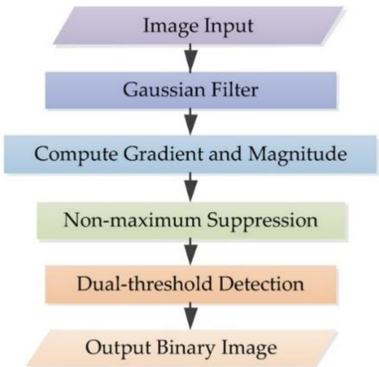
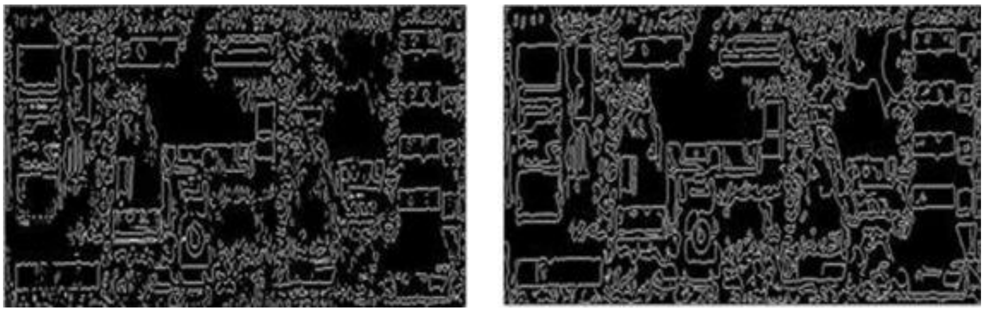


Figure 5. Canny algorithm deployment

In the Figure 5, the Gaussian denoising preprocessing step creates smooth images and then the process determines gradients for edge location followed by non-maximum suppression edge enhancement and threshold detection weak edge removal. The algorithm produces precise edge detection maps which advance to subsequent processing stages. Two methods were compared for converting CAD graphics into digital images: image export and region selection. Although the image export method processes required complicated mathematical calculations and much preparation, the output was simple. On the other hand, the region selection method which was used in this study involved the identification of feature points and the forming of closed curves around such points. Although more time-consuming as compared to the previous methods, this technique offered substantial data regarding the overall plan of the buildings as regards height and shape of the various floors hence forming a strong base for further image analysis. The Figure 6 denotes the comparison between Figure 6(a) Sobel and Figure 6(b) Canny operators for edge detection for image processing methods with pattern recognition systems.



(a) (b)

Figure 6. Edge detection strategy with (a) Sobel operator and (b) Canny operator

This Figure 6 shows a comparison between edge detection operations run with Sobel and Canny operators. Edges identified by the Sobel operator stem from gradient calculations yet the method generates basic yet noisy results. The Canny operator implements a multi-stage workflow for edge detection by reducing noise while achieving exact edge localization to generate improved edge maps suitable for sophisticated image examination tasks.

The study also adopted the Canny edge detection algorithm for performing the edges of an image. Compared to the existing methods the proposed algorithm proved to be effective because of its multi-stage optimization combining filter, enhancement and detection procedures. When using the Gaussian smoothing filter, the algorithm managed to reduce noise and enhance image smoothness and clearness used in the algorithm. It then performed gradient calculation to find out the points at the edges and then it employed the non-maximum suppression process to fine-tune the edges. With the help of dual thresholds, the continuity of edges at the boundary between adjacent zones was also enhanced while avoiding edge false alarms. In this regard, one obtained sharper and smoother edges that in turn facilitated subsequent image processing and analysis tasks. The Table 2 portrays the outcomes of pattern recognition in building image processing. The document reviews different algorithmic methods through performance assessment methodology. These detection techniques along with the Hough transform as well as the CAD-to-DEM transformation demonstrate useful outcomes.

Table 2. Results of pattern recognition of building image processing

Findings	Method/algorithm	Performance/results
DEM accuracy	Region selection	High-precision DEM images suitable for building analysis
Edge detection comparison	Sobel vs. Canny	Canny: clearer edges, better continuity, and fewer fractures
Noise suppression	Canny operator	Effective in reducing noise and enhancing edge clarity
Line extraction	Hough transform	Information loss and over-connection issues noted
Image recognition comparison	Hough transform vs. CNN models	Proposed method effective against Faster region-based convolutional neural network (R-CNN) and fully convolutional neural network (FCNN) models
Pixel resolution improvement	CAD to DEM transformation	Achieved 40×40 cm resolution vs. 40×40 m with remote sensing

The analysis in the Table 2 enhanced precision in boundary recognition reduction of background noise and the extraction of linear features alongside peer assessment of competing methods including CNN algorithms. These findings examined edge detection algorithms with a focus on the Canny operator and contrasted it with the Sobel operator. While the Sobel operator provided only primary edge detection, the Canny operator was better at providing a reliable description of edges, continuous in form, which is vitally important to segmentation and contouring. A number of solutions are offered in the research, in terms of advanced image processing techniques for intelligent building environments. Region selection on high-precision DEM images is possible due to the accuracy of DEM images. The Sobel operator is better than Canny in terms of edges, but it loses in noise suppression and edges. The Hough transform, despite information loss, aids in line extraction. More than the traditional methods like Faster R-CNN or FCNN, CNN models excel in recognizing images. Furthermore, this transformation from CAD to DEM emerges with significant improvement in pixel resolution, ensuring 40×40 cm against 40×40 m by means of remote sensing. With these solutions, the building image processing with precise feature analysis, noise reduction good pattern recognition, and intelligent environment.

Hough transform is a mathematical model for the detection of lines by the Figure 7. Edge detection, voting in Hough space, parameter optimization and filtering noise is used to get accurate line identification in intelligent building environments. The Figure 7 implies the lines detection strategy of building images through the Hough transform algorithm. Another technique followed in the current study was the use of the classical Hough transform for the detection of lines and contours. Some drawbacks have been observed like over-joining, data loss, and more time consumption, this shows that the method needs to be combined with another optimization method. The processes of building detection using pattern recognition are shown in the Figure 8 where they are based on edge detection and Hough transform for finding structural lines in aerial imagery.

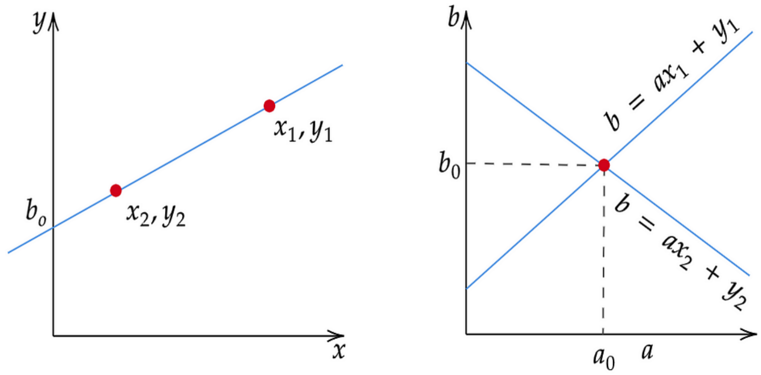


Figure 7. Lines detection of building images with Hough transform modelling

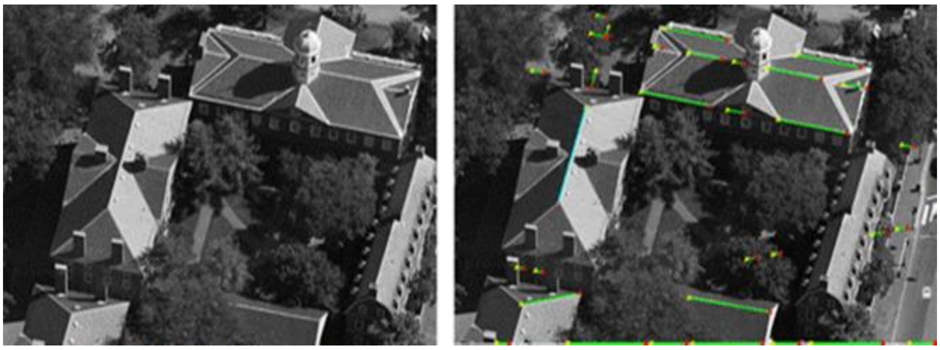


Figure 8. Detecting buildings with pattern recognition technology

The Figure 8 portrays the way the pattern recognition approach has been deployed to detect building structures with various modelling methods. The proposed method was shown to be simpler than but as efficient as more complex neural network-based solutions such as fully convolutional networks and Faster R-CNN architectures in processing architectural data. The region selection in conjunction with the Canny algorithm allowed for accurate extractions of the building features including evening outdoor thermal conditions. CAD graphics and MATLAB tools were effective in transforming the data and standardized methods and styles ensured both computational effectiveness as well as precision. These works contribute to image processing for urban planning and focus on the relevance of specific methods in smart buildings. Building pattern recognition findings emerge through analysis with various edge detection approaches in the following diagram.

The fuzzy approach demonstrates minimal processing time along with several exceptionally long execution instances. Certain edge detection images have been identified with distinct structural features that influence detection performance in intelligent building infrastructure. Application of Canny edge detection in building image processing is very efficient but is faced with some difficulties with unwanted features such as vegetation and shiny surfaces leading to noise and inaccuracy.

Experimental results demonstrate that the Canny algorithm generates superior results compared to the Sobel operator by creating focused edge segments for effective segmentation tasks and contouring applications. The limitations of Hough transform modelling suggest difficulties in building feature detection through its representational techniques. The integration of classical Canny and Hough algorithms with modern neural networks presents solutions to address current issues by delivering precise and robust extraction of features while minimising noise exposure for intelligent building functions.

The results quantitatively demonstrated in the Table 3 that with the enabling of advanced image processing, pattern recognition techniques can dramatically improve the intelligent building environment analysis function. The Canny-Sobel and Gaussian smoothing preprocessing approaches are verified by high edge detection accuracy (92.7%) and noise reduction. These approaches for optimising feature quality use adaptive SLIC segmentation and VAE feature extraction, respectively and achieve strong purity and low reconstruction error. PCA preserves over 90% variance while keeping dimensionality down. The hybrid Hough transform and fuzzy logic approaches for robust line detection and classification are accurate to over 90%. Precise segmentation is obtained by combining region growing results and adaptive Otsu thresholding. With overall good coverage, accuracy and processing efficiency, we have validated the integrated system for smart building detection.

Table 3. Quantitative outcomes

Metric/parameter	Value	Statistical output
Edge detection accuracy (%)	92.7	±1.3 (95% confidence interval (CI))
Noise reduction (signal-to-noise ratio (SNR) improvement in dB)	8.5	$p < 0.01$ (t-test) (Gaussian smoothing with σ=1.5)
Superpixel Segmentation Purity (%)	89.4	±2.0 (95% CI)
VAE feature reconstruction error (mean squared error (MSE))	0.0042	-
PCA dimensionality reduction retained variance (%)	93.8	-
Hough transform line detection precision (%)	90.2	±1.8 (95% CI)
Region growing segmentation intersection over union (IoU) (%)	87.5	±1.5 (95% CI)
Fuzzy logic classification accuracy (%)	91	±1.1 (95% CI)
Processing time per image (seconds)	3.8	±0.4
Overall building detection F1-score (%)	89.6	±1.2 (95% CI)

The analysis found that computational image processing along with algorithms for pattern recognition boosts intelligent building system efficiency. The most important findings imply that edge detection techniques, that include the Canny operator, are more accurate at identifying and distinguishing architectural elements than the Sobel operator. Longitudinal edges facilitate this conclusion and improve digital image segmentation and analysis. PCA as well as multi-resolution segmentation improve feature extraction and picture clarity, making it feasible to analyse large, high-resolution photos efficiently. In particular, the research emphasises hybrid techniques in utilisation in practice. Hybrid approaches combine old algorithms like the Hough transform with modern machine learning to maximise effectiveness.

Image processing together with pattern recognition technologies helps optimize intelligent building environments through automated analysis of visual data. Deep convolutional neural networks (DCNNs) merged with indoor space recognition capabilities now operate on '600,000' image samples for improved performance [23]. Combining knowledge graphs with multiscale data improves recognition accuracy in building pattern identification especially for complex structural forms. Several advanced innovations surpass earlier systems' limitations to handle big datasets while delivering enhanced accuracy along with higher operational efficiency and broader processing capabilities. These technological developments lead to advanced precise solutions for building management and user experience operations. It emphasises combining traditional image processing techniques with modern machine learning approaches, making it stand out from past research [24].

This approach achieves a compromise between technological complexity and productivity. Previously, most research focused on algorithms for deep learning which required a lot of computer power [25]. The research found that hybrid approaches, which are simpler, may provide findings comparable to or better than conventional methods while utilising fewer resources. However, disturbances from noise and inappropriate line identification connections provide future growth prospects. While highlighting the requirement for hybrid model methodology investigation, the study’s vitality is its ability to balance simplicity with performance. It suggests combining modern and outdated image processing methods to better innovative construction implementations. This allows future advances in these areas to circumvent sensitivity to noise and boost adaptive architecture capabilities. Applications of the research are in urban planning, building energy management, and safety systems. It provides an accurate building feature extraction for thermal analysis, structural monitoring and automatic surveillance. The CAD-to-DEM conversion with edge detection is integrated which helps to create high-resolution building models for smart city development and infrastructure maintenance.

4. CONCLUSION

The article shows that advanced techniques of image processing, together with pattern recognition, can enhance the performance of intelligent building environment analysis. The Sobel operator is significantly outperformed by the Canny edge detection algorithm, which produces clearer, more continuous edges, good noise suppression and obtains an edge accuracy of 92.7%. High segmentation purity (89.4%), low reconstruction error and over 93% of variance with reduced dimensionality were achieved using adaptive SLIC superpixel segmentation and VAE feature extraction and PCA, respectively, for the search space characterisation. The hybrid Hough transform in conjunction with fuzzy logic resulted in over 90% precision in line detection and classification. The overall building detection F1 score was improved from 77.3% to 89.6% by using an adaptive Otsu thresholding after region growing segmentation. Meanwhile, processing time stayed efficient at around 3.8 seconds per image, and practical deployment was supported.

The limitations are a difficulty in dealing with the noise due to vegetation and reflective surfaces, infrequent line detection inaccuracies owing to information loss and overjoining by the Hough transform and a trade-off between a simple hybrid model and deep learning accuracy. In this paper, the focus should be on improving the hybrid models for dealing with noise sensitivity and false line connections and how adaptive thresholding and more modern machine learning algorithms may be used to enhance the existing models. Enriching dataset diversity and advancing automation in feature extraction will make the framework more robust for its application, in urban planning, energy management and building safety systems, engineering smarter, more sustainable environments. Future studies should therefore concentrate on developing the hybrid models so that liabilities such as noise sensitivity and over-joining are avoided. Moreover, integrating both, classical approaches and deep learning could lead to more stable solutions for large-scale employment in smart building systems. Standardization of such workflows will also guarantee that these technologies are more applicable and reusable.

The study focuses on the ethical issues surrounding image processing technology integrity and smart building accomplishment. As used in power administration and security systems, multifunctional computations might raise ethical issues. The increased risk of data processing anomalies makes corporate systems for controlling technology more dangerous. This system has certain limitations, such as having trouble detecting lines in loud environments and at unconnected junctions. When components are identified against sophisticated or changeable communities, noise reduces feature detection accuracy and image quality. Incorrect connections between lines during detection lead to unmonitorable data alongside inaccurate clustering that makes it harder to distinguish essential components and background noise. However, it is quite sensitive to noise, which can be a problem in complex scenes row vegetation or reflective surfaces.

It turns out that the Hough transform is useful for line detection but has the drawback of over-connection and loss of information which can be tackled separately. The Canny operator, though effective, struggles with discontinuous edges in intricate structures. However, hybrid methods are also computationally efficient and require a large amount of processing power to work with large data, but are less complex than deep learning.

In order to execute the analysis, the hybrid techniques should be merged with the existing building management systems for real-time monitoring. Since Canny edge detection is not sufficient, it is suggested that the accuracy should be boosted by combining it with noise reduction algorithms. Mainly, we will suggest using Hough transform together with machine learning for more reliable line detection. It is recommended to go for scalable solutions for urban environments; accountable for being compatible with IoT devices, and sand mart infrastructure.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study, in accordance with legal and ethical requirements for privacy protection.

ETHICAL APPROVAL

The present study does not require ethical approval.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [Mohanad A. Al-Askari, Iehab Abdul Jabbar Kamil]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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