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Advancements in Learning-Based Techniques for Automated Floor Plan Analysis on Raster Images: A Comparative Study

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ABSTRACT

Automated floor plan analysis and recognition have long been focal points in computer science research. Recently, there has been a notable increase in the use of learning-based techniques to automatically reorganize floor plans from raster images. This advancement aims to extract valuable insights from architectural drawings, which are essential for understanding building layouts and their intended functions. These drawings often feature a variety of notations and constraints, and the lack of standardized notation leads to significant variability in both style and semantics across different floor plans. Addressing this challenge is a key focus of this review.

This paper provides an extensive literature survey to tackle the issue of variability in floor plans. The review concentrates on methodologies that treat floor plans as raster images, with particular attention to learning-based approaches. By offering concise summaries of datasets, research scopes, and specific tasks, this review aims to guide future research and development in the fields of construction and design. The in-depth examination of automatic floor plan analysis and recognition methods presented here contributes to the evolving field of computer-assisted architectural understanding and design.

Keywords - **Floor plan analysis, Recognition techniques, Learning-based approach, Object classification.**

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I. INTRODUCTION

Architectural floor plans show both the shape and purpose of rooms[2-3]. They include details like outer and inner walls, windows, furniture, dimension lines, grids, text, or icons. Analyzing and extracting information from these plans in raster images is a challenging task because of the various elements and relationships between them [1].

Architectural floor plans are more than just blueprints; they provide important details about room dimensions, door placements, and object arrangements. Architects and designers use software like BriskCad, AutoCAD, and Ares to create these plans. Before computer-aided design (CAD) tools, plans were drawn on paper and then scanned to create digital versions for storage and future use [7]. Home buyers and renters use rasterized plans to understand and get a clear idea of a house or flat. However, rasterized plans don't include important details like layers or object information [8].

Examining and understanding rasterized floor plan images using an automatic method is a complex challenge in computer vision. There are few challenges in this process Raster images often have complicated and unclear architectural drawings[10]., no consistent way architects and engineers use symbols, colors, and line thickness[9]. Not only this contains high-level geometric, topological, and semantic constraints like, doors are part of walls, which are made of parallel lines, and walls outline the boundaries of rooms.

From a technical perspective, analyzing floor plans involves automatically extracting important information from architectural drawings saved as images. This process includes tasks like identifying walls, windows, and recognizing and categorizing rooms. Additionally, it involves creating 2D or 3D models of buildings. These tasks span various areas in computer science, such as image processing, pattern and symbol recognition, object vectorization, and graph modeling.

In recent times, new methods that use advanced learning techniques have been suggested for recognizing and modeling building objects. These methods make use of technologies like convolutional neural networks (CNNs), graph neural networks (GNNs), and generative adversarial networks (GANs). By employing these technologies, there's been an improvement in accuracy, and the methods can adapt to different input styles [27].

A study reviewing various methods for floor plan analysis can help shape future advancements in construction, design, and engineering. For example, it can aid in the development of Building Information Modeling (BIM), 3D reconstruction, or the retrieval of similar plans from large databases [37]. This review serves as a quick guide, suggesting datasets and algorithms suitable for specific tasks. It addresses the research problem, discusses available datasets, outlines methodologies and their evolution, and highlights challenges and opportunities for future work. The upcoming research in floor plan analysis, along with its applications, is expected to enhance efficiency and reduce costs, particularly in industries looking to automate processes and improve software.

The review is focuses on presenting previous work related to recovering, classifying, and modeling building elements and layouts. The study specifically looks at raster images of architectural floor plans as input. The research organizes datasets and discusses recent changes in learning-based approaches. Approximately 38 peer-reviewed articles from 2018 to 2023 were selected for this review.

This paper has several goals. First, it aims to identify and analyze the main trends in automated floor plan analysis research. Second, it explores the practical uses and applications of learning-based advancements, looking at how they impact real-world scenarios, construction projects, and design processes. Third, the paper provides insights into the methods, datasets, and scopes of studies in this comparative analysis. Overall, it aims to guide and inspire future research in this rapidly changing field.

II. LITERATURE REVIEW

This study employed content analysis to systematically select literature for review, a method commonly used to make objective and valid inferences based on collected data. Content analysis enables both qualitative and quantitative operations, disclosing central aspects of previous studies. In this case, it facilitated a comprehensive exploration of AI applications in floor plan analysis and object detection, ensuring reliable study results.

The sample collection process involved searching and selecting peer-reviewed articles from reputable academic databases, including Web of Science, Scopus, Science Direct, ASCE Library, ACM Digital Library, IEEE/IET Xplore, Wiley Online Library, Sage, and Emerald. The search utilized keywords such as "artificial intelligence," "pattern recognition floor plan," "floor plan recognition and interpretation," "parsing floor plan images," "machine learning floor plan analysis," "deep learning floor plan analysis," "convolutional neural networks floor plan analysis," and "computational intelligence floor plan analysis".

A total of approximately 150 candidate articles were identified within the timeframe of 2019 to 2023. The selection criteria focused on articles applying pattern recognition, machine learning, and deep learning in floor plan analysis. A two-round article selection technique was employed, with the first round checking titles, abstracts, and keywords for relevance. The second round involved reading and analyzing the entire articles, resulting in the selection of 30 articles closely aligned with the review objective.

Qualitative and quantitative analyses were then conducted to identify emerging AI methods' applications in structural engineering, the algorithms used, and their applicability for the noted applications. This comprehensive approach allowed for the identification of promising AI applications and future research directions in the field.

III. ARCHITECTURAL FLOOR PLAN ANALYSIS AND RECOGNITION

Bingchen Yang et.al. 2023 proposes a novel method for semantic segmentation of vector floor plans using a two-stream graph attention network, achieving superior results in room boundary and region classification. It give Mean accuracy 88.41 [1] .

Teng Wang et. al. 2023 introduces RCNet, a novel network for parsing floor plan images, enhancing room segmentation accuracy through text features. The inclusion of a text branch and merge module significantly improves room type prediction, and the RC Constraint Module enforces regularity in floor plans, achieving state-of-the-art segmentation [2].

Mingxiang Chen et. al., 2023 introduces GLSP, a Graph Neural Network-based Line Segment Parser, for floor plan recognition. This approach predicts line segment endpoints using a junction heat map, utilizes graph neural networks for line segment extraction, and outputs vectorized structural elements, demonstrating superior performance in multi-class line segment detection tasks on the LRFP dataset. The method introduces the task of multi-class line segment detection and leverages an attention-based GNN for accurate relationship capture, outperforming state-of-the-art wireframe parsing models [3].

Lingxiao Huang et. al., 2023 presented MuraNet is an attention-based multi-task model for floor plan segmentation and detection, simultaneously handling pixel-level wall segmentation and vector-level detection of doors and windows. The attention mechanism enhances accuracy by leveraging architectural element correlations, demonstrated through experiments. The study explores classical models, presents MuraNet architecture, and suggests future research directions [4]

Aleixo Cambeiro Barreiro et. al., 2023 introduces a 3D model reconstruction pipeline from 2D floor plans, involving tasks such as wall segmentation, symbol detection, and polygon extraction. The process culminates in the creation of a 3D building model exportable as an IFC (Industry Foundation Classes) format model, showcasing effectiveness with state-of-the-art results on a reference dataset and generalization to diverse plans [5].

Bisheng Yang et. al., 2022 use a three-stage strategy, involving modified CNNs for segmentation, mixed-integer programming for identifying relationships and removing errors, and an optimization strategy for addressing topological inconsistencies. This approach produces vectorized floor plans with correct topology and semantics across diverse datasets [6].

Zhengda Lu et. al., 2021 introduces a deep learning framework for rural residential floor plan recognition, addressing diverse design styles. Leveraging a new

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dataset, the algorithm simultaneously recognizes graphical elements and detects text, reconstructing floor plans through optimization and MIQP-based (Mixed-Integer Quadratic Programming) room segmentation. This novel framework outperforms state-of-the-art methods on both the new and benchmark datasets [7].

Sungsoo Park et. al., 2021 presents the 3DPlanNet Ensemble method for converting 2D raster drawings to 3D vector models. This approach combines data-based models trained with only 30 data points and rule-based heuristic methods. Achieving 95% wall restoration accuracy and 97% size accuracy, this approach combines limited data-trained models with heuristic methods for high precision [8]

Rasika Khade et. al., 2021addresses scan-time rotations in floor plans images. The three-phase framework, involving outer shape analysis, internal object feature extraction, and matching and retrieval, exhibits superior accuracy in experiments with the ROBIN dataset. Notably, its superior retrieval accuracy, highlighting its distinct advantage in handling rotations and scale variations compared to other techniques. [9]

Fig. 1. Illustration of the problem with a floor plan and three instances with varying orientation from the dataset proposed by Sharma et al. [38]

Iordanis Evangelou et. al., 2021 proposes a method for recognizing architectural floor plan elements, emphasizing minimal user input. It employs Haar kernel-based for structural elements feature extraction and PU learning for identify different structural elements without relying on labeled samples, demonstrating superior retrieval accuracy across diverse notation styles in experiments. [10]

Mantaro Yamada et al., 2021 introduces a method to automatically convert floor plan images into structured graphs, facilitating computer-based comparison and retrieval. This approach employs deep learning to recognize floor plan contents, transforming them into well-organized graphs, enhancing precision in retrieving similar floor plans based on layout. The use of graphs ensures highly accurate retrieval, independent of diverse image styles. [11]

Xiaolei Lv et al.,2021 has presents an automatic framework for residential floor plan recognition and reconstruction using deep learning, incorporating multi-modal information. The approach utilizes YOLOv4 for ROI detection, DeepLabv3+ for structural identification, and OCR, YOLOv4 for text and symbol detection. Various algorithms, including FCN, Resnet50, and K-Means, are employed for scale calculation, achieving an average accuracy of 97%. The proposed dataset, featuring 7000 annotated images, supports the approach, with key contributions including accurate recognition and reconstruction, an iterative optimization-based vectorization method, and the creation of a large annotated dataset for residential floor plans. [12]

G. Murugan et. al., 2021 uses Cascade Mask R-CNN for precise spatial data extraction from floor plans, achieving a mean IoU of 72.7%, surpassing the baseline of the CubiCasa5k database (57.5%). This demonstrates the effectiveness of Cascade Mask R-CNN over Mask R-CNN for enhanced performance across different classes. [13]

Jaeyoung Song et. al., 2021 Novel floor plan analysis framework: images vectorized, classified by Graph Neural Network using inductive learning for high accuracy, maintaining vector format. Demonstrates effectiveness across datasets; future work on low-resolution images and improved classification [14].

A Repository of Unique Buildings (RUB) dataset for floor plan analysis, featuring vectorized representations of significant public buildings. Addresses scarcity of vectorized floor plan data, includes CAD files, and encompasses 81 diverse floor plans, facilitating method development and comparison [15].

Dong et al. (2021) propose a novel Vectorized Floor Plan (VFP) framework utilizing the generative adversarial network (GAN) EdgeGAN. Their private dataset, ZSCVFP, comprises 10,800 colorful samples with diverse textures. EdgeGAN, treating VFP as an image translation task, excels in speed and quality, outperforming traditional object-detection frameworks. The paper introduces two inspection modules to ensure connectivity and consistency in the primitive feature map, demonstrating EdgeGAN's efficiency through experimental results [16].

Seongyong Kim et al. 2021 The study utilizes deep networks for style transfer to convert diverse floor plans into a unified format, streamlining the vectorization process. This approach, emulating human perception, proves effective in constructing indoor spatial information from various architectural floor plans with a consistent post-processing step [17].

Seongyong Kim et. al. 2021 introduces an innovative method for extracting indoor structures from complex floor plan raster images, excelling in room and opening recognition amid intricate patterns. Using conditional generative adversarial networks, it unifies floor plan formats before vectorization, demonstrating superior room detection and recognition in complex drawings compared to existing methods [18].

Yuli Zhang et. al 2020 presents a new floor plan recognition network aiming to explore spatial relationships, reduce noise, and improve pixel label accuracy. Three key contributions include specially designed kernels for understanding diverse floor plan elements, their application in convolutional blocks and context modules, and the use of adversarial techniques to enhance accuracy and reduce noise in pixel labels. [19]

Abhishek Paudel et. al. proposes using graph neural networks (GNNs) to enhance room classification on building floor plans represented as undirected graphs. Experiments on the House-GAN dataset show that GNNs, particularly TAGCN and GraphSAGE, outperform other models like GCN, GAT, and MLP. GraphSAGE and Topology Adaptive GCN achieve accuracies of 80% and 81%, respectively, surpassing the baseline MLP by over a 15% margin, indicating the effectiveness of GNNs in this context. [20]

Yijie Wua et. al. 2020 The author presents a two-stage Indoor Mapping and Modeling (IMM) approach from floor plan images. The first stage simplifies building elements into rectangles based on regularity, while the second stage optimizes rectangle vertices to address topological inconsistencies, significantly improving room detection accuracy. The approach outputs instance-separated walls with consistent topology, suitable for direct modeling into Industry Foundation Classes (IFC) or City Geography Markup Language (CityGML). Key contributions include simplifying boundary elements, optimizing topological constraints, and enhancing room detection accuracy, meeting the requirements of indoor Location-Based Services (LBS). [21]

Ruiyun Zhu et. al. 2020 evaluates the application of convolutional neural network (CNN)-based image segmentation methods for floor plan parsing, as opposed to traditional approaches like template matching. The focus is on analyzing samples with challenging features for CNN-based models. To enhance the learning accuracy for these complex samples, the authors propose two training strategies: separate training and the use of a weighted loss function. Experimental results show that these strategies perform well for complex samples, yielding more favorable parsing outputs [22].

S. Dong et. al. 2020 used Google DeepLabV3+ for deep learning on architectural drawings, achieving 87.83% accuracy for elements and 92.09% for spaces in apartment floor plans. Challenges like insufficient data, image size, and unlabeled spaces are addressed through augmentation, resizing, and hybrid approaches. Practical applications include automatic 3D model generation, evacuation path planning, energy rating analysis, and AI-based architectural design techniques [23]

Hiren K. Mewada et. al. 2020 introduces a floor plan retrieval algorithm using shape extraction and room identification. The algorithm utilizes α-shape for accurate shape detection, enabling precise room area calculation. It incorporates a regression model-based binary classification for room types and non-room types. Tested on the CVC-FP dataset, the model achieves 85.71% room detection accuracy and 88% room recognition accuracy [24].

Vage Egiazarian et. al. 2020 presents an innovative method for vectorizing technical line drawings, involving three stages: deep learning-based cleaning, transformer-based vector estimation, and optimization. Trained on synthetic data and manually vectorized scans, the approach outperforms existing techniques across various technical drawings, showcasing superior quantitative and qualitative results [25].

Ilya Y. Surikov et. al. 2020 combines computer vision, computational geometry, statistical analysis, and deep learning for precise floor plan recognition and vectorization. Utilizing UNet and Faster R-CNN, it outperforms existing methods in Intersection over Union (IoU). Additionally, a dataset enlargement technique using back perspective transform enhances robustness to shadows with a 1.5% increase in IoU [26].

Hanme Jang et. al. process extracts information from architectural floor plans, addressing missing geometric details. Utilizing U-net, it preprocesses images, extracts wall thickness, and identifies connectivity and potential junction nodes through skeletonization. Extracted junctions guide edge identification, forming an adjacency matrix. The method specifically focuses on walls at arbitrary angles, emphasizing wall thickness restoration via image processing and adjacency matrix utilization. [27]

Hanme Jang et. al. 2020 introduces an automated method for extracting vector data from floor plan images to generate indoor spatial information compliant with OGC standards. Utilizing a modern CNN architecture, the approach achieves accurate segmentation, forming a reliable node-edge graph with thickness attributes. Overcoming challenges in segmenting complex structures, the method demonstrates improved accuracy through deep learning techniques. The study presents a novel approach for automatically generating vector data from 2D floor plan images, emphasizing its utility and compatibility with OGC standards like CityGML and IndoorGML. [28].

Ahti Kalervo et. al. 2019 introduces CubiCasa5K, a large-scale floor plan image dataset with 5000 samples annotated in over 80 categories using polygons. The annotations offer dense and versatile information. The study proposes an improved multi-task CNN for automatic floor plan image analysis, providing a robust research tool. CubiCasa5K excels in dataset size and annotation variety, surpassing existing datasets, and achieves state-of-the-art performance with the proposed multi-task CNN [29]

Zhiliang Zeng et. al. 2019 introduces a novel method for comprehensive floor plan recognition, using a deep multi-task neural network. It predicts room-boundary elements, room types, and incorporates a spatial contextual module for enhanced predictions. Results show superiority over state-of-the-art methods [30].

Yuki Takada et. al 2018 introduces a novel framework for real estate property searches, utilizing floor plan images as queries. To address challenges in similar property searches, a multitask learning approach is proposed, using deep neural networks for layout type and room presence

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classification. Experiments with 22,140 floor plan images in Tokyo demonstrate that the method outperforms others, achieving the best precision@5 of 15.7%. Learning both layout types and room presence simultaneously enhances classification performance, enabling effective retrieval of structurally similar floor plan images [31]. Xingyu Guo et. al. 2018 proposes a method for floor plan structure classification using Convolutional Neural Network (VGGNet) features, Auto-encoder for dimensionality reduction, and Multi-Layer Perceptron (MLP) for classification. This approach improves accuracy compared to traditional machine learning models and demonstrates the positive impact of transfer learning on structured image classification [32].

Zahra Ziran et. al. 2018 assesses the application of object detection architectures, initially designed for image object recognition, in identifying furniture, doors, and windows in floor plans. Despite the relative simplicity of the problem compared to the original, the small available datasets pose challenges for training deep architectures. Additionally, the paper contributes by creating two datasets, covering various floor plan types and characteristics, for conducting experiments [33]. JongHyeon Yang et. al. 2018 focuses on utilizing deep neural networks to segment walls and doors in architectural floor plan images. Additionally, it aims to create a dataset with ground truth information specifically for wall segmentation [34].

Weixin Huang et. al. 2018 has created Pix2pixHD software, an implementation of Generative Adversarial Networks (GAN). This application can generate output data with comparable or identical characteristics to the input [35].

Toshihiko Yamasaki et. al. 2018 has formulated and enhanced the MCS extraction algorithm, employing the FCN and graph model algorithm on floor plan images. This algorithm is utilized for analyzing apartment structures and segmentation, effectively addressing apartment structure searching problems with a mean accuracy of 0.8402. [36]

Chen Liu et.al. 2017 employed a three-step solution approach. Firstly, they applied CNN to transform a raster floor plan image into the initial junction layer. Secondly, they utilized Integer Programming to choose the appropriate subset, ensuring adherence to high-level geometric and semantic constraints. Lastly, a simple post-processing step was implemented to convert the floor plan data into the final vector-graphics representation, achieving approximately 90% precision and recall [37]. Srinivasan et.al [45] has presented Big Data based Machine Learning approach for exploring rock arts.

Samuel Dodge et. al. 2017 presents a method for analyzing floor plan images, incorporating wall segmentation, object detection, and optical character recognition. It introduces a new real estate floor plan dataset, R-FP, and assesses various wall segmentation methods. The proposed fully convolutional networks (FCN) achieve a mean Intersection-over-Union score of 89.9% on R-FP [38].

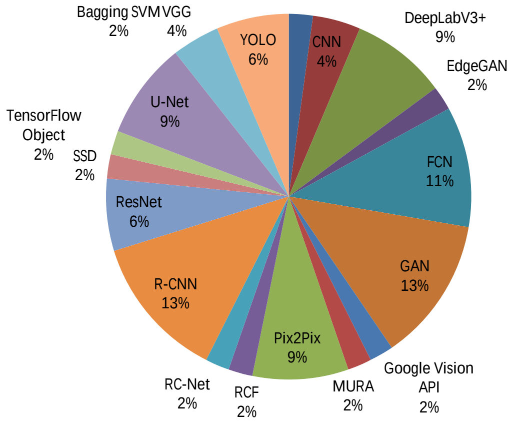

Fig. 2. Illustration of Learning based Algorithms used in recent years for floor plan analysis.

Table 1: Learning-based research, considering Methodology and findings

S. No.	Author	Referenc e (year)	Methodology	Wal l	Door/ Window / furnitur e/ Others	Roo m	OCR / Dimensio n	Room Size Identificatio n	Text Detectio n	Accuracy/ end Result
1	S. Dodge, J. Xu, B. Stenger	2017	FCN-2s, Faster R-CNN, Google Vision API	Yes	Yes	Yes	Yes		–	obtaining a IoU score 89.9% on R-FP,& 94.4% on CVC-FP data set.
2	C. Liu, J. Wu, P. Kohli, Y. Furukawa	2017	CNN, ResNet-152, Integer programming	Yes	Yes	Yes	–		–	achieves around 90% precision and recall,
3	T. Yamasaki, J. Zhang, Y. Takada	2018	FCN , graph models.	Yes	Yes	Yes	–	Yes		achieve a pixel mean accuracy of 0.89
4	W. Huang, H. Zheng	2018	Pix2PixHD	–	–	Yes	–		–	generates new images based on the input.
5	J. Yang, H. Jang, J. Kim, J. Kim	2018	U-Net - PixelDCL	Yes	Yes	–	–		–	Mean acc 97

6	Z. Ziran, S. Marinai	2018	Faster R-CNN	–	Yes	–	–		–	precision 0.86, recall of 0.92.
7	X. Guo, Y. Peng	2018	Predefined ruleVGG-16,MLP	Yes	–	–	–		–	Accuracy/ 92.4%
8	Y. Takada, N. Inoue, T. Yamasaki, K. Aizawa	2018	MCS, multi-task, VGG-16	–	–	Yes	–		–	0.9 at a precision of 15.7% with precision@5
9	Z. Zeng, X. Li, Y. K. Yu, C.-W. Fu	2019	VGG, RCF , DeepLabV3+, PSPNet	Yes	Yes	Yes	–		–	overall accu 0.89 (0.90)
10	A. Kalervo, J. Ylioinas, M. Häikiö, A. Karhu, J. Kannala	2019	Modified ResNet-152	Yes	Yes	Yes	–		Yes	propose annotated floorplan dataset with 5K samples
11	H. Jang, K. Yu, J. Yang	2020	DeepLabV3+	Yes	Yes	–	–		Yes	yielding an IoU of 0.7283
12	I. Y. Surikov, M. A. Nakhatovich, S. Y. Belyaev, D. A. Savchuk	2020	U-Net - PixelDCL, Faster R-CNN	Yes	Yes	–	–		Yes	average precision of 86%
13	V. Egiazarian, O. Voynov, A. Artemov, D. Volkhonskiy	2020	U-Net - PixelDCL, Transformers	–	–	–	–		Yes	Avrage accuracy 89%
14	H. K. Mewada, A. V. Patel, J. Chaudhari, K. Mahant, A. Vala	2020	a-shape, liner regression	–	–	Yes	–	Yes	–	accuracy of 85.71%
15	J. Seo, H. Park, S. Choo	2020	DeepLabV3+	Yes	Yes	Yes	–		–	MIOU 0.8068
16	R. Zhu, J. Shen, X. Deng, M. Walldén, F. Ino	2020	Fcn-2s,DeepLabV3+	Yes	–	–	–		–	Validation mIoU 85.8
17	Y. Wu, J. Shang, P. Chen, S. Zlatanova, X. Hu, Z. Zhou	2020	Mask-RCNN	Yes	Yes	Yes	–		Yes	IOU 79.4%
18	Abhishek Paudel, Roshan Dhakal, Sakshat Bhattarai	2020	YOLOv3	Yes	Yes	Yes	–		–	accuracy of 80% -81%
19	Y. Zhang, Y. He, S. Zhu, X. Di	2020	GAN	Yes	Yes	Yes	–		–	over all accuracy 92%
20	S. Kim, S. Park, H. Kim, K. Yu	2021	Pix2Pix,multi-task DL	Yes	–	–	–		Yes	detection rate 88.37 & recognition accuracy 87.87
21	S. Dong, W. Wang, W. Li, K. Zou	2021	EdgeGAN,GNN	Yes	Yes	–	–		Yes	Max Accuracy 84.35%
22	C. P. Simonsen, F. M. Thiesson, M. P. Philipsen, T. B. Moeslund	2021	GAT GNN	–	Yes	–	–		–	new dataset contains image & and graph-based floor plan
23	J. Song, K. Yu	2021	GNN	Yes	Yes	Yes	–		Yes	F1 score of 95%,
24	X. Lv, S. Zhao, X. Yu, B. Zhao	2021	YOLOv4, DeepLabV3+, FCN	Yes	Yes	Yes	Yes		Yes	Accuracy 97%
25	G. Murugan, V. Moyal, P. Nandankar, O. Pandithurai, E. John Pimo	2021	Cascade Mask-RCNN	Yes	–	Yes	–		–	Mean accuracy 79.0
26	M. Yamada, X. Wang, T. Yamasaki	2021	DeepLabV3+	Yes	Yes	Yes	–		–	92% Accuracy
27	I. Evangelou, M. Savelonas, G. Papaioannou,	2021	Bagging SVM, PU-Learning	Yes	–	–	–		–	92% Accuracy
28	R. Khade, K. Jariwala, C.	2021	Predefined rule Faster R-	Yes	Yes	–	–		–	proposed a geometric

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	Chattopadhyay, U. Pal		CNN, YOLO							feature-based approach for roteted floor plans
29	S. Park, H. Kim	2021	Predefined rule TensorFlow Object detection API	Yes	Yes	Yes	–		Yes	Wall accuracy 95% & size accuracy 97%
30	Z. Lu, T. Wang, J. Guo, W. Meng, J. Xiao, W. Zhang, X. Zhang	2021	VGG-16, U-Net,SSD	Yes	Yes	Yes	Yes		–	mean accu 81%
31	Bisheng Yang, Tengping Jiang, Weitong Wu, Yuzhou Zhou, Lei Dai	2022	FCN,MIP	yes	yes	yes				average accuracy 0.76, 0.81, & 0.83 for 3 data set
32	Aleixo Cambeiro Barreiro,Mariusz Trzeciakiewicz,Anna Hilsmann,Peter Eisert	2023	RCNN ,FPN,ResNet			Yes				IoU mask 81%
33	Jung-Hsuan Wu, Chiching Wei, and Wilson Li	2023	MURA & YOLOX							By using Model SegNeXt+MURA Wall IoU 76.3 %
34	Mingxiang Chen, Cihui Pan	2023	Graph Neural Networks (GNN).	Yes	Yes	Yes				average accuracy 94.55 +-0.04
35	Teng Wang, Weiliang Meng, Zhengda Lu, Jianwei Guo, Jun Xiao, Xiaopeng Zhang	2023	RC-Net	yes	yes	yes	yes			Mean accuracy 76%
36	Bingchen Yang, Haiyong Jiang, Hao Pan, Jun Xiao	2023	CNN, GNN							Mean Accuracy 89.86

Recent advancements in machine learning have led to increased accuracy in floor plan segmentation. Methodologies such as CNN, RC-Net, YOLO, and DeepLabV3+ are commonly used in this floor plan segmentation. Researcher use these methods to identify features like walls, doors, windows, furniture, dimensions, room sizes, and text. However, during the study, it was observed that text detection features were not widely considered by the majority of researchers. So the use of Machine Learning methods may produce the better outcomes in floor plan detection.

IV. CONCLUSION

The comparative study on learning-based techniques for automated floor plan analysis underscores notable progress in the field. Learning-based approaches, such as CNNs, have demonstrated their prowess in handling the complexities inherent in raster images, offering superior performance in tasks like recognition, segmentation, and vectorization. The integration of recurrent neural networks (RNNs) and attention mechanisms has further augmented the models' capabilities showcased their efficacy in tasks such as floor plan segmentation, recognition, and vectorization. The continuous evolution of these techniques, often driven by extensive datasets and innovative architectures, signals a growing inclination toward automation and enhanced efficiency in floor plan analysis. With ongoing technological advancements, further research and development in learning-based approaches have the potential to reshape the landscape of architectural floor plan analysis, influencing applications ranging from urban planning to interior design and real estate.

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