Machine Learning Recognition Models in Construction: A Systematic Review

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Abstract

Due to its growing acceptance and success in many sectors, there is a rapidly rising adoption and application of machine learning recognition models within construction. As a result of this adoption and usage surge, there is copious knowledge residing in different repositories. This surge makes it a daunting task for researchers and other stakeholders to access concise and summarised evidence of existing research showing the usage and adoption of different recognition models in construction. As a result, a systematic review of machine learning recognition models with their different applications in construction is inevitable. We leveraged PRISMA protocol and PICOC technique to retrieve 819 construction-related studies from SCOPUS. We grouped recognition models into Image Recognition, Pattern Recognition, Voice Recognition, and Natural Language Processing (NLP). Our thorough analysis and approach show that 53% of existing studies use Pattern Recognition, 42% Image Recognition, and 2% Voice Recognition. We identified that 45% of the studies focused on buildings, 31% on worker's health and safety, while 24% was on equipment detection, efficiency, and usage. We recommend that future studies leverage the textual and voice data generated from construction-related activities and studies. This will build more voice and NLP recognition models for training robots and other assistive technologies that can support construction workers to improve their safety and productivity. This study will guide researchers and other stakeholders in this field to widen their horizons on trends in recognition model application to construction, making informed decisions, and establish gaps in the literature while suggesting lasting contributions.

Keywords: construction, machine learning, recognition models, prisma, systematic review.

1. INTRODUCTION

Machine Learning (ML) recognition models have been applied in various domains, including construction. ML is a field in Artificial Intelligence that builds systems with the capability to learn from experience (i.e., historical data) and make good decisions from it. In the last few decades, it has been adopted and applied to solve numerous problems across many sectors, such as agriculture (Husen et al., 2021), banking (Donepudi, 2017), aerospace (Chen et al., 2021), oil & gas (W. H. Wu et al., 2021), health (Ma et al., 2021), education (Gomes et al., 2020), capital market (Hajek & Henriques, 2017), security (Tahsien et al., 2020), e.t.c. As a result of its growing adoption, the construction domain has proposed numerous resolutions to problems that cut across road maintenance and survey (H. Wu et al., 2019; L. Zhang et al., 2016), automation and improved productivity (Deng et al., 2020; Dorafshan & Azari, 2020; J. Zhang et al., 2020), tooling and machinery operation (Q. Fang et al., 2018; W. Fang et al., 2018; Guo et al., 2020), health and safety, (W. Fang et al., 2018, 2019; J. Wu et al., 2019), building information modelling (Akinade et al., 2015; Charef et al., 2018) and so on. Due to the surge in its adoption and usage, there is copious knowledge residing in different repositories. This surge makes it a daunting task for researchers and other stakeholders to access concise and summarised evidence of existing research of recognition models in construction.

As a result, a systematic review of ML models with their different applications in construction-related studies becomes inevitable. A systematic review is a repeatable and unbiased factual examination of a subject matter to ascertain the current state of existing knowledge on the subject matter (i.e., construction) with complete interpretation. Systematic reviews were conducted in other domains for different purposes, such as bankruptcy prediction (Alaka et al., 2018), character recognition (Khan et al., 2020), healthcare and big data (Nazir et al., 2020), network protocol (Rashid & Louis, 2019), software and design (Freddy Paz & José Antonio Pow-Sang, 2015; Torres-Carrión et al., 2018) navigation system (Khan et al., 2021), and in other domains. According to our review, recognition models in construction-related studies can be grouped into four classes: Image Recognition, Pattern Recognition, Voice Recognition, and Natural language Processing (NLP).

This systematic review aims to establish various studies within existing literature by defining the adoption and usage of each class of recognition model in construction and the area it was applied. This establishment will guide researchers in this field to widen their horizons on construction trends, make informed decisions, and establish gaps in the literature while making lasting contributions.

2. RESEARCH METHOD

This study reviewed different guidelines and protocols used in conducting a systematic review. (Kitchenham & Charters, 2007) established a guideline in the medical domain for conducting a comprehensive systematic review, while (Petticrew & Roberts, 2008) provided for social sciences. This study's preferred protocol is Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021a). PRISMA protocol believes systematic review needs to be described in adequate detail to permit users to assess the reliability and relevance of the review discoveries (Page et al., 2021b). Even though PRISMA was primarily developed for the medical and health domain, it was preferred because of its comprehensiveness and wide adoption and applications to other fields (Page et al., 2021a).

After careful assumptions and thorough analysis, we formulated a few research questions that give insight into this study's main subject. The research questions are.

1. What are the relevant ML recognition models used in construction-related studies?
2. Why is the recognition model essential in construction?

While searching and selecting relevant research studies, we leveraged the PICOC technique (Petticrew & Roberts, 2008). PICOC stands for Population, Intervention, Comparison, Outcomes, and Context. Considerations were only given to studies with a publication date between 2015 and 2021. The choice of starting the literature search from 2015 is due to the general progression in the number of research carried out, which have considerably increased after 2015 (Xu et al., 2021). Other considerations used for filtering the search include language, subject area, publication stage, and document type. This filter was applied to get a close range of the relevant studies. Finally, keywords were extracted from the research question and the filtering parameters and some relevant synonyms to form a logical search criterion.

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("machine learning" AND "recognition" AND "construction" OR "building" OR "sites") AND
PUBYEAR > 2014 AND PUBYEAR < 2022 AND ( EXCLUDE ( SUBJAREA , "PHYS" ) OR EXCLUDE ( SUBJAREA , "BIOC" ) ) A
ND ( EXCLUDE ( EXACTSRCTITLE , "Lecture Notes In Computer Science Including Subseries Lecture Notes In Artificial Intelligence
And Lecture Notes In
Bioinformatics" ) ) AND ( EXCLUDE ( PUBSTAGE , "aip" ) ) AND ( EXCLUDE ( DOCTYPE , "ch" ) OR EXCLUDE ( DOCTYPE , "
bk" ) OR EXCLUDE ( DOCTYPE , "no" ) OR EXCLUDE ( DOCTYPE , "le" ) OR EXCLUDE ( DOCTYPE , "dp" ) OR EXCLUDE (
DOCTYPE , "ed" ) ) AND ( EXCLUDE ( SUBJAREA , "MEDI" ) OR EXCLUDE ( SUBJAREA , "SOCI" ) OR EXCLUDE ( SUBJAREA
 , "EART" ) OR EXCLUDE ( SUBJAREA , "NEUR" ) ) AND ( EXCLUDE ( LANGUAGE , "Chinese" ) OR EXCLUDE ( LANGUAGE ,
 "Russian" ) OR EXCLUDE ( LANGUAGE , "Japanese" ) OR EXCLUDE ( LANGUAGE , "Turkish" ) OR EXCLUDE ( LANGUAGE ,
"Korean" ) OR EXCLUDE ( LANGUAGE , "Spanish" ) ) AND ( EXCLUDE ( SRCTYPE , "k" ) OR EXCLUDE ( SRCTYPE , "b" ) ) A
ND ( EXCLUDE ( SUBJAREA , "AGRI" ) OR EXCLUDE ( SUBJAREA , "ARTS" ) OR EXCLUDE ( SUBJAREA , "BUSI" ) OR EXCL
UDE ( SUBJAREA , "ECON" ) )
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Searching for relevant studies was done on the widely recognised literature database, SCOPUS, which is reported to be the leading intellectual and citation database with the highest number of peer-reviewed studies (Cantú-Ortiz, 2017). This database contains publications from several publishers. Other databases that do not cover peer-reviewed literature was excluded. The initial search with the logical search criteria was conducted on the 17^{th} of June 2021, with eight hundred and nineteen (819) records fetched from different publishers within SCOPUS. These records were exported to a Comma Separated Value (CSV) file for further review.

We thoroughly evaluated each primary study fetched from the search to establish its addition or removal in the systematic review. The addition and removal criteria that were used are summarised in Table 1 below.

Table 1. Criteria for Addition and Removal of studies

S/N	Addition Criteria	Removal Criteria
1	Publications must be in the English language	Exclude publications in other languages
2	Publications must be between 2015 and 2021	Exclude publications before 2015 and after 2021.
3	Publications must be a journal or conference paper	Exclude publications outside journal and conference papers
4	Include peer-reviewed publications	

The evaluation of each study includes careful assessment of the title, abstract, background, methodology, case study, results, conclusion, and other relevant PRISMA checklist criteria. In addition, the primary selection criterion assessed parts of each study must have an answer to one of the research questions. Table 2 gives a summary of all the reviewed studies. This summary includes the author, title, type of document, specific recognition model used, area of construction where the model was applied, and other relevant information about each study.

Table 2: Summary of Selected Construction-related Studies

	Authors	Title	Area of application	Country	Recognition model	Document Type
1	*Akalya et al. (2015)*	Security solution for meta-recognition in construction	Workers	India	Pattern recognition	Article
2	*Akhavian and Behzadan (2015)*	Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers	Equipment	United States	Image recognition	Article
3	*Akhavian and Behzadan (2016)*	Smartphone-based construction workers' activity recognition and classification	Workers	United States	Pattern recognition	Article
4	*Chen et al. (2017)*	Principal Axes Descriptor for Automated Construction-Equipment Classification from Point Clouds	Equipment	South Korea	Pattern recognition	Article
5	*Chen et al. (2018)*	Performance evaluation of 3D descriptors for object recognition in construction applications	Equipment	United States	Image recognition	Article
6	*Chen et al. (2020)*	Day-ahead prediction of hourly subentry energy consumption in the building sector using pattern recognition algorithms	Building	China	Pattern recognition	Article
7	*Djenouri et al. (2019)*	Machine learning for smart building applications: Review and taxonomy	Building	Norway	Pattern recognition	Article
8	*Hernandez et al. (2019)*	A Deep Learning Framework for Construction Equipment Activity Analysis	Equipment	Canada	Pattern recognition	Article
9	*Kim and Cho (2020)*	Effective inertial sensor quantity and locations on a body for deep learning-based worker's motion recognition	Workers	United States	Image recognition	Article
10	*Kudo et al. (2020)*	Using vision-based object detection for link quality prediction in 5.6-GHz channel	Equipment	United States	Image recognition	Article
11	*Lee et al. (2020)*	Advanced Sound Classifiers and Performance Analyses for Accurate Audio-Based Construction Project Monitoring	Building	Italy	Voice recognition	Article
12	*Olukan et al. (2019)*	Predicting the suitability of lateritic soil type for low-cost sustainable housing with image recognition and machine learning techniques	Building	UAE	Pattern recognition	Article
13	*Panchal et al. (2019)*	Flooding Level Classification by Gait Analysis of Smartphone Sensor Data	Building	India	Pattern recognition	Article
14	*Pour-Rahimian et al. (2020)*	On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning	Building	United Kingdom	Pattern recognition	Article
15	*Rashid and Louis (2019b)*	Times-series data augmentation and deep learning for construction equipment activity recognition	Equipment	United States	Pattern recognition	Article
16	*Shan et al. (2019)*	Neural-signal electroencephalogram (EEG)methods to improve human-building interaction under different indoor air quality	Building	Australia	Pattern recognition	Article
17	*Yan et al. (2021)*	Helmet detection based on deep learning and random forest on UAV for power construction safety	Workers	China	Image recognition	Article
18	*Yang et al. (2016)*	Vision-based action recognition of construction workers using dense trajectories	Workers	China	Pattern recognition	Article
19	*Yang et al. (2016)*	Vision-based action recognition of construction workers using dense trajectories	Workers	China	Pattern recognition	Article
20	*Yang et al. (2016)*	Vision-based action recognition of construction workers using dense trajectories	Workers	China	Pattern recognition	Article

21	*Kim et al. (2021)*	Pressure pattern recognition in buildings using an unsupervised machine-learning algorithm	Building	China	Pattern recognition	Conference
22	*Kuritcyn et al. (2016)*	Increasing performance of supervised machine learning methods by analysis of construction and demolition waste	Building	Germany	Pattern recognition	Conference
23	*Potapov and Kasian (2019)*	Recognition of interior objects from photographs and their subsequent transformation into a drawing for building IoT systems	Equipment	United States	Image recognition	Conference
24	*Slaton et al. (2020)*	Construction activity recognition with convolutional recurrent networks	Equipment	United States	Image recognition	Conference
25	*Sohrab et al. (2020)*	Facial expression based satisfaction index for empathic buildings	Building	Finland	Image recognition	Conference
26	*Sultanum et al. (2020)*	A teaching language for building object detection models	Equipment	Canada	Image recognition	Conference
27	*Yu et al. (2020)*	Architectural Facade Recognition and Generation through Generative Adversarial Networks	Workers	China	Image recognition	Conference
28	*Zhao Jand Obonyo (2018)*	E-health of Construction Works: A Proactive Injury Prevention Approach	Workers	United States	Image recognition	Conference
29	*Zhong et al. (2020)*	Deep learning-based extraction of construction procedural constraints from construction regulations	Building	China	Pattern recognition	Conference
30	*Abhishek et al. (2021)*	A systematic review of techniques, tools and applications of machine learning	Workers	India	Pattern recognition	Conference
31	*Akhavian and Behzadan (2015)*	Construction activity recognition for simulation input modeling using machine learning classifiers	Equipment	China	Pattern recognition	Conference
32	*Budke et al. (2018)*	Towards the empathic building - detection and recognition of well-being of individuals and groups	Building	CEUR-WS	Image recognition	Conference
33	*De Rocha et al. (2020)*	Machine Learning Applied to Topological Mapping for Structure Recognition	Building	Brazil	Pattern recognition	Conference
34	*Fábián and Gulyás (2020)*	De-anonymising facial recognition embeddings	Workers	Hungary	Image recognition	Conference
35	*Ferrando et al. (2019)*	Pattern recognition and classification for electrical energy use in residential buildings	Building	Norway	Pattern recognition	Conference
36	*Golparvar-Fard et al. (2019)*	Model-based detection of progress using D4AR models generated by daily site photologs and building information models	Building	United States	Image recognition	Conference
37	*Huang et al. (2019)*	A novel approach for sand liquefaction prediction via local mean-based pseudo nearest neighbor algorithm and its engineering application	Building	China	Pattern recognition	Conference
38	*Jung et al. (2019)*	Machine learning without real-world data	Workers	South Korea	Image recognition	Conference
39	*Kim et al. (2019)*	Evaluation of Machine Learning Algorithms for Worker's Motion Recognition Using Motion Sensors	Workers	United States	Image recognition	Journals
40	*Narumi et al. (2020)*	Indoor visualisation experiments at building construction site using high safety UAV	Building	Japan	Pattern recognition	Journals
41	*Nath et al. (2017)*	Human activity recognition and mobile sensing for construction simulation	Workers	United States	Pattern recognition	Journals
42	*Rashid and Louis (2019a)*	Window-warping: A time series data augmentation of IMU data for construction equipment activity identification	Equipment	United States	Image recognition	Journals
43	*Sohrab et al. (2020)*	Facial expression based satisfaction index for empathic buildings	Building	Finland	Image recognition	Journals

44	*Yang et al. (2015)*	Automatic recognition of construction worker activities using dense trajectories	Workers	China	Pattern recognition	Journals
45	*Zhang et al. (2018)*	A supervised machine learning-based sound identification for construction activity monitoring and performance evaluation	Equipment	Italy	Voice recognition	Journals
46	*Zhang et al. (2021)*	Recognition of Building Health Status Based on Machine Learning Algorithm	Building	China	Pattern recognition	Journals
47	*Zhao (2020)*	A review on machine learning and gesture recognition	Workers	United States	Image recognition	Journals
48	*Zheng and Vega (2019)*	Landscape-freestyle: Restyling site plans for landscape architecture with machine learning	Building	United States	Pattern recognition	Journals
49	*Arashpour et al. (2021)*	Scene understanding in construction and buildings using image processing methods: A comprehensive review and a case study	Building	Hong Kong	Image recognition	Review
50	*Huang et al. (2019)*	A novel approach for sand liquefaction prediction via local mean-based pseudo nearest neighbour algorithm and its engineering application	Building	China	Pattern recognition	Review
51	*Jin et al. (2018)*	Exploring BIM Data by Graph-based Unsupervised Learning	Building	United States	Pattern recognition	Review
52	*Lee et al. (2020)*	Evidence-driven sound detection for prenotification and identification of construction safety hazards and accidents	Equipment	Brazil	Voice recognition	Review
53	*Li et al. (2019)*	Interactive Machine Learning by Visualisation: A Small Data Solution	Workers	United States	Pattern recognition	Review
54	*Sun et al. (2021)*	Machine learning applications for building structural design and performance assessment: State-of-the-art review	Building	United States	Pattern recognition	Review
55	*Zhu et al. (2015)*	Smartphone-based Human Activity Recognition in buildings using Locality-constrained Linear Coding	Building	China	Image recognition	Review

3. MAIN DISCUSSION

After relevance evaluation, only fifty-five (55) were eligible for this review. Figure 1 shows the distribution of studies used in this SR. 18% of the selected studies is journals, 36% articles, 33% conference papers, while only 13% reviews. Since these studies are between 2015 and 2021, we identified that most recognition models used in the last six years were between 2017 and 2019. This evidence means research around the recognition model's application to construction was at its highest before the peak of the COVID-19 pandemic.

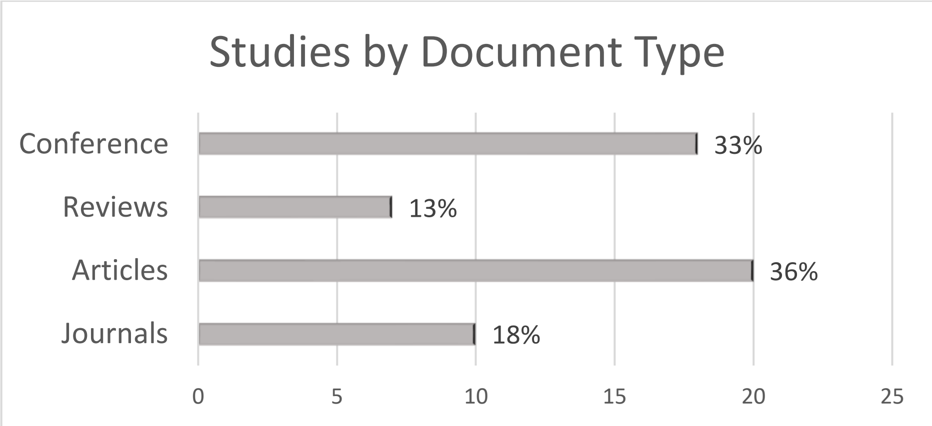

Figure 1: Distribution of Publication by Type

Each selected study was analysed to determine the recognition models employed —table 3 established that many researchers conduct their studies using pattern recognition, having 53% usage. Image recognition also got widely used in object and motion detection of construction workers and equipment, totalling 42%. However, with limited application to construction, and voice recognition has only 2% usage and adoption.

Table 3: Usage Analysis of Different Recognition Models

	Recognition Models	**Total Number of Usage**	**Percentage (%)**
1	Pattern Recognition	29	53%
2	Image Recognition	23	42%
3	Voice Recognition	3	5%

We evaluated the areas within construction where each class of recognition model were utilised. Most researchers focused on buildings and other structural setups, with 45% utilisation. Worker's health, safety, and productivity also got sizeable attention with about one-third (31%) of the studies. In contrast, equipment detection, efficiency, and usage on and off construction sites had the lowest construction-related studies with 24% utilisation. Figure 2 gives a summary of these area-specific utilisations.

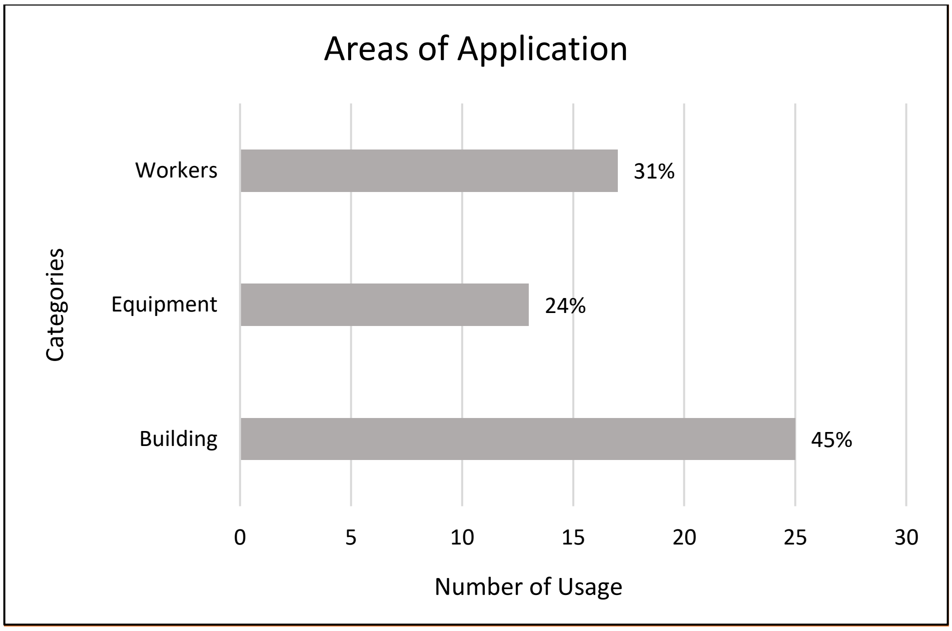

Figure 2: Recognition Application Area in Construction

4. CONCLUSSION AND RECCOMMENDATION

Numerous ML recognition models have been applied to host construction-related processes and components such as object detection, structural maintenance and survey, automation and improved productivity, tooling and machinery operation, health and safety, BIM, workers and equipment activities, and motion sensing, e.t.c. This broad application has resulted in numerous studies residing in different repositories with no concise and summarised explanation of different types of models used in these studies. Therefore, it became inevitable to systematically review and establish the adoption and usage of different ML recognition models used in existing construction-related studies. As a result, this research adopted the PRISMA protocol and PICOC technique to establish usage and adoption of recognition models, with PR having 53% usage. In comparison, Image recognition and voice recognition have 42% and 2% usage, respectively.

These models have 45% utilisation in building-related studies, while 31% of utilisation focused on workers' health, safety, and productivity. On the other hand, equipment-related studies only have 24% utilisation. We believe future studies can leverage the textual and voice data generated from construction-related activities and studies. This will build more Voice and NLP recognition models needed to train robots and other assistive technologies and tools that can aid construction workers in improving their safety and productivity.

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