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Review article

# Assimilation of 3D printing, Artificial Intelligence (AI) and Internet of Things (IoT) for the construction of eco-friendly intelligent homes: An explorative review

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ABSTRACT

The construction industry is witnessing a transformative shift towards sustainable and intelligent housing solutions driven by advancements in 3D printing, Artificial Intelligence (AI), and the Internet of Things (IoT). Several architectural and construction firms have adopted innovative technologies to make construction easier, sustainable, efficient, cheap, fast, low generation of waste etc. This explorative review critically examines the integration of these technologies in the construction of eco-friendly intelligent homes. Drawing on a comprehensive analysis of literature spanning from 2010 to 2024, the review explores the synergistic potential and challenges associated with amalgamating 3D printing, AI, and IoT in construction processes. The increase need of smart homes equipped with sensors that can sense and regulate temperature, prevent or control fire, sense gas leakage, motion detectors and alarms for security and other application is in high demand. These types of smart homes can only be achieved by integrating different technologies together which include 3D printing (3DP), AI and Internet of Things (IoT). Despite the growing research in the field of automated construction, there are few articles that attempt to integrate these technologies together for futuristic smart homes and potential of smart cities. This study is aim at providing up-to-date advancement in technological innovation within the construction sector with regards to applications of 3DP, IoT, and AI. Key findings highlight how 3D printing enables rapid prototyping and customization of building components, AI enhances energy efficiency and occupant comfort through predictive analytics and automation, while IoT facilitates real-time monitoring and control of building systems. Furthermore, the review discusses the environmental benefits, cost-effectiveness, and societal implications of adopting such integrated approaches. However, challenges such as regulatory barriers, technological limitations, and the need for skilled labor are identified as critical barriers to widespread implementation. Future research directions are proposed to address these challenges and further optimize the integration of 3D printing, AI, and IoT for the construction of sustainable intelligent homes. In this review

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article, the need for 3DP in construction, advantage and disadvantage of 3DP, (AI) and IoT and the application of these technologies in addressing challenges regarding 3DP and promoting sustainability in the construction industries were comprehensively explored.

## 1. Introduction

Some radical changes started taking place recently in the construction industry due to the integration of some sophisticated technologies. Convergence of cutting-edge technologies integrated in the recent past has brought a lot of change and sustainable innovations in the field of construction engineering and intelligent design. What has come to the front as a transformative force in redefining our ideas in visualization, creation, construction of ecological smart homes is the combination of 3D printing, Artificial Intelligence (AI), the Internet of Things (IoT). Construction industry is one of the industries that is highly concerned with safety which contribute to its slow adoption of new technologies. The risk associated with the industry is critical to implementation of newly developed or inventing method and products which are untested or required continuous evaluation and regulation for approval [1]. However, many scholars perceived that conventional construction which revolves around the use of manually operated equipment or tools and traditional construction approach has reach it technological peak ([2,3]).

As a result of technological advancement in the field of construction, conventional or traditional construction approach lagged behind in terms of customers' core standards of quality, cost, and timeliness ([4,5]). In comparison to other industries, the construction industry saw a decrease in productivity, reduced in profits margins. Moreover, even though with the increase in population and demand for houses, building standard houses from scratch is expensive for average working class and also the fear of mortgage by the general public which contributing to the stagnating productivity of the industry [6].

The advancement in science and technology has led to several scientific innovations. In the field of civil engineering, 3DP of building has been trending throughout the 21st century. Consequently, while still in its infancy, 3D printed construction is perceived as the promising technological advancement with the potential to revolutionize the construction industry. 3D-printed construction is regarded as an advanced construction approach which use machines and additives for construction of wide range of complex geometries and building structures without the need of framework based on layer-by-layer material deposition approach ([7,8]).

Construction of smart homes is another area that receive tremendous attention and become a prominent area of research in the last few decades. "The concept of today's fiction is tomorrow's reality" is evident in the case of smart homes as a result of technological advancement in the field of sciences and engineering. The integration of automation using internet such as Internet of Things (IoT), Industrial Internet of things (IIoT), AI and material science are the main drivers of smart homes. Smart homes or home automation revolves around the monitoring and controlling of home devices and appliances remotely using IoT-based systems [9]. The major

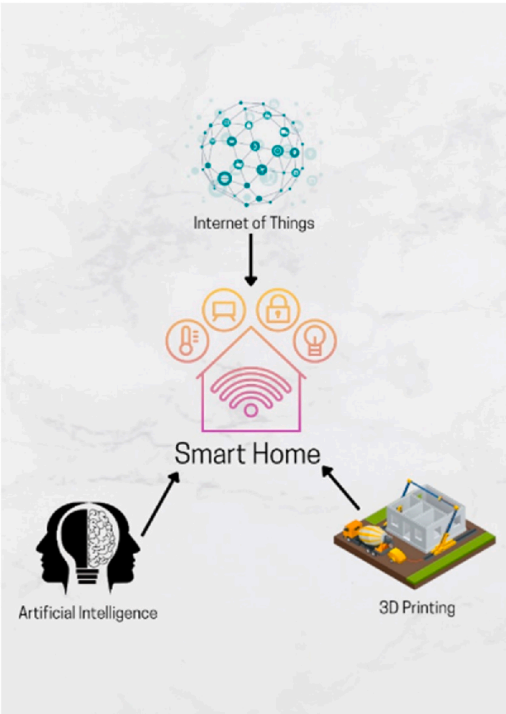


**Fig. 1.** Framework of the study.

challenges facing these sectors revolves around the need to improve safety and efficiency of IoT devices, promote the adoption and implementation of 3D printing and the need for huge amount of data that can be used to feed artificial intelligence models. The framework of this study is presented in Fig. 1.

- **Problem**

While there is increasing interest in integrating 3D printing, AI, and IoT for constructing eco-friendly intelligent homes, there is a lack of comprehensive understanding regarding the synergistic potential and challenges associated with this integration. Existing literature often focuses on individual technologies' applications rather than exploring their combined impact on sustainable housing solutions. Moreover, there is limited research addressing the specific challenges, regulatory barriers, and societal implications of assimilating these technologies in the construction industry.

- **Literature Gap**

The literature gap lies in the absence of a holistic examination of the integration of 3D printing, AI, and IoT in the context of constructing eco-friendly intelligent homes. Existing studies tend to be fragmented, focusing primarily on the applications of each technology in isolation rather than their combined utilization. Additionally, there is a scarcity of research exploring the regulatory frameworks, societal acceptance, and potential risks associated with implementing these integrated solutions in the construction sector ([10,11]). This review aims to address these gaps by providing a comprehensive analysis of the synergistic potential, challenges, and future directions for integrating 3D printing, AI, and IoT in the construction of sustainable intelligent homes.

- **Methodology**

To conduct this explorative review, a systematic search of scholarly databases including PubMed, Scopus, Web of Science, and Google Scholar was performed. Keywords such as "3D printing," "Artificial Intelligence," "Internet of Things," "construction," "eco-friendly," and "intelligent homes" were used to identify relevant literature published between 2010 and 2024. Inclusion criteria encompassed peer-reviewed journal articles, conference papers, and books written in English, focusing on the integration of 3D printing, AI, and IoT in the construction sector for eco-friendly intelligent homes. Exclusion criteria comprised studies not directly

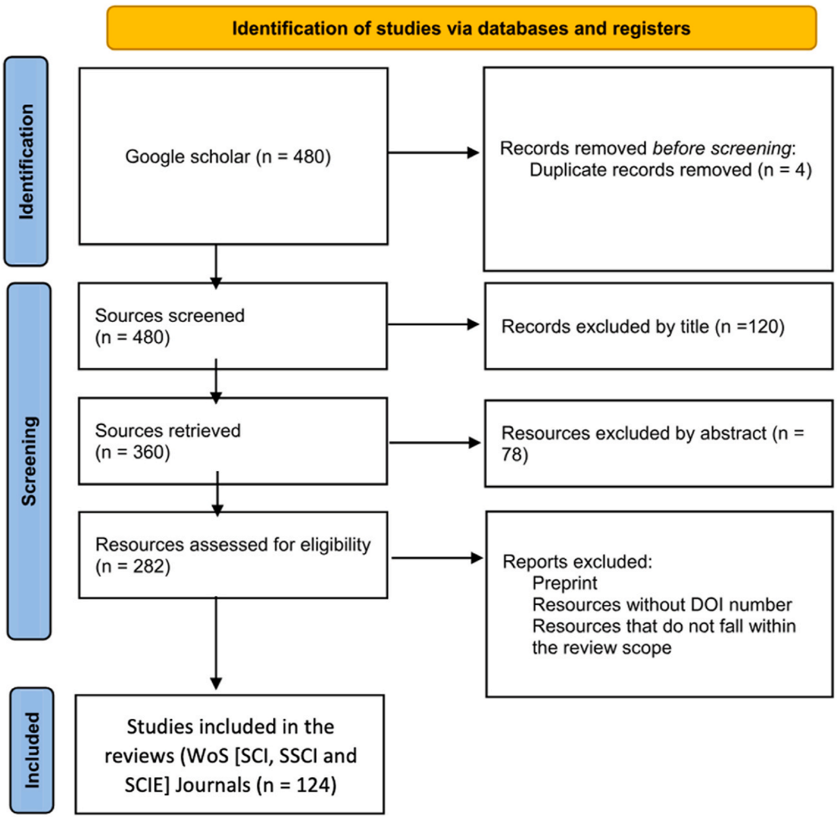


**Fig. 2.** Flow diagram of screening process.

related to the integration of these technologies, duplicates, and non-peer-reviewed sources, see Fig. 2.

The initial search yielded a total of 480 articles. After screening titles and abstracts, 360 articles were identified for full-text review. Following a thorough assessment, 124 articles met the inclusion criteria and were included in the final analysis. Data extraction was conducted using a predefined framework, including information on the integrated use of 3D printing, AI, and IoT in construction processes, environmental implications, challenges, and future research directions. A thematic analysis approach was employed to identify key themes, patterns, and gaps in the literature. Themes were iteratively refined through discussions among the research team to ensure comprehensive coverage and accuracy.

### 1.1. Literature search

The literature contains hundreds of articles that comprise the review keywords. The initial choice of articles to be included in this review was created using Google Scholar search for articles with the following keywords or phrases: 3D printing (3DP), 3D printing in construction, Factors affecting 3DP, AI, Machine Learning (ML), IoT, application of AI/ML in 3DP, application of IoT in 3DP.

We have reviewed 123 total articles in which majority from top journals and publishing platforms such as ScienceDirect, Springer, IEEE, Frontier, MDPI, Taylor and Francis, Hindawi etc. 100 of the articles are from 2015 and above, 23 are below 2015 and 4 from website. Some of the criterial for selection include articles that are sound in terms of scientific contents, peer reviewed, written in English and assigned with Digital Object Identifier (DOI) number except. Among these articles 30 discusses about 3DP, 3D printing in construction, factors affecting 3DP. 34 discusses about AI (definition, types, supervised, unsupervised and reinforcement learning). 20 articles focus IoT, definition, component, classifications and application. 40 articles provide the literature for the integration of 3DP, AI/ML and IoT in smart buildings. The summary of literature search is presented in Table 1. Additionally, Table 2 below presented a list of abbreviations.

### 1.2. Research motivation, Contribution and novelty

The motivation behind this article comes from the goals set by the research center of for AI and IoT, Near East University in collaboration with Girne American University, department of Architecture in promoting the applications of automated innovative technologies in different disciplines such as medicine, smart homes, smart cities, smart grid, agriculture etc. As automated constructions are perceived as drivers of smart homes, consequently, smart homes are regarded as units of smart cities. Constructing smart homes require the integration of several technologies, among which 3DP, AI and IoT are recognized as crucial ones. Thus, this article is aim at providing up-to-date state of art of innovation in the building industry, as well as pros and cons of these technologies in advancing smart homes.

This article only intent to overview how smart and innovative technologies are fostering or helping in realizing the dreams of smart homes. In addition, this article does not cover extensively on smart cities, rather it is focus on smart homes which are regarded as one of the units for realizing smart cities. Thus, this article stands to provide extensive and broad overview for researchers in different fields such as architecture, civil engineering, computer science and AI as a summary of concepts and applications of emerging technologies in the context of smart buildings. Therefore, this article is set to contributes the following aspects.

1. To provide both researchers and professionals in relevant field of architecture, civil engineering, construction management, project management, computer scientists etc. with holistic overview of applications of emerging technologies in promoting smart buildings and smart cities.
2. To explore the gap in the current state of art by focusing on literature that discuss the current and prospect of these technologies in construction industry.
3. To provide an overview of components and classifications of these technologies and their applications in different disciplines.
4. To identify challenges and limitations of applying these technologies in the construction and building industry such as security issues and limiting manpower.

**Table 1**
Summary of literature search.

| Classification | Number |
|---|---|
| Articles from 2015 upward | 100 |
| Below 2015 | 23 |
| With DOI number | 112 |
| Without DOI number | 11 |
| Review and Research articles | 111 |
| Conference articles | 12 |
| Online sources | 5 |
| Introduction | 9 |
| 3D printing | 30 |
| AI/ML | 34 |
| IoT | 20 |
| Integration of technologies in smart home | 40 |

**Table 2**
List of Nomenclatures.

| Abbreviations | Full Meaning | Abbreviations | Full Meaning |
|---|---|---|---|
| **AI** | Artificial Intelligence | INNOprint | Innovation Printer |
| **ANN** | Artificial Neural Networks | IoMT | Internet of Medical Things |
| **AM** | Additive Manufacturing | IoT | Internet of Things |
| **BIM** | Building Information Modelling | IoNT | Internet of nano things |
| **BD** | Big Data | IoTH | Internet of Things Health |
| **C3DP** | Construction 3D Printing | IP | Internet Protocol |
| **CC** | Cloud Computing | KNN | K-Nearest Neighbors |
| **CNN** | Convolutional Neural Networks | LR | Linear Regression |
| **COVID-19** | Coronavirus Disease 2019 | MAPE | Mean Absolute Percentage Error |
| **CPU** | Central Processing Unit | MC | Monte-Carlo |
| **CMS** | Content Management System | ML | Machine Learning |
| **DA** | Data Analytics | MIoT | Military Internet of Things |
| **DOI** | Digital Object Identifier | MSE | Mean Squared Error |
| **DCP** | Digital Construction Platform | NASA | National Aeronautics and Space Administration |
| **DNN** | Deep Neural Network | NBC | Naïve Bayes Classifications |
| **DMD** | Direct Metal Deposition | OL | Output Layer |
| **DT** | Decision Tree | PCA | Principal Component Analysis |
| **DL** | Deep Learning | RF | Random Forest |
| **DOI** | Digital Object Identifier | RFID | Radio Frequency Identification |
| **EMON** | Energy Monitoring | RL | Reinforcement |
| **FDM** | Fused Deposition Modelling | RMSE | Root Mean Squared Error |
| **FoF** | Factories of the Future | SDGs | Sustainable Development Goals |
| **GBM** | Gradient Boosting Machine | SLA | Stereolithography |
| **GB** | Gradient Boosting | SLS | Selective Laser Sintering |
| **GHG** | Green House Gases | SVM | Support Vector Machine |
| **GMM** | Gaussian-Mixture Model | TD | Temporal Difference |
| **GPS** | Global Positioning System | UN | United Nation |
| **HL** | Hidden Layer | WSNs | Wireless Sensor Network |
| **ICT** | Information Communication Technology | Wi-Fi | Wireless Fidelity |
| **IIoT** | Industrial Internet of Things | VULMA | Vulnerability Analysis using Machine-learning |
| **IL** | Input Layer | | |

The reminder of this article is structured as follows: Section 2 discusses about 3DP, 3D printing in construction, factors affecting 3D printing and advantage and disadvantage of 3DP in construction. Section 3 provides a brief introduction to the concept of AI, ML, classifications. Section 4 discusses about IoT, significance of IoT, components, working principle and applications. Section 5 overview research articles that discusses on the on application of AI/ML, 3DP and IoT in construction and building smart homes as well as challenges facing the integration of smart technologies in construction. The article is concluded in section 6, highlighting the need of these technologies, as well as the current challenges and future directions in both academic and commercial settings.

In relation to the novelty of the research, technological advancement in the field of construction is changing the landscape of smart homes. The construction sector is highly competitive due to the high demand. Thus, 3DP offers construction engineers with an edge over competitors. The application of 3D printing in construction offers several advantages over conventional building which include cost reduction, minimize accident and injury, minimize construction time, construction waste and reduce construction time. Artificial Intelligence on the other hand is used extensively in construction management and system modelling. Moreover, AI also aid architect and other construction experts in designing, bidding, financing, procurement, construction operations (smart construction). The development of several data storage platforms and techniques contribute to the acquisition and storage of massive amount of construction data. These data (such as the ones generated from drones' videos, images captured using mobile phones, Building Information Modeling (BIM), security sensors etc.) can be analyze using AI-system or AI-powered algorithms.

The construction and housing sector is currently undergoing transformation due to the integration of IoT which revolves around the use of sensors. Most of the IoT applications in building are limited to post constructions where sensors are used to control homes appliances and storage of data generated from IoT-based devices in the cloud. These three [3] technologies (3DP, AI and IoT) are the forefront driving smart construction and smart homes. Despite ample number of existing studies, only few attempted to overview the application of these technologies together. Majority of existing studies discuss the concepts separately. Therefore, this article overview how 3DP, AI and IoT is transforming construction sectors as well as their applications, challenges and future perspectives.

## 2. 3D Printing (3DP)

The building sector has been using conventional and traditional techniques for constructing various types of structures, including apartments, hotels, cinemas, museums, religious centers, hospitals, and more. Although there have been some technological improvements over the past century, such as mixing, painting, and cementing machines, there is still a significant gap in achieving fully automated construction from 2D plans to final completion [12]. The construction sector is known for generating significant amounts of waste, consuming non-renewable energy, and releasing greenhouse gases that contribute to climate change and global warming.

The growing need for urbanization and infrastructure development has led to a surge in large-scale construction projects worldwide, exacerbating these environmental concerns [13]. Traditional building techniques, combined with the lack of certification for builders and the effects of climate conditions, have resulted in buildings that are prone to collapse, damage, and poor structural and material quality. In addition, these conventional methods require a significant amount of labor which is costly, and the construction process is prolonged, resulting in a high production of waste [14]. The Key challenges facing building and construction revolves around the use of suitable materials, the desperate need to build faster, stronger, efficient, less susceptible to weather and climatic conditions and natural disasters has led scientists and engineers from different field such as Civil engineering, Architecture, Material science, Computer engineering and AI to developed a 3DPsystem which has the potential to replace conventional method [15]. 3D printing is then leading that technological revolution, as perhaps one of the most representative disruptive manufacturing processes that have revised any capacity to design and build for the architectural field. In comparison to other construction methods that depend upon laborious labor processes that have larger wastages, 3D printing builds up 3D structures by the use of additive material layering; an aspect that ensures minimal material wastage and that materials are added exactly where they are required so as to build up a complex structure. Of all the most convincing aspects of 3D printing in construction, its potential to abundantly make sustainability is absolutely among them. Architects and builders achieve a reduction in their environmental footprint significantly through 3D printing by use of reusable material and minimizing waste. Additionally, the flexibility of 3D printing enables generation of energy-efficient optimized structures while it issues approaches to designs that make use of passive strategies in heating and cooling so that they reduce energy.

Additive manufacturing (AM), or 3D printing, has the potential to revolutionize the construction industry by offering a faster, more efficient, and sustainable alternative to traditional construction methods. With 3D printing technology, buildings can be created layer by layer, using materials such as concrete, plastic, and metal, to create complex structures and intricate designs. This technology has the potential to significantly reduce the waste and energy consumption associated with traditional construction, while also providing opportunities for customization and precision [16]. Lack of standardization, and high initial costs of 3D printers and materials. Another challenge is the limited size of objects that can be printed, which means that larger structures such as skyscrapers cannot yet be printed in one go [17]. However, with ongoing research and development, it is expected that these challenges will be addressed and 3DP will become more widely adopted in the construction industry ([14,17,18]).

The construction industry plays a vital role in achieving several of the Sustainable Development Goals (SDGs) of the United Nations (UN) 2030 agenda, particularly Goal 9: Industry, Innovation and Infrastructure and Goal 11: Sustainable Cities and Communities. The integration of innovative engineering based on material science and information technology, such as 3D printing, can significantly contribute to achieving these goals by reducing the emission of GHG, minimizing waste generation, and conserving energy and water resources. 3D printing technology has been utilized in various fields and industries, including healthcare, construction etc. Its potential for on-demand production, customization, and material efficiency has led to the exploration of its applications in different sectors such as building construction [19].

The integration of IoT and cloud computing technologies with 3DP has the potential to revolutionize various industries and can help to address some of the challenges faced in the construction industry, while also enabling digital construction of buildings. The idea of 3DP has been widely discussed in various scientific forums and media outlets in the 21st century. Initially, 3DP was created mainly for prototyping projects and products. The first 3D printer was developed by Charles Hull in 1986. However, in recent times, 3DP technology has been repurposed for the development of mainstream products in various sectors and industries. This technology has been applied in diverse fields such as medicine (creating drugs and organs such as teeth and bones), bioengineering, aviation, food processing, tool designs, and presently, the construction industry. Combining different technologies and fields has transformed the construction industry [20].

The process of Stereolithography (SLA) uses materials like liquid resin that are transformed into solid material using a powerful laser. SLA is a form of additive technology that builds products layer by layer from the bottom up. Despite advancements in technology, SLA remains one of the most commonly used 3D printing technologies for creating product components. Other popular additive technologies include Direct Metal Deposition (DMD), Fused Deposition Modeling (FDM), and Selective Laser Sintering (SLS) ([21,22]).

The 3DP technology operates by utilizing a computer-generated set of instructions to produce a digital design of the desired object. The 3D printer then builds the object layer by layer based on the model. This technology has been successful in handling cements and constructing walls, which could potentially revolutionize the construction industry ([23,24]).

### *2.1. Advantages of 3D printing technology in construction*

The construction industry is under pressure to meet deadlines, utilize resources, and maximize profits [25]. To overcome these challenges, construction companies invest heavily in modifying tools and equipment, as well as developing new innovations. While there have been many advances in the sector, 3D printing technology is highly regarded for its potential to address many of these challenges and improve efficiency and safety in construction. Construction 3D Printing (C3DP) has attracted significant attention from scholars in recent years. Compared to conventional and prefabricated building approaches, C3DP offers several advantages, including cheaper, sustainable, and durable construction, improved safety, reduced reliance on human labor, reduced material waste, and better branding and market share. ([26–29]).

Integration of 3DP in technology has solved so many challenges faced by construction engineers such as less construction time and waste, minimum human errors, sustainability, etc. as shown below:

***Design freedom***: Unlike conventional approach that limit design freedom, 3DP technology offers viable design freedom which allows creative innovation. 3D concrete printing enables construction engineers to engineer different shapes that can be bended and structured in different angles [30].

***Sustainability***: The construction industry has prioritized the construction of sustainable buildings, with many developed countries setting goals for sustainable megacities, bridges, roads, and tunnels. These goals can only be achieved using 3D printing (3DP) technology, which can withstand extreme weather conditions and operate for extended periods without rest. Additionally, construction with aluminum silicate can resist earthquakes of less than 8 magnitude. Consequently, the automation of construction has become a field in which many construction companies invest, with the goal of making buildings easier to construct, with fewer errors and greater sustainability. Engineers are using 3DP to fabricate walls with technical materials such as a printable one-component geopolymer mixture of aluminosilicate, which contributes to the walls' resistance to environmental factors and extreme weather. ([30–33]).

***Affordability***: The use of 3D printing (3DP) technology for constructing houses has proven to be more cost-effective than conventional building methods. In Germany, Netherlands, United States of America (USA), and China, constructing printed houses currently costs an average of $4000, depending on the size and specific requirements. The low cost of constructing houses using 3DP technology is attributed to its speed, reduced reliance on extensive human labor, and reduced material use and construction waste. ([28,29]).

***Speed***: The shortage of resources and manpower in the construction industry has made meeting deadlines a significant challenge. However, the emergence of 3D printing (3DP) technology has demonstrated that small homes can be built from start to finish in days, and large-scale buildings in weeks. This indicates that 3DP outpaces conventional construction in terms of construction duration, which takes months to years. 3DP technology has been shown to save over 60 % of on-site time and reduce labor by more than 70 %. In China, 3DP technology has successfully been used to build 10 villas in 24 h with less construction waste compared to traditional building methods in 2014 [30].

***Minimize human errors***: Conventional construction faces major challenges due to a shortage of skilled labor, leading to an increase in human errors and mistakes that have caused many destructions and fatalities throughout history. Compared to 3D printing (3DP) technology, which is more accurate and precise due to its automation and programmability, building houses through conventional methods is more susceptible to errors. Additionally, conventional construction has a high risk of accidents and fatalities among workers, with an estimated 5000 construction workers dying every day. Therefore, the use of 3DP technology can save lives, prevent injuries, accidents, and fatalities. ([30,34]).

***Minimize labour***: The construction industry relies heavily on effective manpower for its operations, which can be costly and negatively impact a company's profits. Moreover, human errors in the construction process can result in fatal destruction and injuries to both house occupants and laborers. However, the invention of 3DP technology has shown to significantly reduce the need for human labor, by up to 80 %, resulting in cheaper construction costs and increased profits for construction companies. ([30,35]).

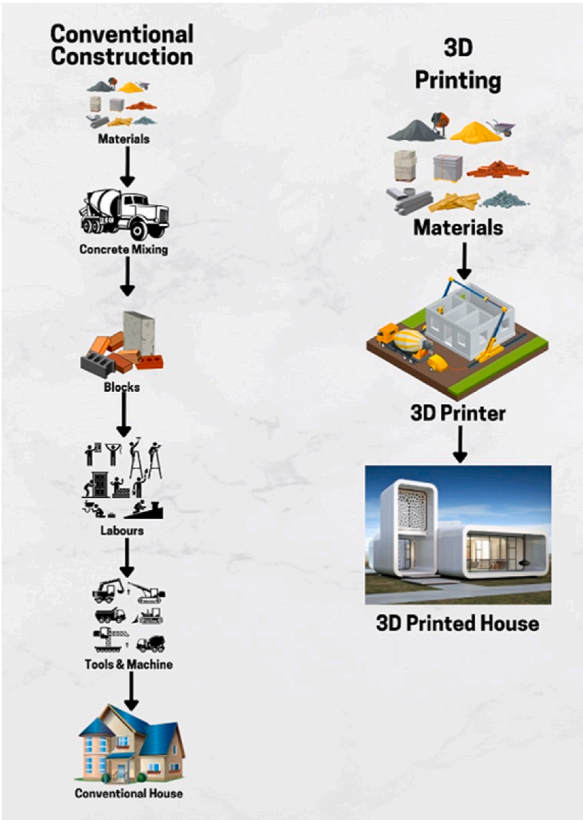


**Fig. 3.** The advantage of 3DP compared to traditional building.

***Waste reduction***: The construction industry is known to produce a significant amount of waste every year, with estimates suggesting that it produces over 1 billion tons of waste annually. This number is expected to double by 2025, reaching a staggering 2 billion tons. Reducing waste and managing resources is a goal for many construction companies. In contrast to conventional construction methods, 3DP technology can minimize construction waste and effectively manage resources.

This is possible due to the facts that 3DP machine is an additive technology that only utilize calculated usage of materials for creating structures and parts [30]. The advantage of 3DP compared to traditional building is shown in Fig. 3.

### 2.2. Disadvantage of 3D building

Although 3DP technology has the potential to revolutionize the construction industry and pave the way for automated and smart buildings, there are still some challenges that need to be addressed. These challenges include concerns about the impact of 3DP on employment, the high cost of acquiring and maintaining the printing machine, and the need for skilled experts who can operate and maintain the machine.

***High cost of 3DP machine***: Although 3DP technology offers a more cost-effective way of building compared to traditional methods, the initial expenses of purchasing and installing the machine on the construction site can only be afforded by wealthy companies. Furthermore, the cost of maintaining the equipment and purchasing materials can be high, which makes it challenging for construction experts to justify replacing traditional methods with this technology [30].

***Increasing rate of unemployment***: The global COVID-19 pandemic has led to massive unemployment and one of the sectors that is hit hard is the construction sector due to suspension of works as a result of lockdowns. Apart from the pandemic, construction industries harbor many professionals who depends on the industry for livelihood. However, the adoption of 3DP in construction is set to minimize human labour which will lead to massive unemployment [36].

***Shortage of professional operators***. Even though 3DP technology is set to replace human labour, however, one of the limitations of the approach is the shortage of skilled professionals who can operate the machine effectively and its maintenance. Thus, there is high demands for skilled operators that can operate the machine without causing damages ([35,36]).

***Fear:*** For every advent of technology, it comes with fear from the general public. The general public is usually slow to accept technology due to the fear of using computer aided technology in place of humans. In recent years, both professionals and general public have raised concerns over the use of 3D printed building. Many scholars highlighted that the technology need time and assessment before it will be deemed safe and viable [35].

***Regulations***: In order for 3D technology to gain wider acceptance, it must undergo safety regulations. Public buildings must undergo testing over a period of years to ensure that they are safe and suitable for construction. While some countries have begun to regulate this technology, its impact on the construction industry remains limited. Although there is growing awareness of the benefits of 3D printing technology in construction, its adoption is largely contingent upon state and country laws and regulations [36].

## 3. Artificial Intelligence (AI) and Internet of Things (IoT)

### 3.1. Artificial Intelligence (AI)

The prospects and concepts of AI have been buzzing throughout the last 5 decades. Definition of AI has been subjected to debate and variations from several scholars. Thus, this led to so many definitions. AI can be defined as a branch of computer science that is concerned with the development of computers that can imitate human-like features such as reasoning, learning and solving problems. The definition of the concept has undergone several modifications over time, one of the recent definitions of AI is termed as any technique that enables computers to mimic human behavior or a branch of computer science that revolves around the use of machine that mimics human cognitive system such as learning, pattern recognition, problem solving and decision making [37].

### 3.2. Machine Learning (ML)

ML is a subset of AI and computer science that allows computers to comprehend information from past experience. ML can also be

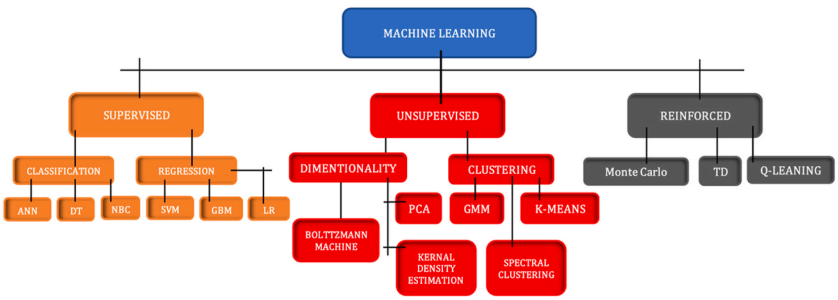


**Fig. 4.** Classification of ML techniques.

defined as a branch of AI that focuses on the use of algorithms and data to mimic human behavior such as learning and gradually improving over time. ML is a branch under AI that utilize statistical approach to give computers and machine the ability to learn from data without being explicitly programmed. AI models require data to function effectively in the same manner where vehicles require fuels to function. Computational approaches are used for ML algorithms to specifically learn information from input, without using a fixed model equation. ML is one of the basic drivers of the growing field of data science, automation and smart systems [38]. The concepts of ML have been applied in the form of algorithms or statistical method to make predictions, classification and uncover patterns in data. Thus, the use of large amount of data is crucial for boosting the efficiency and accuracy of ML-models ([39,40]). The classification of ML techniques is presented in Fig. 4.

### 3.2.1. *Supervised learning*

Supervised Learning is a type of machine learning approach that involves obtaining information on the input-output relationship of a system using a given set of input-output training data. This approach is referred to as supervised because the correct output is known and the algorithm iteratively makes predictions on the training data, which are later corrected using gradient descent. The training process ends when the algorithm achieves a satisfactory level of performance. There are two primary techniques used in supervised learning: Regression and Classification. Examples of regression algorithms include Gradient Boosting Machine (GBM), Linear Regression, and Support Vector Machines (SVM). On the other hand, examples of classification techniques include Deep Learning (DL) architectures like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNNs), Decision Trees (DT), and Naïve Bayes Classifiers (NBC) ([39,41,42]).

*3.2.1.1. Deep learning.* Deep learning is a subfield of ML which is inspired by how human brain's function due to connections or synopsis of nerve cells or neurons. Model learn as a result of data connection between neurons in the network. A simple neural network is termed as perceptron which take input as data set and produced an output as classification category or prediction outcome. Deep learning neural networks are made of multiple perceptron's with an Input Layer (IL), and many hidden layers (HL) before Output Layer (OL) [43]. An example of deep learning includes ANN and CNNs. ANN consists of a network of strongly integrated processing elements (known as neurons), which work together to address a particular problem. CNN is a class of ANN with multi-layer perceptron which are fully connected network in which each neuron from one layer is connected to all neurons in the next layer. CNNs are termed as networks that utilize series of mathematical operations knows as "convolution" [44].

*3.2.1.2. Linear Regression (LR).* The concept of Linear Regression (LR) is popular as a result of its application in statistics. LR is use in several disciplines such as marketing such as prediction of profits and prices of commodities, prediction of weather and climate, healthcare (progression and spread of diseases, data analytics of medical records etc.) LR is an approach use to model target values using independent predictors. LR is crucial for prediction and evaluating the causes and effect correlation between variables. Liner regression and logistic regression are the two most common type of regression. The differences between regression types revolve around the number of independent variables and type of connection between dependent and independent variables. The concept where there is only one independent variable and introducing dependent variable resulted in linear relationship between the independent (y) and dependent (X) variable is known as simple LR ([41,45]). The formula for LR take the form of:

$$Y = a + bX$$

and expanded to

$$Yi = f(Xi + \beta) + ei$$

Where,

Yi = dependent variable
F = function.
Xi = independent variable
Beta = unknown parameters
Ei = error terms.

The formula for LR take the form of: $Y = a + bX$ and expanded to $Yi = f(Xi + \beta) + ei$ Where, dependent variable is denoted as Yi, function as f, independent variable as Xi, unknown parameters as $\beta$ and error terms as ei.

*3.2.1.3. Support Vector Machine (SVM).* SVM is a simple type of supervised machine learning which is used for both classification and regression. The main objective of SVM is to locate a hyperplane in an N-dimensional space which clearly classifies the data points. Despite the fact that SVM can be used for both regression, outlier detection and classification, most researchers applied SVM for binary and multi-class classification which makes one of the most popular supervised machine learning techniques [46].

SVM classifiers utilize the method of segregating classes through the maximization of the margin, which involves maximizing the distance between the nearest points using a hyperplane. In the SVM decision function, the application of classes of training points is denoted as support vectors. The SVM algorithm employs a technique called the kernel trick, which transforms low dimensional space inputs into a high dimensional space. SVM is highly beneficial in categorizing complex or sparse data into simple groups based on predefined labels. Unlike most deep learning algorithms that employ SoftMax as the final fully connected layer for probability-based classification, SVM employs five cross validations to classify inputs. One of the major advantages of SVM over other machine learning models is its low computation, faster speed, and better performance with a small amount of data. In contrast, deep neural networks (DNNs) require substantial amounts of data for higher accuracy.

*3.2.1.4. Decision Tree (DT).* SVM classifiers utilize the method of segregating classes through the maximization of the margin, which involves maximizing the distance between the nearest points using a hyperplane. In the SVM decision function, the application of classes of training points is denoted as support vectors. The SVM algorithm employs a technique called the kernel trick, which transforms low dimensional space inputs into a high dimensional space. SVM is highly beneficial in categorizing complex or sparse data into simple groups based on predefined labels. Unlike most deep learning algorithms that employ SoftMax as the final fully connected layer for probability-based classification, SVM employs five cross validations to classify inputs. One of the major advantages of SVM over other machine learning models is its low computation, faster speed, and better performance with a small amount of data. In contrast, deep neural networks (DNNs) require substantial amounts of data for higher accuracy.

*3.2.1.5. Naïves Bayes Classifiers (NBC).* NBC is a subtype of supervised ML which employ Bayes theorem of probability to predict class of unlabeled datasets. This machine assumes features of a data point as being totally independent of one another and that's why it's called NBC. The classifier uses in naïve bayes take into accounts "that the presence of specific trait in a group or set has no relation with the presence of any other traits". They use the probabilities of defined circumstances being true (input) to make predictions for new data points [47]. Application of NBC follow several steps which include data conversion (into frequency table), finding probabilities or creating likelihood table and finally the use of naïve bayes equation to calculate class problem as shown in the equation below:

$$P\left({}^{C}\!/_{X}\right)=\frac{P\left({}^{X}\!/_{C}\right)P(C)}{P(x)}$$

Where P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes).

P(c) is the prior probability of class.

P(x|c) is the likelihood which is the probability of predictor given class.

P(x) is the prior probability of predictor.

Application of NBC follow several steps which include data conversion (into frequency table), finding probabilities or creating likelihood table and finally the use of Naïve Bayes equation to calculate class problem. The equation is represented mathematically as P (c|x) is equal to P(x|c) multiply by P(c) over P(x), Where P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes), P(c) is the prior probability of class, P(x|c) is the likelihood which is the probability of predictor given class and P(x) is the prior probability of predictor.

One of the advantages of NBC is it is very easy to build, can be apply for large number of datasets and can be used for both binary and multi-class classification. Some of the advantage of this technique is that it performs better using categorical dataset compared to numerical dataset, assumption of independent predictors or it takes time and assumes data point features are independent and bad estimator which ends up slightly less accurate compared to other classifiers [48].

*3.2.1.6. Gradient Boosting Machine (GBM).* This method utilizes a logical approach where subsequent predictors learn from the errors made by previous predictors. Consequently, the likelihood of observations appearing in subsequent models is not uniform, with those having the highest errors appearing most frequently. This means that the process is not based on the bootstrap method, but is primarily focused on minimizing errors. The resulting ensemble is designed to enhance accuracy, albeit with some degree of risk in terms of coverage. One of the major advantages of this technique is that it can deliver highly accurate predictions for both categorical and numerical data [49]. However, it is more difficult to fine-tune than other models because of its numerous hyperparameters, which can make it prone to overfitting. On the positive side, it optimizes various loss functions and offers several options for hyperparameter tuning, making it more adaptable. In contrast to linear classifiers, it lacks interpretability, meaning that there is no straightforward way to determine how variables interact and contribute to the final prediction. Although it is not particularly fast in terms of training or scoring, it does not require imputations when dealing with missing data [49].

*3.2.1.7. K-nearest Neighbor (KNN).* The concept of "similar features flock together" is the basis of KNN algorithms. Thus, KNN models are associated with "proximity" due to similarity concepts or closeness. Even though KNN can be used for regression, however, it is widely used for classification problems. The working principle of KNN revolve around storage of dataset during training session and the subsequent addition of new set of data which result in classification of the new input dataset into categories according to the store dataset. KNN is very effective in classifying similar datasets into categories using nearest data point ([50,51]).

The steps involve for application of KNN include selection of K numbers of the neighbors, estimation of Euclidean distance of the neighbors, calculation of data point of each category and assigning of new data points. One of the disadvantages of KNN algorithms is that it is a "lazy learner" as it does not learn immediately from training dataset but store them. It is also non-parametric technique which does not make any assumption on primary datasets (55).

### *3.3. Unsupervised learning*

Unsupervised ML is a type of ML which use unlabeled inputs. Unsupervised ML models learn functions by identifying patterns in input data and cluster them together in the form of groups or classes. This subtype of ML gives more insight into the type of inputs which makes it crucial for classifying unsorted, sparse and complex data. It is applicable generally in clustering and dimensionality approaches. Clustering techniques can vary to K-means, Principal Component Analysis (PCA), spectral clustering and dirichlet process, and density estimation are like boltzmann machine, kernel density estimation and gaussian mixtures [52].

#### *3.3.1. K-Means*

The k-means clustering algorithm aims to allocate an identified unspecified data set into a defined number of clusters. K-means are simple to execute and calibrated to large sets of data as well as easily adapted to different examples in which clusters of distinct shapes and dimensions are generalized. However, the “k” has to be chosen manually where it depends on the initial values. For instance, it is a big problem when using the euclidean distance because it calibrates with a number of dimensions. So, whenever the number of dimensions lean to infinity, the distance between any two points in the dataset merge. It has trouble clustering data when using different shapes and sizes, so it should be generalized [53].

#### *3.3.2. Principal Component Analysis (PCA)*

PCA is a long-established feature of extraction and data characterization technique significantly used for statistics primarily for dimensional reduction, extracting and representing data. Its main role is to reduce the dimensions of a data set consisting of many variables correlated with each other, while maintaining the variation at hand in the dataset. Its objective was to orthogonally project data points onto an L dimensional lateral subspace [54]. In order to capture or ignore the easiest invariance, a greater number of functionalities is required for calculation and performance reasons. PCA concerning covariance tends to lack information and to hide certain data structure and interactions. This makes the covariance matrix difficult to assess properly, but that doesn’t alter the fact that the original data is preserved with extraordinary performance [54].

#### *3.3.3. Spectral clustering*

Spectral clustering is a technique that operates in graph theory, it is used to recognize sets of nodes in a graph based on the edges linking them, they are mainly used for exploratory data analysis. The purpose is to allocate unlabeled data to groups, where similar data points get exploited to the same group. Some of its advantages is that they reduce the computation lay out efficiently, works for any choice of weights, produces consistently high-quality results, validates and improve the phase labels in the utility model and shows potential in the detection of other types of errors in the topology of the model. On the other hand, if the resolution of the image is high, it can lead to an intensely large adjacent matrix. It is not effectual with noisy, sparse data, and the prediction can be made only for one cluster model at a time ([55,56]).

#### *3.3.4. Boltzmann machine*

A boltzmann machine is a bidirectional network of aligned neuron-like units linked together to assemble debatable decisions about whether to be on or off. It generates data from the training process (without expecting input data) and feed it to the machine as input to help the system regulate its weight. The learning process is done from the input where it scans the possible connections between the parameters and how they affect each other [57].

#### *3.3.5. Gaussian-Mixture Model (GMMs)*

GMMs are a parametric probability density function for representing normally distributed sum of Gaussian component densities. Their architecture works by limiting the spectrum of normal data to be collected through the clustering and learning of upper and lower bounds or distances to each centre of each cluster. GMMs can be very useful for identifying cases where there is limited number of sample class of interest and substantial number of samples of other classes. Its covariance structure allows mixed membership of points to clusters which makes it very flexible. One of GMMs drawbacks include having a lot of parameters to fit that usually require loads of data and multiple iterations to get quality results [58].

### *3.4. Reinforcement Learning (RL)*

RL is the training of ML models to assemble a series of decisions where an agent learns from a bilateral domain by trial and error using judgement from its attained experience and actions. RL uses rewards and punishments as alerts for the desired or undesired behavior. It is used to quantify a behavioral approach, a policy optimizing a criterion of fulfilment. As such, a long-term amount of reward comes from engaging with a certain setting through discovery and error. Its goal is to find a suitable action model that would boost the total cumulative reward of the agent. It is divided into two main types: Policy iteration and value iteration based. Policy-iteration based are like Monte-Carlo simulation and Temporal Difference (TD) learning, and value-iteration based is like Q-learning ([59,60]).

#### *3.4.1. Monte-Carlo simulation (MC)*

The MC simulation method manifests all the feasible outcomes of your choices and estimate the risk effect, granting for a finer decision making when it’s unpredictable. It carries out risk analysis by constructing models of potential results by switching a variety of values using probability distribution for any factor that has ingrained uncertainty. After calculating the results multiple number of times using a distinct set of irregular values from the probability functions. The MC simulation could involve a great deal of recalculations before it concludes [61].

#### 3.4.2. Temporal Difference (TD)

TD refers to an agent that employs unsupervised learning to predict the value of an inconsistent variable occurring at the end of a sequence of states. It achieves this by learning from an environment through episodes, without prior knowledge of the environment. TD relies on trial and error to improve and learn how to set rewards, estimate initial values, and update them based on exploration efforts. Qualified traces are used to acquire knowledge from past events and make better predictions. TD is also used to predict the optimal approach for the cost function. However, while the model can estimate the Q-function from the current reward, the estimation for the future reward is done by the model itself, making it unstable since the targets are based on the model. Additionally, TD has a bias towards maximizing outcomes, which is where policy-iteration comes in. Q-values are the ideal targets, but they are unknown, and the model should be trained to estimate them instead [62].

#### 3.4.3. Q-Learning

Q-learning is an off-policy algorithm that takes the best steps in its newest state. It focuses on the quality and how proficient a given action is in acquiring feature rewards. It is considered off-policy because the function seeks to learn the value of the ideal policy independent to the agent's actions to maximize the total reward. This framework combines the advantages of unified and decentralized architectures to achieve reliable decision. This established structure allows he agent to take precise decisions in order to defend themselves against shortcomings in a timely manner without the necessary rewards. Throughout the process of having to learn a policy and the overall approach to maximize the reward, the degree of potential error will be magnifying. In addition to that, it uses the TD and so the drawback of having the model slightly unstable also applies [63].

#### 3.4.4. Limitations of artificial intelligence for the construction of eco-friendly intelligent homes

- Cost and Complexity: Implementing AI systems in intelligent homes can be costly and complex, requiring significant investment in hardware, software, and infrastructure, which may pose barriers to widespread adoption, particularly for low-income households.
- Data Privacy and Security Concerns: AI-powered smart home devices collect vast amounts of personal data, raising concerns about privacy breaches, unauthorized access, and data exploitation, necessitating robust security measures and regulatory frameworks to protect user information.
- Technological Dependence and Reliability: Intelligent homes reliant on AI systems may experience disruptions or malfunctions due to software bugs, hardware failures, or connectivity issues, potentially compromising the functionality and reliability of essential services.
- Skills and Knowledge Gap: Designing, implementing, and maintaining AI-driven intelligent home systems require specialized skills and expertise, which may be lacking among homeowners, contractors, and building professionals, hindering effective deployment and utilization.
- Ethical and Social Implications: AI algorithms embedded in intelligent home systems may perpetuate biases, discrimination, and inequalities, particularly in decision-making processes related to access, affordability, and resource allocation, necessitating ethical considerations and societal dialogue.

## 4. Internet of Things (IoT)

In 1999, a member of the Radio Frequency Identification (RFID) development community coined the term "IoT," which emerged from the integration of various communication technologies, including Information and Communication Technology (ICT), data analysis, and AI. Other forms of IoT include the Internet of Industrial Things (IIoT), the Internet of Nano Things (IoNT), and the Internet of Medical Things (IoMT) or the Internet of Things in Healthcare (IoTH). IoT refers to a vast network of physical devices capable of collecting and sharing data with other devices, systems, or living beings using the internet [64]. Despite its existence for almost three decades, IoT did not become prominent and listed among emerging technologies until 2011. The technological advancement in different fields such as hardware, software, artificial intelligence, and cloud computing contributed to this development. IoT devices have unique identifiers that allow them to exchange data without human intervention, making it possible for the digital and physical worlds to interact.

The concept of IoT revolves around the exchange of information or data between people and devices equipped with sensors and monitors using wireless connections. It is a network of physical objects encompassing the wireless connectivity of devices of all sizes and types, including computers, smartphones, vehicles, cameras, toys, home appliances, buildings, industrial devices and systems, as well as people and animals. IoT involves connectivity, communication, and information sharing according to specified protocols to achieve smart reorganizations, personal real-time monitoring, tracing, positioning, online upgrade, online monitoring, process control, safety, and more. The basic principle of IoT involves the use of smart devices embedded with sensors, processors, and communication capabilities that enable them to acquire, store, and transfer data through an IoT gateway or stored in the cloud. IoT is not limited to the exchange of data between people and devices through a network but also includes the exchange of data between devices [65].

### 4.1. Component of IoT

The three main components of IoT are the devices, software and the internet or network.

#### 4.1.1. IoT-based devices

IoT-based devices are mainly hardware devices designed or embedded with sensors and monitors such as gadgets, appliances, industrial machines, medical equipment which are capable of collecting and exchange data over the internet. These devices are also integrated with Central Processing Unit (CPU), firmware and network adapter. These embedded sensors enable the device to sense physical changes and record, store or transmit the information to a server or other connected devices [66].

#### 4.1.2. Software

The architecture of IoT-based devices requires the use of software which interact with hardware board using the internet. For each device, one input output pin of hardware board is connected with every single relay module which act as a switch for the devices. The hardware board is then assigned with a static Internet Protocol (IP) to allow access or execute it stored scripts with the aid of software applications. Thus, the main function of software in IoT devices revolve around configuration and management [67].

#### 4.1.3. Internet

Internet is a broad term use to describe system architectures that connect devices together through a network. Thus, it is termed as “Network of Network”. The internet provides a means by which people communicate with each other through an online and social media platform which include email, Facebook, WhatsApp, audio, video calls and online conference call or store information in a drive or cloud [68]. The internet has provided a means of transaction and businesses around the world. Internet is not only limited to wireless connections but also physical objects such as cables. Thus, internet is regarded as global network of physical cables which include fiber optic cables, telephone cables, TV cables etc. [69]. With these cables or wireless connections using Wireless Fidelity (Wi-Fi), computer and other smart devices can access the internet through an internet provider network. Thus, internet provide a means where devices can connect with each other, store and transmit data which make internet the backbone of IoT [68].

### 4.2. Significance of IoT

IoT is transforming almost every sector as a result of internet, Cloud Computing (CC), Big Data (BD), Data analytics (DA) and hardware such as computers, smart mobile phones and other electronic devices. IoT is literally the inter connectivity between internet and thing which can be a person, an animal, a device such as implants, biochips, automobile or any other biological or natural and manmade object that can be assigned an internet protocol address in order to transmit data through a network. Currently, several companies and industries from different disciplines are using IoT to improve production and services. Integrating IoT has shown to reduce labor, cut cost or minimize losses, reduce waste and improve service delivery [70].

### 4.3. Classification of IoT

As a result of vast number of IoT devices in existence, classifying them is challenging due to numerous applications in different fields and disciplines. One of the most popular classifications of IoT devices are based on their application such as in the industries also

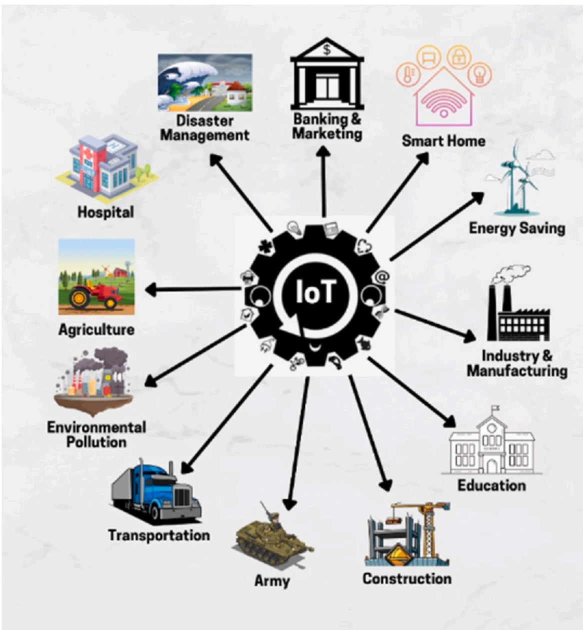


**Fig. 5.** Application of IoT.

known as IIoT, in medicine or healthcare also known as IoMT, in the military also known as IoMT etc. other classification of IoT include consumer-based IoTs, commercial based IoTs, Infrastructural based IoTs etc. [66,71].

### 4.4. Application of IoT

The 21st century is witnessing growing applications of IoT in wide range of human activity. This trend is forecasted to increase exponentially in the next few years from billion United States Dollar (USD) industries to trillion USD industries. IoT has found its applications in several domains which include smart healthcare, energy, security and safety, agriculture, construction and buildings, cities and environment ([72,73]) as shown in Fig. 5. Some of the current's applications of IoT include.

1. Home security: IoT-based devices in the form of sensors, monitors, cameras and motion detectors have been developed to help make home secure [74].
2. Monitoring of vital signs: The growing field of wearable devices integrated with IoT is transforming real-time monitoring of vital signs both at home and in the healthcare settings. Several IoT devices have been developed to monitor body's temperature, heart rate, glucose level, pressure, steps and calories burn and transmit the data to end users such as physicians or cloud storage [75].
3. Transportation: The high need and demand for self-driven cars has led scientist to adopt several technologies which include AI through machine learning such as image classification and RL. However, IoT systems can also be used for inter and intra vehicular communications, Global Positioning System (GPS) and location tracking, smart parking, smart traffic control etc. [76].
4. IIoT: Several industrial processes are now automated as a result of sensors capable of wireless connection and transmission. The dream of smart manufacturing is edging closer with every passing year. The increase demand of smart industry and safer industrial environment has led so many organizations to promote the integration of IoT in the industry in order to increase productivity, flexibility while reducing the cost. Some of these strategies and campaigns includes the industries 4.0 strategy, the European initiative for the Factories of the Future (FoF), Industrial Internet (II) and the effort for smart factories [76]. Recently scientists developed platform that allow machine to machine communication. The application of Wireless Sensor Networks (WSNs) has shown great promise in promoting IIoT in terms of enhancing efficiency and productivity of both current and prospective manufacturing industries [77].
5. Military Internet of Things (MIOT): The exponential technological advancement in the field of ICT and related technologies such as software, network and mechatronics have led to the development of several new military information technologies which include information security technology, sense detecting technology, command decision-making technology, information fusion technology etc. Collection of these technologies have shown to aid the military on information processing, system design and technology innovations centered around IoT. The MIOT is driven by the use of sensors and other devices equipped with information

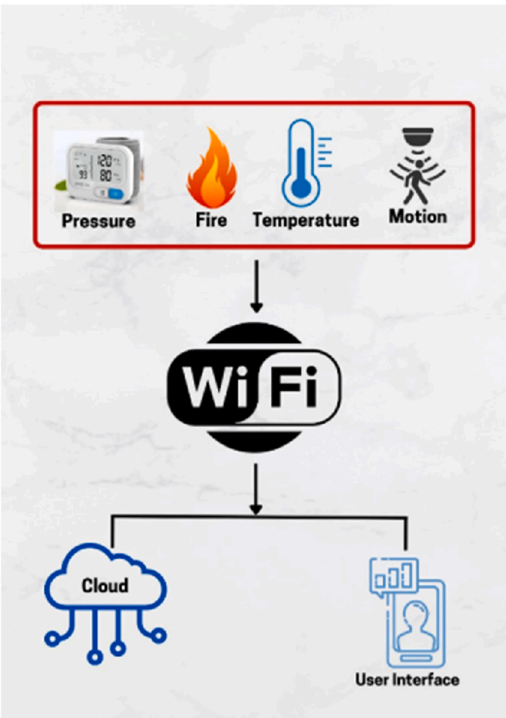


**Fig. 6.** Application of IoT in smart homes.

system technologies which enable them to capture physical attributes and provide state information of enemies, their war tools and materials using various sensing technologies [78].

## 5. Integration of smart technologies in construction sector

Buildings are among the basic and fundamental unit of human beings as it offers shelter against environmental factors and intrusion from animals. Throughout history, humans have transformed buildings from construction using old-age or primitive tools using mud and clay to concrete, wood, steel and glass buildings constructed using advanced and sophisticated devices such as Building Information Modelling (BIM) and 3D printing technology. The second phase of transformation in construction sector is associated with the invention of electricity which powered homes with light and electrical devices such as television, microwave, oven, fridge, washing machine etc. ([79,80]).

Developing smart homes has become a trending topic in the last two decades as it offers better quality of living through the integration of technology and services by harnessing hardware or electronic devices and internet. Smart homes provide ease and convenience to users and their daily activities through automation. Smart homes utilize several wireless connection technologies which allow devices communicate with each other through the internet, cable broadband, bluetooth etc. as shown in Fig. 6. Building smart home requires the placement of devices and networks around the house such as living room, bedroom, kitchen, bathroom, storage, garage etc. Smart home provides users with several features and applications which include security, energy management, comfortable living as well as added benefits for disabled people [81]. Moreover, smart homes are integral to realizing smart cities [82].

Among many IoT applications, smart homes play an important role in realizing smart cities. The idea behind smart buildings originated as a result of increase automated innovations in construction and maintenance of buildings. Smart homes offer several advantages over traditional or conventional homes in such a way it can be remotely operated and controlled which improved comfortability, convenience, energy-saving and minimize cost. The adoption of IoT, AI, CC, BD, sensor technologies, data analytics in buildings give rise to a concept known as Intelligent Buildings (IB) which is prerequisite and driver of smart homes ([83,84]).

Building smart homes required the use of automated technologies which can provide several advantages over traditional approaches and various application. Starting from construction, the use of 3D printing has shown to offer several advantages which include efficiency, speed or time saving, affordability, resource and waste management etc. Next is the interior and decoration of smart homes which require the use of IoT-based devices that can be used to connect different devices together [73].

### 5.1. *Construction of buildings and components using 3D printing technology*

#### 5.1.1. *3D Printing in construction*

The first reported engineering of 3D printing is dated back to the 1986 and subsequently, the technology has been adopted in other fields such as healthcare, architecture and other designs. 3D printing technology has attracted interest from researchers and firms in the construction sector [35]. Lim et al., 2012 developed a full-scale concrete printing of walls and frontage which are limited in size (i. e., 5.4x4.4 × 5.4m). However, the first full-scale printing of houses was developed in 2014 by a Chinese company known as Winsun who developed several printed houses within one day [5].

In construction industry, 3D printing technology was firstly introduced for a quick and precise creation of prototype parts. However, the technology was improved due to integration of automation which expands it viable application to onsite construction of buildings. 3D printing was also adopted by architects to design sale models prior to introduction of BIM [23]. Since the first inception or an attempt to incorporate 3D technology into construction in 2004, construction engineers have deployed 3D technology for building construction structures and full-scale construction [85].

The transformation of small-scale structures to full-scale structures was made possible due to the developments of large-scale 3D printers which led to the construction of offices, houses, shelters, bridges, pavilions, etc. [86]. These buildings show the potential of the technology and the prospect of employing the technology for construction of large-scale, high and tall buildings in small time frame, limited resource, less waste and construction error ([28,34]).

Apart from building structures using 3D printers, the technology has also been deployed in other construction such as military bunkers, printing of pedestrian bridges, reproduction of historical buildings, in situ repair work which are not accessible or difficult for humans, printing of structural and non-structural elements with complex geometries, quick construction of disaster relief shelter or refugee camps, printing of metal frames, printing molds for load bearing components, etc. ([5,24,87]).

Scalability is one of the challenges related to the use of 3D printers where the size of the design is impelled by the chamber volume of the printers. In order to address this issue, scientists turn to printing smaller pieces off-site which can then be assembled on-site [88]. However, these generates extra work such as transportation, assembling which create potential weaknesses. Thus, Zhang et al. (2018A) [89] addressed this issue by proposing the use of multiple robot printers in multi-agent environment to print separate portion of large print structures. These printers have shown to be capable of collision avoidance, localization and effective and organized printing. Keating et al. (2017) [90] who are group of scientists from media lab at the Massachusetts Institute of Technology (MIT) developed an automated construction system known as Digital Construction Platform (DCP) which has the ability for customized on-site printing of architectural-scale structures. The design of the system revolves around a compound arm system which consists of both electric and hydraulic robotic arms and the use of AM approach for constructing insulated frameworks cast concrete structures using two-part spray polyurethane foams [91].

Currently, the largest building printed by 3D printer is the 9.5m high and 640 square meter flow space office building in Dubai which was constructed by Apis Cor in 2016. After the completion of the office building, the constructors claimed that the construction generated approximately 60 % less waste compare to conventional approach, utilize 50 % less human resource and was completed within 14 days [92]. Apart from printing structures such as the office walls, it took the company extra 2 months to fix ceilings, fittings and electronics ([34,93]).

The office constructed by Apis Cor is the current largest building in terms of space, while the five-story apartment constructed by Winsun is the tallest (highest) 3D printed building as shown in Fig. 7(a–c). Unlike the Apis Cor, the Winsun company printed walls and other structural components off site and transport the structure on site for assembling. However, conventional approach was employed for fixing doors, windows and other finishing works. After the completion of the building, the constructors claimed that the construction operations saved construction time by approximately 70 %, construction waste by 60 % and labour cost by almost 80 % [34].

Another construction printed using the 3D printing also located in China was constructed by HuaShang which is a two-story building. Unlike the one developed by Winsun off site and assembled on site, this one was printed entirely on site which save time (i.e., transportation and assembling times). It took the constructors almost 45 days to complete the building from printing to plumbing and other fittings [94]. This demonstrates the speed of using 3DP compare to conventional building approach which would take around 7 months ([34,93]). 3DP has also been applied for other types of construction apart from buildings for daily use such as lunar habitat, drilling unit for ocean mining in frozen lands (such as Antarctic and arctic region) and emergency housing for refugees and those affected by disasters such as earthquakes and floods [95].

A 3D printer known as Innovation Printer (INNOprint) 3D machine was developed by the university of Nantes which is used to construct emergency housing in just 30 min [96,97]. Zhang et al., 2021 [98] proposed the use of a cable-driven printer for construction of lunar architectures. The evaluation of the printers exhibits several advantages such as small weight, simple structure, excellent reconfiguration features and large forming space. Unlike the use of earthly materials for construction of lunar bases, scientists proposed an efficient approach for lunar construction known as the "Lunar Soil 3DP". Some of these techniques include microwave sinter by the Institute of Geochemistry, Chinese Academy of Sciences, microwave sintering and contour crafting by National Aersonautics and Space Administrartion (NASA), solar sinter by Markus Kayser etc. [99].

The timeframe for 3D technology is summarized in Table 3.

### 5.2. Application of ML in construction

The application of AI has the potential to help construction experts realize value, increase efficiency, productivity through various stages of construction project such as design by architects, business modeling, financing, procurement, construction process and operations and asset management. Moreover, the application of AI in construction can help address several challenges which include resource management, cost, labor shortage, waste management and safety. The advancement in AI and its subfield such as ML and DL as well as analytics and big data are transforming construction sector [42].

The potential of ML in construction is unlimited. Several algorithms have been developed to assist project and construction managers on critical issues that require their attention. Several applications of ML are tailored toward prediction and classification using ANNs and CNNs. Currently, Deep NNs are used in predicting cost overruns by imputing data related to factors such as project size, project type, resources available, competence level of team and mangers [100]. These types of models can also be used to predict realistic timeline for completion of construction using store data of previous projects ([42,101]).

Coskuner et al., 2021 [102] applied multi-layer perceptron for the prediction of construction, domestic and commercial waste. The model is feed with several variables which reflect the effect of economic, social, geographical, demographic and touristic factors for the prediction of yearly generation rates of different type of waste. In order to provide an efficient system for evaluating vulnerability of existing buildings, Ruggieri et al., 2021(104) proposed a machine learning model named as VULnerability Analysis using MAchine-learning (VULMA). The proposed algorithm is fed with photographs of existing buildings in Puglia, Southern Italy. The proposed model exhibits high performance in comparison with manual computations conducted by the researchers.

Energy saving in the construction industry has been a major challenge for years. Thus, the study conducted by Maier et al. [32] proposed the use of different machine learning models such as Robust multiple linear regression, non-linear autoregressive exogenous multilayer perceptron, autoregressive model, extreme learning machine, multilayer perceptron, clustering for prediction of temperature in each room of a building using data obtained by stimulating building in TeKton. Among the models utilized, the non-linear autoregressive exogenous multilayer perceptron achieved the best performance with mean error approximately 0.1 °C. Similarly,


**Fig. 7.** 3D printed building in Dubai by Apis Cor: a) and b) during printing and C) finished in its environment.

**Table 3**
History of application of 3DP technology in construction.

| Year | Contribution |
|---|---|
| **2004** | Behrokh Khoshnevis of the University of South Carolina accredited for the first attempt to build printed walls |
| **2014** | Construction of full canal house using 3D printing technology in Amsterdam, Netherlands. |
| **2015** | NASA launched the '3D Printed Habitat Challenge for printing building home prototypes in space |
| **2016** | Construction of office of the future a 2700-square foot building in Dubai UAE in less than 20 days |
| **2016** | Construction of 4300-square-foot home by HuaShang Tengda, a Chinese architectural firm in one and half months |
| **2017** | Construction of a house by Apis Cor a Russian company in just 24 h using 3D printing technology |
| **2020** | Construction of 380 square meters house by Peri group a German construction |
| **2021** | Construction of lunar architecture by Institute of Geochemistry, Chinese Academy of Sciences and NASA |

Olu-Ajayi et al. (2022) [103] applied several machine learning models which include SVM, ANN, DNN, KNN, DT, Gradient Boosting (GB), Random Forest (RF), LR and stacking for predicting annual building energy consumption. Among the models applied on large dataset of residential building, DNN has shown to achieved the best performance with 0.92 Mean Absolute Error (MAE) 1.34 Mean Squared error (MSE), 0.95 R squared and 1.16 Root mean square error (RMSE).

Prediction of cost of construction is crucial for efficient management of projects. The study proposed by Sanni-Anibire et al., 2021 [103] explored this gap by predicting preliminary cost of tall building projects using different machine learning models which include ANN, SVM, multiclassifier system, KNN and other single and hybrid models. The result indicated that the combination of multi classifier system and KNN achieved the best performance with 80.95 % mean absolute percentage error, 6.09 root mean square and 0.81 correlation coefficient. The study conducted by Ngo (2019) [104] proposed the use of ML approach to predict cooling load of buildings. The developed models which include SVM, ANNs, classification and regression tree, and linear regression models were fed with dataset obtained from 234 buildings and the resulting performance is compared with the ones from physics-based. The comparison analysis has shown that the use of ML agrees with physics-based and the use of ensemble achieved the best result with 158.77Kilo Watts RMSE, 0.99 R, 6.17 % Mean Absolute Percentage Error (MAPE) and 112.07Kilo Watts MAE.

The use of ML for automated classification of heritage buildings is proposed by Bassier et al. (2017) [101]. The authors employed SVM for classification of objects and buildings such as churches, offices, houses, industrial buildings acquired using terrestrial laser scanning technique. The model was successful in terms of extracting structural components such as roofs, ceilings, floors, windows. The performance evaluation of the model resulted in 81%average accuracy, 80 % and 82 % average recall and precision. As a result of the significance of occupancy information in building facility design, operation and energy management. Wang et al., 2018 [105] adopted 3 machine which include ANN, KNN and SVM using 3 different datasets, fused data, Wi-Fi data and environmental data. The performance of the models has shown that ANN achieved the best result with 3.0 average RMSE, 2.3 average MEA and 32.2 % average MAPE.

### 5.3. Application of IoT in construction and building

One of the sectors that attracted several applications of IoT is the construction sector. Several houses are equipped with sensors such as temperature, gas leakage, light sensors, camera etc. which is term as smart houses. The use of wireless sensor is transforming smart homes. They play crucial role in sensing environmental parameters which include humidity, temperature, light air quality (such as dust levels and Carbon Dioxide ($CO_2$)). Electronic sensors are becoming hot topic nowadays especially in smart homes. They are used for several applications such as shading, controlling light and room climate. In order to monitor and save energy, scientists integrated IoT systems in homes and other buildings such as hotels, halls, offices etc. ([104,106]).

Home automation can be achieved by placing sensors at different locations around the building [107]. The raw data acquired using these devices can be process by transmitted through wireless connection or other data sharing or transmission platforms to a processor. The processed data can be further translated and transmitted back to the device or another device to be controlled automatically or to a user interference [108]. Several construction and architectural firms such as Intel and IBM have launched smart home buildings to the global market, demonstrating their advantage over conventional buildings. In order to understand how IoT is shaping smart buildings, there is need to review and understanding existing studies attempted to integrate IoT into the industry [109].

Al-Kuwari et al., 2018 [110] developed smart home automation system which is designed by integrating IoT system to allow monitoring and sensing of variables. The device architecture consists of Energy Monitoring and Content Management System (EMON CMS) which is employ for collecting and controlling of home appliances and devices and the use of microcontroller for both real-time data processing and sensing. Mandula et al. (2015) [82] proposed an IoT-based smart home automation system designed using a micro-controller-based Arduino board and Android mobile app. The authors developed two prototypes which include home automation system that use ethernet in an outdoor environment. This type of prototype utilized ethernet module which is used for connecting arduino board from any part of the world using IP address and port number. The second prototype use bluetooth in an indoor environment by establishing connection between smart phone devices and arduino which is an open-source system that can be utilize for prototyping any software and hardware and can receive data from sensor or input from keyboard and simultaneously control several electrical appliances connected to output peripherals [111].

### 5.4. Challenges

Integration of technologies for the development of smart homes is facing both direct and indirect challenges such as adoption of automation in construction sector, the need of large-scale data for AI and security and privacy challenges associated with IoT devices.

#### 5.4.1. Adoption of automation in construction industry

Adoption of innovation and automation in the construction sector is relatively slow and shifting away from conventional construction to automated construction has been facing difficulties due to high cost of machine, equipment and tools, the requirement of professionals or expert that can operate the tools, low technological readiness, lack of organizational support and awareness campaign, as well as lack of policy and regulatory considerations. However, despite the significant benefit of 3DP in construction and its potential or advantages such as speed, affordability, reducing construction errors, waste reduction, labour reduction, sustainability etc. One of the major or leading factor that limit the currents adoption of 3DP in many countries is that the construction sector is one of the direct sources of employment for millions of people ([34,112]).

#### 5.4.2. Privacy and safety

The landscape of IoT-based devices is gradually growing day by day and becoming more diverse in terms of production and applications. As a result, these devices are vulnerable to wide range of security and breach of privacy. Despite the fact that most of IoT devices require authentication as a way to safeguard the system, however, authentication process has shown to only safeguards against few threats or attacks. The application of IoT in smart building is greatly hindered by the issue of user privacy. The omnipresent connectivity of IoT-based devices to the internet and cloud system plays vital role in magnifying privacy concerns from users. Protecting people personal lives is crucial for the growing applications of IoT as well as developing confidence and trust of users [113].

#### 5.4.3. Lack of sufficient amount of data

Despite the growing of big data and other technologies such as cloud computing and data analytics, the application of ML in construction is still hindered by the lack of required amount of data. Development of automated and smart systems require the application of reinforcement ML which allow machine to learn by training and trial and error. The use of deep learning such as ANNs and CNNS require vast amount of data for higher performance. However, the use of transfer learning has shown addressed some of the challenges related to training using small amount of dataset and tediousness of developing model from scratch ([112,114]).

## 6. Conclusion

Technological advancements have significantly impacted the field of civil engineering, prompting a transformation in construction methodologies. Addressing challenges such as time reduction, material efficiency, and resilience to environmental factors and disasters has engendered interdisciplinary collaboration among scientists and engineers. Consequently, the development of 3D printing (3DP) systems has emerged as a promising solution. These systems, informed by integrated design models, exhibit rapid operational capabilities, facilitating the production of intricate shapes with reduced costs and labor inputs.

Moreover, the convergence of Internet of Things (IoT), Big Data (BD), and Cloud Computing (CC) has ushered in a new era of digitization within the construction industry. This integration offers multifaceted benefits encompassing social, technical, environmental, and economic dimensions. However, despite the potential advantages, several challenges impede the widespread adoption of these technologies. Foremost among these challenges are concerns regarding potential unemployment stemming from the automation facilitated by 3DP systems. Additionally, the scarcity of sufficient data for training Machine Learning (ML) models and the imperative to address security and privacy issues pose significant obstacles. Efforts to surmount these challenges necessitate a concerted approach involving academia, industry, and policymakers. Proposed strategies include the establishment of shared construction databases to facilitate ML model training and the implementation of robust authentication mechanisms to safeguard sensitive data.

Nevertheless, despite these challenges, the inevitability of the transition towards automated construction processes remains apparent. Consequently, proactive measures must be undertaken by governments and stakeholders within the construction sector to mitigate potential socio-economic impacts and ensure a smooth transition. In conjunction with 3D printing, Artificial Intelligence (AI) emerges as a pivotal enabler for optimizing design and construction workflows. Leveraging AI algorithms and big data analytics, innovative design solutions can be generated, prioritizing sustainability, energy efficiency, and material performance. Furthermore, AI-driven technologies offer enhancements in project management and construction operations, facilitating precision and efficiency through automated scheduling, resource allocation, and quality control mechanisms.

In conclusion, the integration of 3D printing, AI, IoT, BD, and CC represents a transformative paradigm within the construction industry. Despite the challenges posed, collaborative efforts and proactive interventions can facilitate the realization of a more efficient, sustainable, and technologically advanced construction ecosystem.

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## CRediT authorship contribution statement

**Badr Saad Alotaibi:** Conceptualization. **Abdulsalam Ibrahim Shema:** Writing – review & editing, Writing – original draft. **Abdullahi Umar Ibrahim:** Methodology. **Mohammed Awad Abuhussain:** Validation. **Halima Abdulmalik:** Methodology. **Yakubu Aminu Dodo:** Writing – review & editing. **Cemil Atakara:** Writing – review & editing.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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