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Research Article

Artificial intelligence and internet of things based construction planning management system with multidimensional construction planning

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ABSTRACT

In the construction industry, cost control, resource inefficiency and schedule delays have been persistent challenges especially in large and complicated projects. The available systems of management are inflexible and do not use real-time data, which leads to sub-optimal decisions. To mitigate the drawbacks, the proposed study conceptualizes an AI- and IoT-based building planning management system that makes use of multidimensional planning to enhance forecasting, resources distribution, and risk evaluation. IoT sensors monitor real-time information about the costs, time and resource consumption, and the information undergoes processing by sophisticated models of AI, which are Support Vector Machines and Convolutional Neural Networks. The methodology involves the selection of features through Genetic Algorithm, preprocessing of the data, and the evaluation of performance on the basis of MSE, MAE, and the R 2. It was found in the experiments that the SVM model had the MSE = 0.00093, MAE = 0.022 and R 2 = 0.892, which had a high predictive power and the CNN model had MSE = 0.00107, MAE = 0.024 and R 2 = 0.876. The originality of this study is to integrate real-time IoT information with AI-based multidimensional optimization, and provide a flexible, scalable, and intelligent construction planning system that is highly efficient with minimization of risks in the project.

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INTRODUCTION

The construction industry is one of the most hazardous owing to numerous unforeseen factors involving human components and an unpredictable weather cycle surrounded by high uncertainty. Most countries experience rapid urban and industrial growth, and this factor alone

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makes it very difficult to reduce the incidence of injuries and accidents on construction sites. The most common types of accidents include falls from heights, impacts, abrasions, and electric shocks [1, 2]. The rates of fatal accidents in the construction industry are higher compared to other industries, accounting for 30.44–40.06% of deaths globally [3]. The rates of non-fatal mutilation in the building sector are 71.51% higher compared to various other industries [4]. The main factors responsible for injury rates include poor employee training, a lack of awareness of hazards among project managers, and injudicious behavior on the part of the employees. Artificial intelligence refers to the ability of a computer system to learn, reach decisions, and perform tasks that are normally associated with human intelligence [5].

Artificial intelligence incorporates mathematical calculations, psychological elements, neuroscience, cybernetics, and many other fields. AI technologies help develop software and algorithms to employ computers capable of solving problems autonomously [6]. Approximately 7.23% of the entire global workforce is employed within the construction industry [7]. Despite its importance to the economy, one of the industry's salient problems is the limited productivity of workers, causing inefficient utilization of skilled and unskilled labor, materials, and monetary value [8]. Since construction activities are essential for societal development, effective management of construction must be task-specific to improve productivity [9]. A predicted gain in construction efficiency of 50.11–60.05%, or more, should allow the construction industry to earn an additional RUB 1.6 trillion in the annual economy and provide a significant contribution to GDP on a global scale [3, 10]. Figure 1 illustrates the major applications of Artificial Intelligence (AI) in the construction industry. AI supports critical functions such as project planning and scheduling, cost and duration estimation, contract management, and logistics optimization. Additionally, it enhances site layout selection, traffic and accident management, and real estate valuation, leading to improved project efficiency and decision-making.

The development of Internet of Things (IoT), and mobile communication technologies has made the management and maintenance of the platform of the intelligent IOT more intertwined with human interaction making the interaction between people and objects [10], and among objects more important [11, 12]. The resultant intelligent IOTs operation and maintenance platform is therefore a response to the modern demands. A smart operation and maintenance system of the IOT, namely the management based on the IoT, is built upon several application support platforms and fully incorporates the management and technical technology [13].

The use of modern technologies like AI, IoT, and Building Information Modeling (BIM) is changing the way construction is managed by providing new ways to improve efficiency, lessen delays, and optimize resources. The

Figure 1. AI applications in construction planning.

researchers Hongda et al. (2024) [14] designed an appraisal model concerning the intelligent construction management at multiple levels and dimensions by applying AHP technique and Entropy weighting techniques. An intelligent construction management level assessment model has been recommended by this research where the criterion for appraisal is established using the cloud theory. It has become evident from this model that the structured multidimensional planning could prove instrumental in improving the efficiency of the project. Piras et al., (2024) [15] have further suggested that those methods which involve DT-BIM-IoT along with AI algorithms should be scalable as well as adaptable for any project. As far as the contribution of AI in projects is concerned, it has been highlighted by Pan et al. (2023) [16] that the developments like deep learning and digital twins along with AI hasten the decision-making and project automation process.

The introduction of IoT technology brings the ability to achieve real-time connectivity between structural parts and the whole inventory of the objects in projects. Mazhar et al. (2022) [17] proposed that smart grids and sensors could be incorporated into big networks at the construction sites to implement smart construction systems and adaptive management. On the other hand, Sardianos et al. (2020) [18] and Himeur et al. (2022) [19] analyzed the highly dimensional datasets created by BAMS, and explained how AI analytics was able to process this information to identify patterns in the data. AI analytics could target complex variables in the dataset in accordance with the research conducted by Quinn et al. (2020) [20] and Muntean et al. (2021) [21]. It is worth noting, however, that most cases require significant infrastructure to make analytics more effective. Varlamis et al. (2022) [22] also mentioned the issue of obsolete systems and the necessity to introduce innovations to be able to apply the whole spectrum of analytics and IoT. Moreover, IoT is of extreme importance for monitoring and allocating resources due to the capability to provide current data on construction processes. Lastly, Althoey et al. (2024) [23] explained how IoT was implemented in Malaysia to help perform proactive maintenance, optimize resource usage, and improve workflow. Indeed, all those technologies enable multidimensional planning.

The construction industry is subject to numerous and complex issues such as cost escalation, resources unavailability, and timing issues, most of which are as a result of the growing complexity of structures, as they provided in the above studies [24]. The existing project management systems do not facilitate flexibility in project work

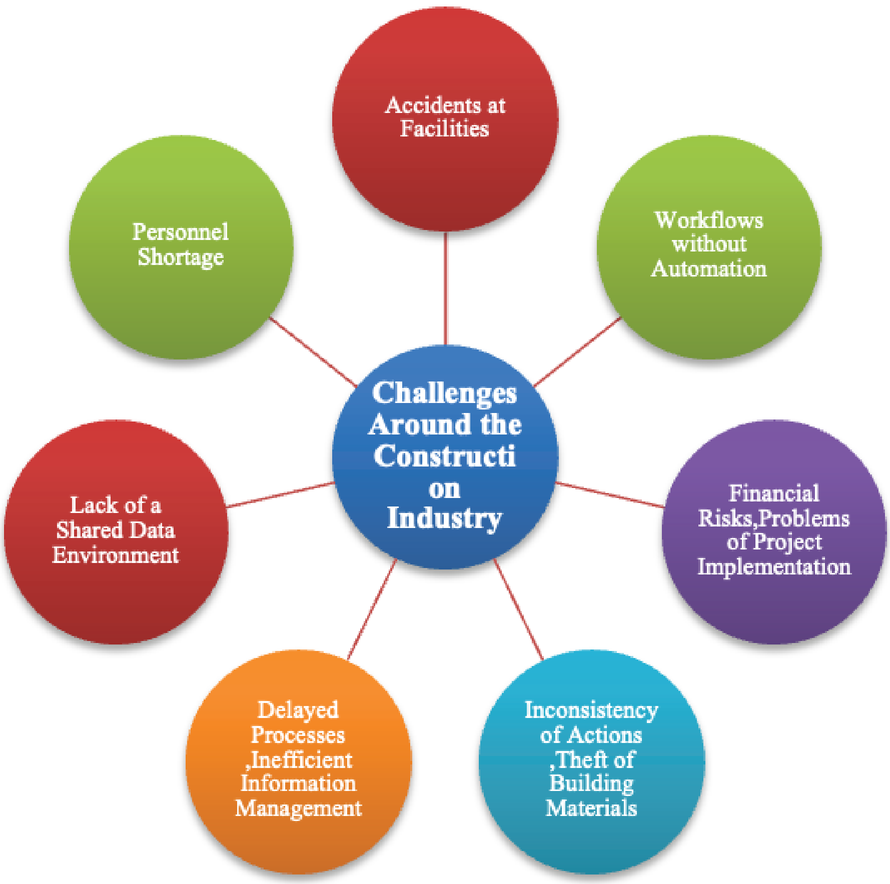

Figure 2. Key problems of construction industry.

environments and do not fully utilize online data. Both AI and IoT have radical opportunities in dealing with these problems. IoT sensors capture time-bound information about the occurrence of the project, the resources consumed, and the existing environment and the AI algorithms analyze this information to offer a solution [25]. This integration will allow polygons or multiple plans, meaning that more than one component of the project, including resources, time, and risk factors among them; can be done in a single plan [26]. This research seeks to establish a conceptual model to design an efficient and economical construction planning management system supplemented by the integration of AI and IoT that delivers better performances and shortens the project delivery period [27]. Figure 2 presents the major challenges faced by the construction industry that hinder project efficiency and productivity. Key issues include accidents at facilities, workforce shortages, workflow inefficiencies, financial risks, delayed processes, and lack of a shared data environment. Addressing these challenges through advanced technologies and improved management practices can significantly enhance project performance and operational effectiveness.

Artificial Intelligence in construction denotes the use of computer systems and algorithms to execute intricate building and construction management activities [28, 29]. AI technologies are anticipated to dictate the developmental prospects of the construction sector in the forthcoming years. During the second decade of the 21st century, several digital technologies, such as augmented reality (AR), IoT, and quantum computing, were amalgamated with AI to address challenges within the construction sector [30, 31]. In recent years, the machine learning study of the construction sector has concentrated on the development and application of diverse methodologies: uncertain, mathematical, and financial methods, encompassing formal reasoning, computational optimization, and ANN, collectively termed architectural AI. The advancement of the construction sector was influenced by the intricacy of the technologies used [32]. Figure 3 presents a hierarchical framework illustrating the progression from construction data sources to Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) technologies. These computational techniques enable intelligent analysis, prediction, and decision-making using data collected from IoT devices, BIM models, sensors, and construction databases.

This research responds to issues like cost control, resource misuse and time optimization which are traditional vices in conventional project management structures [33, 34]. This research is developed out of the increasing large and highly evolved construction projects that do not conform to rigid office based static planning. AI and IoT allow data to be collected and analyzed in real-time and planning is viewed from multiple-dimensions [35]. The purpose of this study therefore resides in its unique

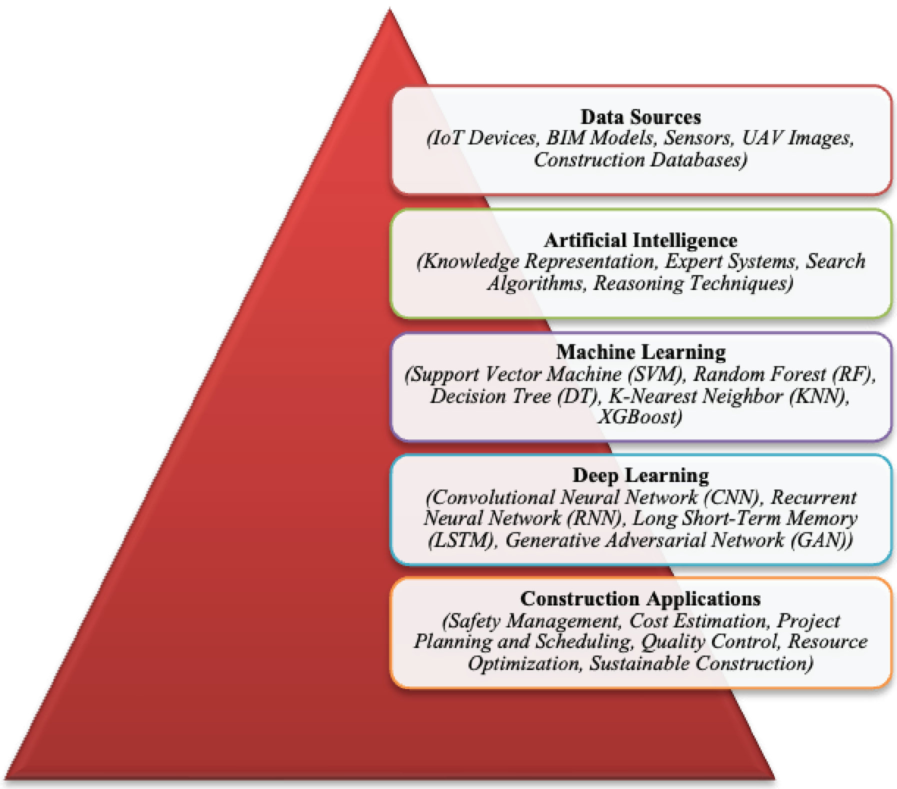

Figure 3. AI and IOT in smart building.

opportunity to provide construction management solutions that are flexible, comprehensively informed, and efficient which can effectively respond to the dynamic needs of the construction industry and foster improved performance through management of time and costs. The objectives of this research are as follows:

i) To determine the way that resources can be used efficiently for construction projects
ii) To develop an AI-integrated system utilizing ML, DL, and optimization algorithms for predictive and adaptive decision-making in construction planning and management.
iii) To compare the efficiency of AI-driven construction planning systems with traditional methods by measuring such as MSE, MAE, and R^2 score.
iv) To improve the management of risk factors for construction projects.

This paper seeks to propose a new construction planning management system that includes the impact of Artificial Intelligence and IoT (Internet of Things), expanding the multidimensional approach to conduct project planning. The system takes IoT sensor data into account in its automated tracking of critical characterisations in the construction project, such as inventory levels, machinery utilisation or emplary conditions. All data is processed for the purposes of AI algorithms that can deploy predictive scheduling, improve resource problems and address risk. These levels of planning can contribute to better project planning by incorporating real-time data and flexibility in resources used, which will lead to increases in general project productivity. If using a multidimensional optimization approach, the framework can address more complicated issues of resource, time, and risk interdependence in order to create a comprehensive solution. The innovation in this research study is in suggesting a new intelligent approach which can be scaled into the next generation of construction planning projects. Major contributions of the research are:

i) The research highlights the use of IoT and AI to facilitate effective construction planning.
ii) This research gives a detailed analysis of the performance of both SVM and CNN models by showing their high precision, minimal MSE value, and high R^2 and minimal MAE value.
iii) This study compares the performances of SVM and CNN models and establishes the superiority of the SVM model in terms of MSE, MAE, and R^2 scores.
iv) The error distributions of the SVM and CNN models have been analyzed to establish the consistency of predictions. It is found that CNN models provide more consistent prediction results compared to variable SVM predictions.

Despite substantial advancement in applying AI, IoT, BIM, and digital twin technologies in construction management, there are still gaps in the research findings, making the practicality of these solutions difficult to implement. Most of the research papers cover individual parts like resource allocations, delay reductions, or automations while ignoring the possibility of creating an overall real-time, multidimensional construction planning system that incorporates all these aspects. Also, none of the researches have covered the possibility of combining predictive AI models and real-time IoT data in order to make consistent improvements in schedule, risk management, and resource dependency. It is necessary to develop a framework that integrates the use of real-time sensor inputs with predictive AI models in order to optimize dynamic decision-making processes. Since the construction projects are becoming increasingly complex and dynamic, a flexible solution rather than a static one is required. To achieve this goal, future research must focus on developing an integrated system that uses scalable data pipelines, along with intelligent optimization techniques capable of learning from continuous IoT data. The innovative nature of this research is in the creation of a fully connected AI-IoT framework that not only utilizes SVM and CNN models for outcome predictions but also optimizes them using GA-based feature selections.

The paper is organized as follows. First, the introduction, literature review, and gaps in the previous studies will be discussed in Section 2. Section 3 covers the methodology of analysis, including data collection and feature acquisition as well as model selection. Lastly, in Section 4, the research results will be presented and Section 5 concludes the discussion.

Research Methodology

In the methodology of the AI and IoT-based Construction Planning Management System, both the historical and the real-time primary data will be used. For instance, IoT platforms such as Procore will provide relevant real-time primary data. The method involves preprocessing operations including feature selection using optimization, data cleaning via imputation, and data normalization using MinMaxScaler. Then, advanced AI models such as SVM for predictive analytics, CNN for pattern recognition, and for optimization will be utilized within the methodology. Lastly, the approach will concentrate on performance evaluation considering KPIs like MAE, MSE, resource utilization, and risk mitigation to ensure efficient planning, decision making, and project management. Figure 4 represents the proposed methodology framework.

Thus, the novelty of this research resides in creating an AI-IoT-based multidimensional system for construction planning beyond fragmented approaches from existing literature. In contrast to previous studies focusing on single issues including delay prediction, resource tracking, and BIM automation, the study proposes a comprehensive framework that combines IoT sensing in real-time, feature optimization via GA, and AI prediction models-SVM and CNN for dynamic construction planning. In other words, the proposed system will enable continuous data-driven changes in terms of cost, duration, and resources, leading to highly accurate and adaptive decisions regarding construction planning.

Data Collection

Real time data

The real-time data collection process to obtain primary data from the Procore IoT-based construction management system [36], which has IoT-based monitoring capabilities to track on-site activity, was performed. In total, there were three data sets that corresponded to the major predictors of the analysis, Cost, Duration, and Resources, which were provided in detail by the corresponding IoT sensors.

For the IoT Network, the following sensors were connected and the frequencies defined as follows: High frequency sensors (runtime of equipment, employee presence beacons, and material dispensed) at one reading per minute. The low frequency sensors, which include environmental conditions such as temperature and humidity, will read once every five minutes. The cost and schedule updates would occur every hour using the project accounting tool in Procore.

The total number of data points was 18,720, which spanned two weeks of data collection. The data set comprised about 10,080 equipment and resource data points, 5,040 environmental data points, and 3,600 cost duration records, all after pre-processing and elimination of any missing values. The split was 70%, 15%, and 15% for training, validation, and testing of the SVM and CNN models respectively.

Data Preprocessing

Feature selection

Inadequate data may compromise design correctness and make the model ineffective in examining these minor components. Consequently, the issues related to feature selection are framed as an optimization problem designed to discover relevant attributes.

Data cleaning

Mean and median interpolation is a technique used to fill data gaps by substituting the missing data with the corresponding average and central values, respectively. Below are detailed descriptions of each method, along with their corresponding mathematical equations: Below are detailed descriptions of each method, along with their corresponding mathematical formulae:

- ***Mean imputation:*** Data imputation is the procedure of substituting values that were missing in information set with the average value of the existing data. Mean imputation replaces missing values with the numerical averages of other values in a column or defined rows

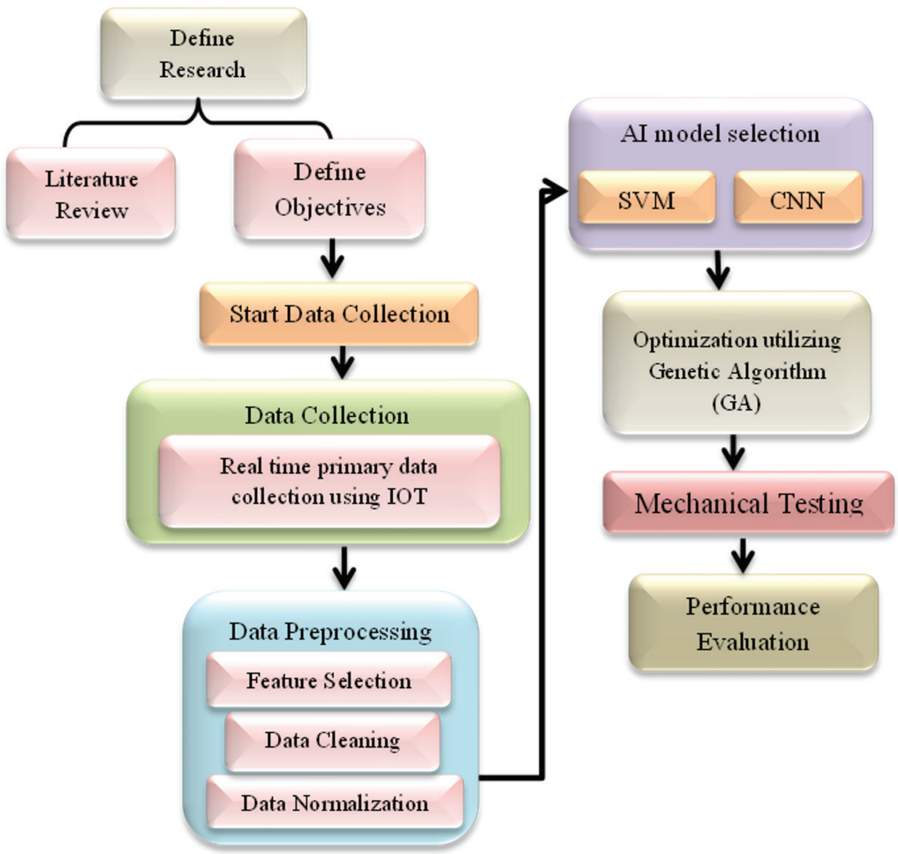

Figure 4. Proposed framework.

or situations. Taking the assumption that missing values occur randomly, this procedure is straightforward.

$$Mean = \frac{\sum_{i=i}^{m} y_i}{m} \tag{1}$$

The variable y_i is defined as each integer in the column that is not absent, and m represents the total count of these values.

- ***Median Imputation:*** The method of interpolation replaces the missing value by using the median of the other values for each of the columns or dependent variables. Interpolation is more resistant to outliers than mean imputation and therefore may be preferable in certain scenarios.

$$Median = Median\ (\{y_1, y_2, y_3, \ldots \ldots, y_n\}) \tag{2}$$

The set $\{y_1, y_2, y_3, \ldots, y_n\}$ consists of all of the characteristics in the row, except the omitted attributes.

Data normalization

The MinMaxScaler is a very efficient scaling method employed to tailor the range of characteristics or data to a predetermined interval, usually ranging from 0 to 1. This method maintains the imbalance and peak end characteristics of the initial distributed while simultaneously modifying the spectrum of the data. The technique of data normalization is employed to convert features within a predetermined range. This scalar implements a standardization method on features by rescaling each feature to a predetermined range, typically [0, 1] or [-1, 1], determined by the attribute's lowest and highest values.

The MinMaxScaler algorithm applies the following modification to every feature x listed in the dataset:

$$V_{scaled} = \frac{V - V_{min}}{V_{max} - V_{min}} \tag{3}$$

The variables V_{min} and V_{max} indicate the minimum and maximum values of the features V and x, respectively, in the dataset.

AI model selection

For a more effective decision in construction planning and construction management, the application of Artificial Intelligence (AI) through Machine Learning (ML), Deep Learning (DL) and optimization algorithms are crucial. AI techniques help in effective management of large data that can in turn improve decision making, enhance efficient use of resources and in addition predict possible risk or a project delay. Below is a detailed explanation of the methods employed:

Machine learning model

Support vector machine (SVM)

Support Vector Machines (SVMs) are a specific type of supervised learning models that use specialized learning methods to evaluate and classify data. SVM regression methods strive to find a model that closely approximates the data that has been observed, using parameters that minimize the likelihood of errors, instead of pursuing a hyper plane that separates the data. The goal of the SVM is to maximize the provided equation:

$$Maximize_{\alpha_i} = \sum_{i=1}^{m} \alpha_i - \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j \beta_i \beta_i < y_i y_j > \tag{4}$$

In equation (4), the vector $< y_i, y_j >$ can be derived using various kernels such as the "Radial Basis Function" (RBF)" and "Sigmoid kernel" [37].

Deep learning model

Conventional neural network (CNN)

CNN comprises many sorts of layers. The input layer retains unprocessed data, while the convolution layer generates volume using the dot product of filters and information patches. The "Activation Function" (AF) layer implements an element-wise activation function on the output of the first or convolutional layer (C1 & C2). The pooling layer (P1 & P2) decreases volume and enhances computing efficiency.

This model will use categorical scores in stochastic form to determine the probability of classification. The strengths of CNNs lie in their ability to identify correlations in data, which makes object identification possible. The reduction of the input image size decreases training parameters and the time taken for training. In this research, we applied the DLNN approach to the Wisconsin BC dataset. Here, a neural network is used for analyzing the biological process of a human being. In this study, we need to supply inputs and receive outputs. These are the parameters used [38].

$$U = \frac{1}{n} \sum_{i=1}^{n} u_i \tag{5}$$

Machine learning model

Support vector machine (SVM)

The SVM model is highly effective in regression-based prediction for small-sized and large-dimensional datasets in construction prediction modeling. On the other hand, the CNN algorithm is very capable in detecting nonlinear relationships in multi-dimensional planning data. Both the SVM and CNN algorithms deliver highly accurate predictions with low computational complexity, which makes them ideal for IoT applications. While the LSTM, XG Boost, and RF machine learning algorithms were considered theoretically, their implementation was not possible due to lack of sequential data and interpretability issues.

Optimization utilizing Genetic Algorithm (GA)

Genetic Algorithms (GAs) mimic nature selection and genetic systems, and therefore they are useful in feature selection applications such as CKD detection in machine learning. In a GA, a population of potential solutions – which are binary strings, encodes subsets of features. The feature selection process uses CKD prediction images, which are:

$$[W_{p\times x}]=\left\{\{k_1^1, k_2^1, \dots k_x^1\}, \{k_1^2, k_2^2, \dots k_x^2\}, \dots, \{k_1^p, k_2^p, \dots k_x^p\}\right\}, \quad (6)$$

In this context, the symbol [W] denotes the word embedding, while k_x^p indicates the xth aspect of the pth prediction [39].

Here the bits of the string translated directly to the features: the value of '1' means inclusion, and the value of '0' means exclusion. The fitness of each individual in the population is then assessed using a pre-determined fitness function and these can be other factors such model accuracy. Fitness can be calculated using the formula:

$$Fitness = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

There are four principal stages in the GA process, and these are selection, crossover, and mutation. The chosen solutions generate new solutions (offspring) according to their fitness value - a higher fitness value increases the reproduction probability. In the selection process, the fittest individuals are selected to produce the next generation, by application of method such as roulette wheel or tournament selection. Crossover involves choice of selected two individuals and interbreeding to produce children while mutation involves random alteration to do away with stagnation of genes.

Although the study used a standard configuration such as a population size of 30, crossover probability of 0.8, mutation rate of 0.05, and a stopping criterion of 50 generations or fitness convergence. Through this optimization, GA consistently selected Cost, Duration, and Resources as the most significant features for accurate construction planning predictions.

Performance Evaluation

Key performance indicators (KPIs)

Efficiency: Measures how effectively the system completes tasks compared to traditional methods.

$$Efficiency = \left(\frac{Time\ for\ time\ completion\ (Traditional)}{Time\ for\ task\ completion\ (Proposed\ system)}\right) \times 100 \quad (8)$$

A higher percentage indicates better efficiency. If the proposed system takes less time, the ratio increases.

Mean Squared Error (MSE): MSE is a measure of the average squared differences between the actual and predicted values. It penalizes larger errors more heavily.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

Where y_i is actual value, $\hat{y}_i$ is predicted value and n is number of data points.

Mean Absolute Error (MAE): The Mean Absolute Error measures the average of the absolute differences between the predicted and actual values. It provides a straightforward measure of prediction error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (10)$$

R² Score (Coefficient of Determination: The R^2 Score measures the proportion of the variance in the actual values that is predictable from the model. A value close to 1 indicates a well-fitting model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (11)$$

Where $\bar{y}$ is mean of actual value.

RESULTS AND DISCUSSION

Experimental Setup

All trials are conducted on Google Colab using a setup including an Nvidia Tesla K80 GPU with 12 GDDR5 VRAM and Intel Xeon CPUs featuring two 2.20 GHz cores with 13 GB of RAM. The study omitted the creation of novel machine learning algorithms using the Sklearn1 package and other Python platforms.

Experiment Result

Table 1 represents the key features and performance metrics of GA-Optimized SVM used in an AI and IoT-based construction planning management system. The model uses three key features as identified by the Genetic Algorithm (GA): 'Cost,' 'Duration,' and 'Resources,' which are very crucial for efficient management of a construction project. Different evaluation metrics are used to measure how the model performs. MSE, at 0.0011, is very low with an error between predicted values and real values; R2 of 0.876 shows that there was strong correlation between actual and actual outcomes from the model prediction; the MAE of 0.024 shows that it had low average deviation from the actual values. These metrics indicate that the GA-Optimized SVM model is very effective in giving accurate and reliable predictions for construction planning tasks, which allows for better decision-making in project management.

The performance Metrics of the CNN model utilized in AI-IoT-based multi-dimensional system for construction planning management have been displayed in Table 2. The

Table 1. Selected features and performance metrics for the GA-optimized SVM model

Feature	Value
Selected Features by GA	['Cost', 'Duration', 'Resources']
Mean Squared Error	0.001075065
R2 Score	0.875868917
Mean Absolute Error	0.023973268

Table 2. Performance metrics of the CNN model optimized for AI and IoT-based multidimensional construction planning management

Feature	Value
Selected Features by GA	['Cost', 'Duration', 'Resources']
Mean Squared Error	0.0009317885
R2 Score	0.8924121690
Mean Absolute Error	0.0223818404

model had been optimized for the selection of the three major features— 'Cost,' 'Duration,' and 'Resources,' which were arrived at through GA-based optimization, as these are crucial for the effective management of construction projects. The performance of the model is measured through three main metrics: a Mean Squared Error of 0.00093 which means that the prediction error is extremely low; an R2 score of 0.892 which indicates a very good match of the predicted data with the actual one; and a Mean Absolute Error of 0.022 that signifies a tiny average deviation from the true values. These results show that CNN model provides highly accurate prediction, which offers great values in optimizing construction planning through using AI and IoT technologies with more efficient decision-making and better resource management.

Comparative Analysis

This section compares AI and IoT-based construction planning management systems with traditional methods using predefined metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and cost efficiency. AI-driven systems, especially those using advanced models like CNNs and SVM, are compared with each other and with previous researches.

Table 3 shows the two models that have been used in the implementation of the construction planning management system, and the two models are the Support Vector Machines (SVM) and Convolutional Neural Networks (CNN); the SVM has the Lower Mean Square Error (0.0009317885) and Mean Absolute Error 0.0223818404 compared to CNN. Moreover, the SVM has a higher R^2 Score of 0.8924121690 compared to the CNN, which achieves 0.875868917. These results show that while both of the models work perfectly, SVM shows a bit higher accuracy and reliability for

Table 3. Comparison of performance metrics between SVM and CNN for predicting construction planning

Features	Mean Squared Error	R2 Score	Mean Absolute Error
SVM	0.0009317885	0.8924121690	0.0223818404
CNN	0.001075065	0.875868917	0.023973268

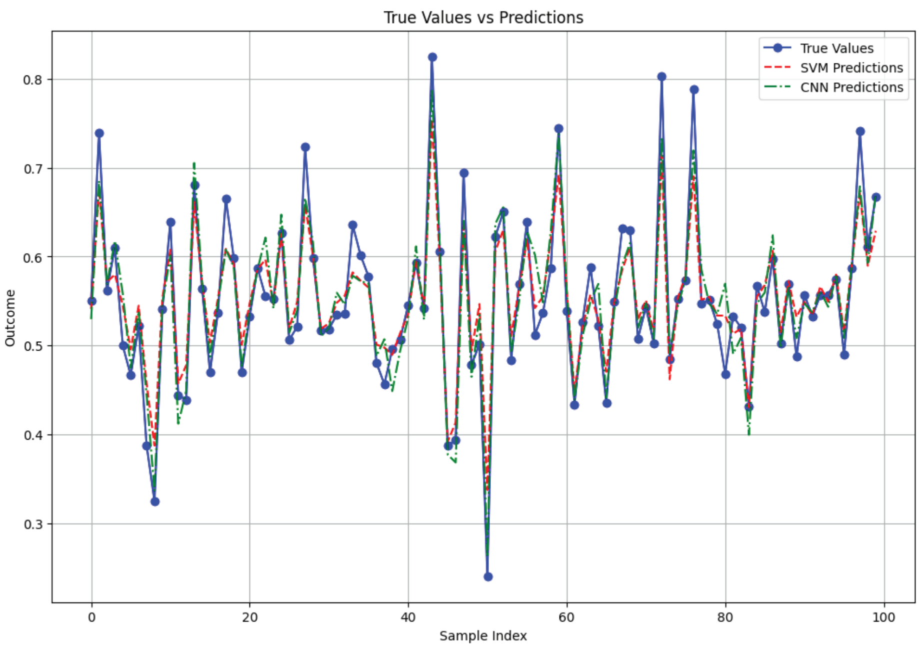

Figure 5. Comparison of true values with SVM and CNN predictions for construction planning outcomes.

prediction purposes concerning resource allocation and scheduling in multidimensional construction planning.

Figure 5 presents a graph which shows the comparison between the actual outcomes and the predictions of SVM and CNN models in an AI and IoT-based construction planning management system. The blue line represents the true values, while the red dashed line and green dashed line represent the SVM and CNN predictions, respectively. The closeness of both prediction lines to the true values indicates that models are closely aligned, and this ability of SVM and CNN capture underlying patterns well. Thus, this visualization depicts the ability of models to track variation in multidimensional construction planning output to make accurate decision-making procedures.

Scatterplot in figure 6 shows the relation between actual and predicted results for both the support vector machine and convolutional neural network models. The red and green circles represent the results from the SVM and CNN models, respectively, while the blue dotted line represents the perfect prediction line. The dots that fall closely along

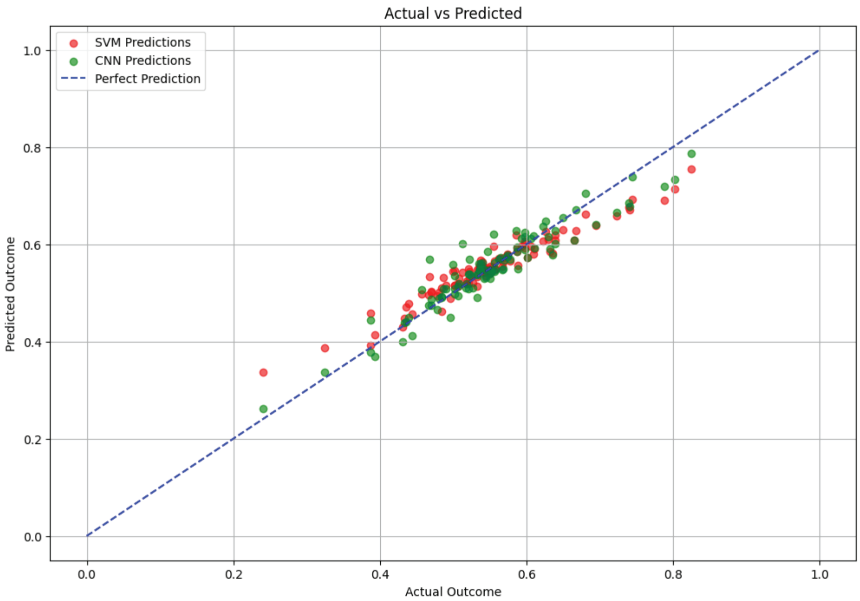

Figure 6. Scatter plot of actual vs predicted outcomes for SVM and CNN models.

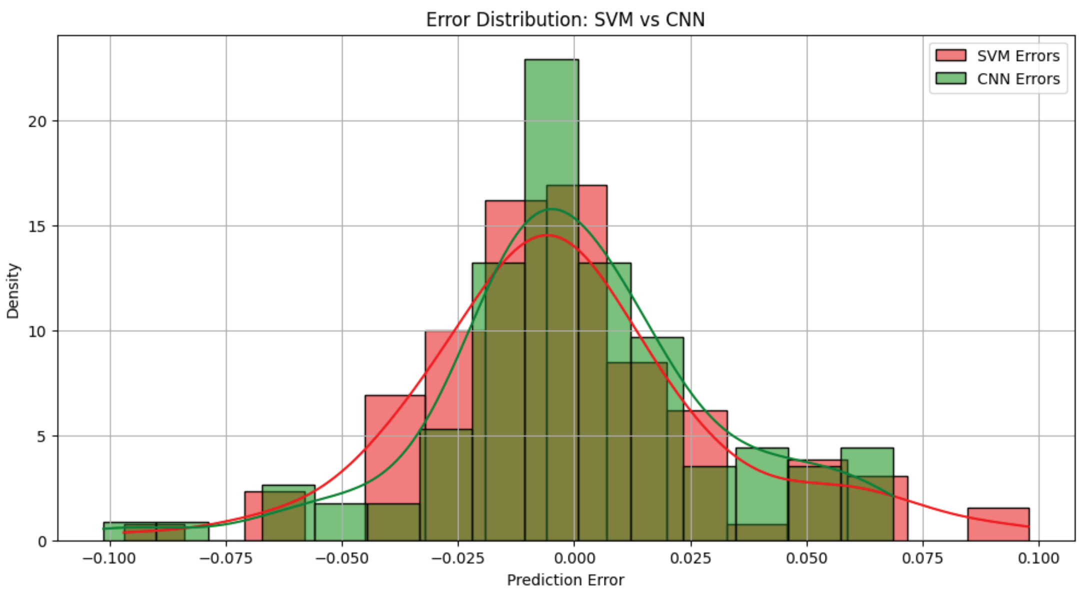

Figure 7. error distribution comparison of SVM and CNN models for classifying the construction planning accuracy.

the dashed line indicate accurate outcomes, while those that fall away from the line indicate a prediction error. Both models show good agreement with the actual outcome; although, some marginal differences can be detected. This comparison also shows that AI models are valuable predictors of construction outcome, which adds to the original idea to help be more efficient through better planning, in the context of an AI and IoT based multi-dimensional construction management system.

Figure 7 illustrates the error distributions between the SVM and CNN models, represented here by red and green histograms, and their density curves. It can be implemented on the planning management systems for AI and IoT in the construction industry that involves tasks related to allocation, scheduling, and risks. The margin of error distribution of SVM is larger as compared to CNN. It means that the error variation in the prediction of SVM is higher whereas the error distribution of CNN is much smaller in contrast. Overall, this comparison highlights the better suitability of CNN for multidimensional construction planning due to learning complex patterns of data. Reduction in prediction errors may lead to effective decision-making in the smart planning management system for construction.

CONCLUSION

In conclusion, the construction planning management system based on AI and IoT introduced in this study offers an innovative solution to the major aspects of construction management. The system involves collecting real-time data from IoT sensors and providing advancements concerning AI methods such as machine learning and deep learning to improve forecasts, control quantity usage, and manage risks. The empirical results demonstrate the proposed system was effective, with the SVM model achieving reasonable accuracy (MSE = 0.00093; R^2 = 0.892) and supported reliable estimates from the CNN model (MSE = 0.00107; R^2 = 0.876). As these results indicate, the system provides the potential to reduce schedule delays, control costs, and enhance efficiency of the construction planning process to be more adaptable and flexible. Therefore, this study is positioned to foster the evolution of smart construction management that offers a non-fixed, adaptable approach to addressing the complex and multi-dimensional features surrounding current and future large-scale construction projects, while improving performance and mitigating risks.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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