A Hybrid AI-Based Risk Assessment Framework for Sustainable Construction: Integrating ANN, Fuzzy Logic, and IoT

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***Abstract*—The construction industry is central to the advancement of economic growth all over the world but it has various problems in risk management especially concerning sustainable construction projects. Standard risk management techniques like AHP and Monte Carlo simulation do not afford the flexibility and accuracy needed in construction sites. Based on the identified limitations, this study offers a new system of risk assessment that combines Artificial Neural Networks (ANN), Fuzzy Logic, and Internet of Things (IoT) technologies. Real-time IoT sensor data and historical project data are integrated into a real-time and adaptive system which can identify, suggest, and minimize potential risks for improved decision making. The ANN component is distinctive in pattern recognition and risk prediction while Fuzzy Logic brings ease of interpretation and reasoning in the uncertain environment. Raw IoT data are live data which may be processed and updated frequently relative to the devices and their environment. The effectiveness of this framework can be ascertained through experimental proof; the framework's accuracy is 92.7%; project delay and cost have been minimized. The results reveal that the presented framework is highly resistant to noise, and its performance changes fairly slowly if the project requirements change. This integrative approach ensures the identification of the comprehensive solution for the sustainable construction risk management, which may help with the development of the safer, more efficient and non-harmful to the environment construction techniques.**

Keywords*—*Risk assessment; sustainable construction; artificial neural networks; fuzzy logic; predictive analytics

I. Introduction

The construction industry remains a significant industry of global economic growth and development since most of the world economy relies on employment, infrastructure, and GDP [1]. Sustainability has emerged as an essential consideration in construction projects, which means that they have to respond to the consequences of environment on them as well as on society and the challenges of integrating contemporary technologies [2]. Green construction projects that embody efficiency and utilization of resources, minimal energy wastage and environmental impacts offer projects that are hard to evaluate using conventional risk assessment models.

The conventional risk assessment tools including the AHP and Monte Carlo Simulation are historical based and rely on the experts, crew and are manual in nature [3]. Even though such methods have been proven useful for decades they lack the ability to solve the flexible and intricate problems of the contemporary construction business. For instance, these approaches cannot easily respond to the dynamic environment characteristic of construction sites, for instance, material unavailability, unfavorable climate, or delays due to the supply chain [4]. In addition, decisions made from these models rely on human intuition hence are characterized by subjectivity; this causes inconsistency.

AI has revolutionized one field or the other by offering more sophisticated means of data processing, forecasting, and control. In construction industry, risk assessment using AI approaches such as Artificial Neural Networks (ANN) has been shown to offer a high level of rate prediction [5]. These models perform best when the need is to analyze big data, recognizing patterns, and providing risk assessments. Nevertheless, despite their strengths, AI methods that are implemented independently of each other can encounter such issues as lack of interpretability, as well as inability to work with conditions characterized by uncertainty [6]. For instance, the application of ANN models can be compared to "black box", which means that it is hard for stakeholders to trust the model completely [7]. Bridging IoT into construction projects enhances risk management in that crucial indexes including environment, equipment, and materials can be monitored and controlled in real-time. IoT devices create massive data and analytics with AI-driven models bring solutions for risk prevention [8]. But the use of these technologies can only be managed through an approach that sits somewhere in between conventional and fully automated methodologies, which have their own drawbacks [9].

This paper brings forward a new, integrative AI-based approach that combines the ability of ANN to make predictions with the capability of Fuzzy Logic to reason and the constant flow of data from IoT sensors. The proposed framework has been designed to address the limitations of the current risk assessment tools to provide an as dynamic, adaptive, and interpretable solution for risks governance in the construction of sustainable projects. These technologies are incorporated into the framework to enable precise predictions, constant updates, and useful information thus improving project productivity, safety, and sustainability.

The remainder of this paper is organized as follows: Section II provides a literature review of conventional and advanced AI-based risk assessment tools. Section III describes the proposed methodology. Section IV also gives an account of the performance of the proposed framework against conventional approaches. Results is given in Section V. Last, Section VI concludes and recommendations for future research in Section VII.

II. Related Work

Risk assessment of course remains an important factor in project management especially when it comes to sustainable construction [10]. Risk management is the process of identifying potential dangers that can occur at different phases of construction projects and which are critical to guaranteeing safe delivering of the project at a moderate cost within the stipulated time. Risk management of construction projects increases in sophistication as the project gets more complicated and provides project managers with tools to consider potential problems and control them [11]. This section seeks to examine the current trends concerning risk assessment, particularly with regard to conventional approaches, the use of artificial intelligence, integration of IoT solutions, and the blended solutions, with the primary purpose of identifying the strengths, weaknesses, and applicability to the current construction industry those approaches display.

A. Conventional Approaches of Risk Evaluation

Conventional risk assessment has been in practice for many years, and there is evidence of its utility in the construction industry. These include the Analytical Hierarchy Process (AHP), and Monte Carlo Simulation are standard approaches for assessing risk, measuring the probability of occurrence and estimating the effect [12]. Although these approaches have been widely used in different fields, they have some drawbacks when being implemented in contemporary construction projects.

1) Analytical Hierarchy Process (AHP): Decision making involves breaking of large problems into smaller easier to handle tasks and Analytical Hierarchy Process (AHP) is an example of structured decision making. It entails recognizing the parameters that are used in decision making and ranking them against each other and putting a score on each parameter [13]. In the construction risk assessment framework, AHP is useful in assessing the significance of various risks including the environmental risks, the financial risks and the scheduling risks. Among the strengths of the AHP, the first one is its simplicity and flexibility of application. Not only it provides qualitative information, but also quantifiable information that can be used to make quite reasonable decisions by the project managers [11]. The process is systematic meaning that there is a way of approaching it which enables one to have order of ideas in mind and order of importance. Nonetheless, compared with other methods, the weakness of AHP is that it depends on the assessment of the opinion of some experts and needs to estimate the relative weight of some factors, which may differ greatly or be biased due to the same reason [14]. However, AHP is not efficient in real-time operating contexts or where new risks come frequently and continuously as it is not developed to process a large amount of data or adjust to changes immediately.

2) Monte carlo simulation: Another traditional technique used in risky construction projects is the Monte Carlo Simulation. The best use of it is that it is capable of using probabilistic modeling which enables it to predict various probable outcomes based on a set of input possibilities [15]. Monte Carlo offers a quantitative assessment of possible impacts, or threats, that project managers need to envision in order to avoid mismanagement of resources, time or financial constraints.

Monte Carlo Simulation has one of the most significant advantages of dealing with uncertainty and variability in risk aspects. It enables a project manager to examine a number of possibilities, which helps that person to have a better understanding of what may happen and the chances of it occurring [16]. But as with practically all methods, Monte Carlo Simulation is not without its drawbacks. The method is quite dependent on past data and forecast on the future hoy and may not reflect the current circumstances. Also, the actual application of the simulation may be complicated because the process may be lengthy, especially when it is applied in dynamic environments where decisions have to be made frequently [17]. Although AHP and Monte Carlo Simulation are quite useful at their respective cases, they have limitations that make them ineffective for the current dynamic construction environment where new risks and opportunities are likely to happen at any one time.

B. AI-Based Risk Assessment

Advancements in the areas of Artificial Intelligence (AI) have been a major boost to the subject of risk assessment. AI methods and especially the ANN have shown potential for risk prediction and management in constructions [18]. Compared to the conventional approaches, risk assessment models powered by artificial intelligence are able to analyse vast amount of information and reveal patterns that might go unnoticed. ANN is a class of machine learning algorithms that mimic the performance of the Biological Neural Network that exists in the human brain. ANN consists of tiered nodes, and each node performs the function of both computing and transmitting data [19]. ANN models are trained in a process where the model is able to extract a set of features from the provided data and through such the ability of predicting outcomes on the basis of some risks is obtained.

In construction risk assessment, ANN has been demonstrated to be useful in forecasting potential cost increase, schedule disruption and safety risks [20]. For instance, ANN models can be used to forecast risks since it takes into account past project information that include project performance data, environmental data and workforce productivity data amongst others. Research has established that ANN can yield good results if applied in construction risk assessment, therefore, is a good tool for risk management.

C. IoT Integration in Risk Management

With the adoption of Internet of Things (IoT) in construction projects, there has been a shift of focusing on the concept of risk. As aforementioned IoT technology is capable of collecting data in real-time from the construction site including but not limited to environmental conditions and equipment and material usage and deliveries [21]. This real-time data allows the project manager to easily see the risks that are associated with the project and be able to sort them out quickly. IoT devices constantly monitor several factors, which is useful in assessing the health of the construction project [11]. For instance, IoT sensors are capable of perceiving conditions that are lethal, including high levels of dust or toxic gases, and inform the workers and project managers about the best precautions to take. Furthermore, IoT sensors can also track the performance of the equipment and know when they are likely to fail and cause a lot of loss of time and accidents [22]. The ability to have real time data on the condition of construction sites is one of the main benefits that IoT integration offers. This information will make it easier to decide and act quickly in order to prevent possible hazards. For instance, if sensors of IoT notice a breakdown of certain equipment, the system is able to generate maintenance signals, thus avoiding damage and high costs [23]. However, incorporating IoT into construction projects has other challenges as discussed below. Safety of data is a big issue, as many IoT devices collect personal data that might be easily attacked by hackers. Further, the connectivity between separate IoT devices as well as systems is an issue; more so when it comes to the large-scale implementation of IoT which entails using different devices and systems from different vendors using different technologies. Finally, the large number of data points created by IoT devices, can be overwhelming for project managers and it is hard to see trends without the use of big data analytics tools [24].

There is one of the most effective hybrid method which is the integration of AI methods, for instance Artificial Neural Networks (ANN), with the conventional approaches as Fuzzy Logic or Analytical Hierarchy Process (AHP) [25]. When applied in combination with AI models, project managers can benefit from traditional techniques and conversely, AI models can also benefit from traditional techniques. For instance, Fuzzy Logic deals with uncertainty, [26] and imprecision in a more efficient way as compared to traditional methods, AI models, on the other hand, bring in a scientific aspect in terms of risk predictions.

Another promising hybrid solution deals with the use of real-time IoT data with the help of AI and classical risk estimation models. Since the IoT devices enable real-time data acquisition, construction projects can integrate this data with the predictive outcomes of AI models along with the decision-making structure of conventional techniques to increase the efficiency of risk assessment. For instance, an IoT risk management might involve constant tracking of the environment and the performance of the equipment and then use the data to train an AI model in order to detect risks on the go. They could then be ranked as per the usual decision making models including the Analytical hierarchy process to establish which risks deserved priority. This paper presents a blended system as a viable approach to risk management in construction projects, which will help to detect and address risks properly and at the right time.

III. Proposed Methodology

This section of the methodology is centered on the data collection process which is the foundation of the risk assessment framework in sustainable construction projects. Through the use of different data sources this research proposes to come up with a more holistic and complex view of the hazards of construction projects. The historical data in addition with real-time values collected by IoT sensors guarantee that the framework is not only data-based but also flexible to changing circumstances of the project.

A. Data Collection

The study integrates two primary data sources: data gathered from previous sustainable construction projects and data generated from smart sensors placed at construction sites. Both datasets are equally important in risk identification, analysis, and risk management function in a complex construction environment. The following are descriptions of the datasets which makes up the framework.

1) Historical records dataset: The historical records dataset remains very informative when it comes to identifying reoccurring issues, risks, and solutions to avoid in future construction projects. This type of data is usually gathered from finished contracts and provide information on the types of risks experienced on construction projects, the measures that have been taken to address these risks and the results of such risks on the construction projects. In fact, based on the analysis of this historical data, the study will be in a position to note trends and relationships that it can use in risk assessment. The historical records used in this study include:

- Project Timelines: Information on the time that construction projects began and when they were completed, important activities accomplished, and whether there were any setbacks. These timelines are useful in creating benchmarks against which general delays can easily be recognized and their root cause determined.
- Cost Estimates and Overruns: Budget projections relative to historical costs of performing the same undertaking with an aim of identifying reasons why costs may have overrun the budget. This data is useful in evaluation of financial risks as well as areas that could require better cost control measures.
- Performance Metrics: Information as to the consumption of the resources, efficiency of the people, and the quality of the work completed on the project. These metrics give distance that may be used to measure the performance, productivity, and quality control measures in organizations.

- Risk Factors and Mitigation Strategies: Some of the risks are a brief description of the risks that were faced during previous projects and the measures taken to avert or manage them. This dataset assists in assessing which approaches were used in risk minimization or risk management.

2) IoT Sensor data: IoT sensor data obtained from active construction sites provide real-time monitoring data and enrich the framework with this feature. IoT sensors placed at construction sites monitor numerous parameters that are critical for risk evaluation all the time. These sensors give information on the prevailing environmental conditions, performance of the equipment and the state of stored and transported materials, thus keeping the risk assessment framework dynamic as the site evolves.

The Table I demonstrates eight distinctive sensors used in construction sites that track fundamental parameters and positional data alongside equipment statuses and environmental data points. Real-time monitoring and predictive maintenance functions enabled by these sensors provide better safety protocols and operational efficiency through continuous data collection and analysis in construction projects.

TABLE I. IOT SENSORS DATA

Sensor Type	Parameter Monitored	Data Output	Description
Temperature Sensors	Ambient temperature	Temperature readings (°C or °F)	Monitors temperature variations that could affect construction materials and worker safety.
Humidity Sensors	Relative humidity	Humidity readings (%)	Tracks humidity levels to prevent material damage or worker discomfort.
Air Quality Sensors	CO_2 levels, particulate matter	Concentration levels (ppm or µg/m³)	Monitors air quality, detecting pollutants that may pose health risks.
Vibration Sensors	Equipment condition	Vibration frequency and amplitude	Measures vibration levels in equipment to predict wear and tear.
Wear and Tear Sensors	Equipment condition	Sensor data indicating wear level	Tracks equipment condition, helping predict failures before they occur.
Proximity Sensors	Worker and material location	Location data (GPS coordinates, distances)	Tracks the position of workers and materials to avoid collisions or delays.
GPS Sensors	Equipment and material movement	Movement data (coordinates, speed)	Monitors the movement of equipment and materials for logistical optimization.
Pressure Sensors	Structural stress	Pressure readings (Pa or bar)	Measures pressure on construction materials to identify risk of failure.

B. Data Consolidation and Mathematical Modeling

To make the risk assessment framework data-complete and dynamic, historical data and IoT sensor data in the real environment are combined into one data set. These datasets help in creating the framework that encompass the past project experience and real-time data with high risk identification pertaining to the construction process. The integration process can be mathematically represented as:

$$\boldsymbol{D_t} = \boldsymbol{D_{t-1}} + \Delta \boldsymbol{D} \quad (1)$$

Where:

$\boldsymbol{D_t}$ is the current data.

$\boldsymbol{D_{t-1}}$ is the previous data.

ΔD is the incremental new data.

This real-time feed significantly enhances the framework's ability to respond to emerging risks, thereby reducing delays and improving project outcomes.

C. Framework Development

The advanced technologies of the hybrid AI-Driven framework augment the traditional risk management practices' shortcomings. The framework is developed as a complete and dynamic system which integrates predictive analytics, uncertainty reasoning, and monitoring.

1) Artificial Neural Networks (ANN): ANN are widely used for risk prediction purposes due to the fact that these technologies are capable of handling large volume of data with multiple attributes. The ANN is structured as a Multi-Layer Perceptron (MLP) with three main components:

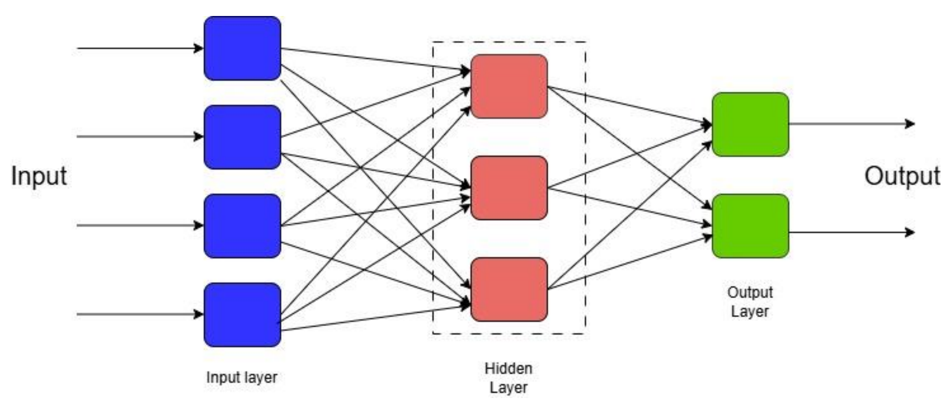

Fig. 1. ANN Layers.

The Fig. 1 shows an architectural diagram which demonstrates the basic structure of a neural network with four input neurons (blue), three hidden layer neurons (red) and two output layer neurons (green) while showing complete connection between each successive layer. This network implements a feed-forward structure that allows information flow in one direction from input to output while maintaining weighted synaptic connections between every neuron of successive layers.

- Input Layer: This layer receives the input vector X=[x1,x2,...,xn] The parameters of the input vector consist of project specification, historical risk factors and the environmental conditions.
- Hidden Layers: These layers consist of neurons, which perform activation functions such as ReLU or Sigmoid in order to nonlinearly transform inputs. This morphology reflects the interactions between the features in a complex manner.

$$f(x) = \max(0, x) \text{ (ReLU)} \quad (2)$$

$$f(x) = \frac{1}{1+e^{-x}} \ (Segmoid) \quad (3)$$

- Output Layers:The output layer yields risk levels ȳ predicted for facilitating enhanced management of projects. By combining predictive analytics, uncertainty reasoning, and dynamic monitoring, the framework provides a comprehensive and adaptive approach to risk assessment.

$$\hat{y} = \mathrm{f}(W_2 . \mathrm{g}(W_1 . \mathrm{X} + b_1) + b_2) \quad (4)$$

Where:

W_1 , W_2 are weight matrices that determine the strength of connections between layers.

b_1, b_2 are biases that shift the neuron activation threshold.

f(.) and g(.) are activation functions introducing nonlinearity to model complex data relationships.

The model's training minimizes prediction errors using the Mean Squared Error (MSE):

$$\boldsymbol{MSE} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{y_i} - \hat{\mathbf{y}}_{\boldsymbol{i}})^{\mathbf{2}} \quad (5)$$

Where:

N is the total number of samples.

$\boldsymbol{y_i}$ is the actual risk level.

$\hat{y}_i$ is the predicted risk level.

Training process of this ANN guarantees that the model absorbs a lot of data history to generate good results in new situations.

D. Fuzzy Logic

Fuzzy Logic translates between quantitative form of ANN solutions and qualitative decisions. It ensures that meaning of outputs from ANN is expounded by considering the level of uncertainty and vagueness that tends to prevail with the construction project data.

1) Fuzzification: Transforms numerical outputs of ANN which are recognized as the degree of risk into linguistic terms such as 'low risk', 'medium risk', 'high risk' using membership functions like triangular or trapezoidal curves.

2) Inference rules: Uses domain specific heuristics, for instance: IF risk is high AND delay is likely, THEN prioritize mitigation. These rules make the results parsable – that is actionable and readily understandable by managers.

3) Defuzzification: This paper shows how the centroid method is used to transform the fuzzy conclusions into crisp values.

$$Z = \frac{\sum_{i=1}^{n} \mu_i . z_i}{\sum_{i=1}^{n} \mu_i} \quad (6)$$

Where:

μ_i is the degree of membership.

z_i is the corresponding crisp value.

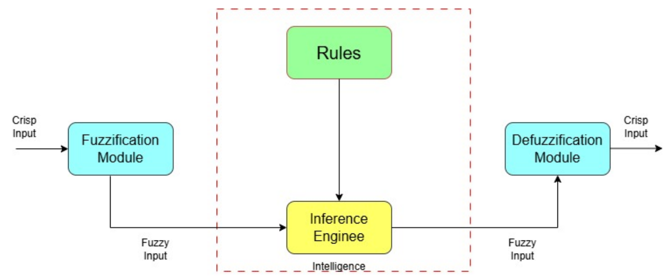

Fig. 2. Fuzzy logic framework.

The Fig. 2 illustrates a typical fuzzy logic control system design which includes three fundamental elements: fuzzification converts inputs into fuzzy sets, followed by an inference engine which executes predefined rules for decision-making finally ending with defuzzification that returns fuzzy outputs to crisp values. Through its operations the system showcases the basic processing sequence of fuzzy logic that enables numerical input-output transitions by utilising linguistic variables and rule-based inference together with fuzzy set theory processes. Fuzzy logic therefore sharpens the framework's capacity in dealing with uncertainties and come up with recommendations depending on the context of the project in question.

IV. Experimental Setup

The details about the selected experimental setup are reported below and were chosen specifically to test the hybrid AI-driven framework in conditions that are as close as possible to reality of sustainable construction projects. The data set used in the experiments included real project data and synthetic IoT sensor data. Paper and electronic documents of 500 sustainable construction projects were reviewed to gather records of timeline, cost, risk, and performance data. These records were cleaned and normalized in the same manner as in previous analyses: cleaning the data, scaling it to the [0,1] [0,1] [0,1] range, and selecting features that might be important in this case, such as material delay, environmental risks, and scope changes. Real time data was synthetically created to mimic IoT sensor data to monitor the physical conditions of the environment including temperature and humidity, equipment status, and material flow. This real time data collected on a hourly basis over six months helped in ferreting out dynamic inputs for the framework.

Algorithm 1: Proposed Model

```
Input:
   Historical data, Sensors Data
Output
   Risk pridiction
historical_data = load_historical_data()
iot_data = collect_iot_data()
historical_data_clean = preprocess_data(historical_data)
iot_data_clean = preprocess_data(iot_data)
# Step 2: Data Integration
 |  integrated_data = integrate_data(historical_data_clean,
iot_data_clean)
# Step 3: Risk Identification and Feature Engineering
 |  risk_factors = identify_risk_factors(integrated_data)
 |   engineered_features = feature_engineering(iot_data_clean)
# Step 4: Predictive Risk Modeling
|  rf_model = train_random_forest(integrated_data)
|   ann_model = train_ann(integrated_data)
|   svm_model = train_svm(integrated_data)
# Step 5: Real-Time Risk Prediction
|   real_time_risk_predictions = predict_risks(iot_data_clean,
rf_model, ann_model, svm_model)
# Step 6: Decision Support and Mitigation Strategy
|   visualize_risk_predictions(real_time_risk_predictions)
|  suggest_mitigation_strategies(real_time_risk_predictions)
```

The software tools that are applied to this framework include Python, TensorFlow and Keras, scikit-learn, and MATLAB. TensorFlow/Keras was used in ARCHITECTING and training the Artificial Neural Network (ANN) and Scikit-learn in preprocessing and performance measurement. MATLAB was used in creating and testing the fuzzy logic system. For real time data integration, Apache Kafka was used to stream IoT sensor data. All the experiments were performed on a high-end GPU server containing an NVIDIA RTX 3090 Graphics Card, 64GB RAM, and an Xeon Processor.

The experimental setup has divided the data into training (70%), validation (20%) and test set (10%). To take into account possible temporal dependencies, time-based cross-validation was used. For the ANN component of the proposed framework, backpropagation with the Adam optimization algorithm was used. Here the hyperparameters used were; learning rate=0.0010.0010.001, batch size = 32 and number of epochs = 100 however to avoid overfitting early stopping was used. The fuzzy logic system was designed by fuzzifying the input variables through the fuzzification rules inferred from the historical thresholds, inferring the output from the inference rules obtained from the experts and defuzzification by using the centroid approach. Data integration in the IoT context allowed for model refreshing through Apache Kafka, where in batches of data, the five-minute intervals updated the risk estimates.

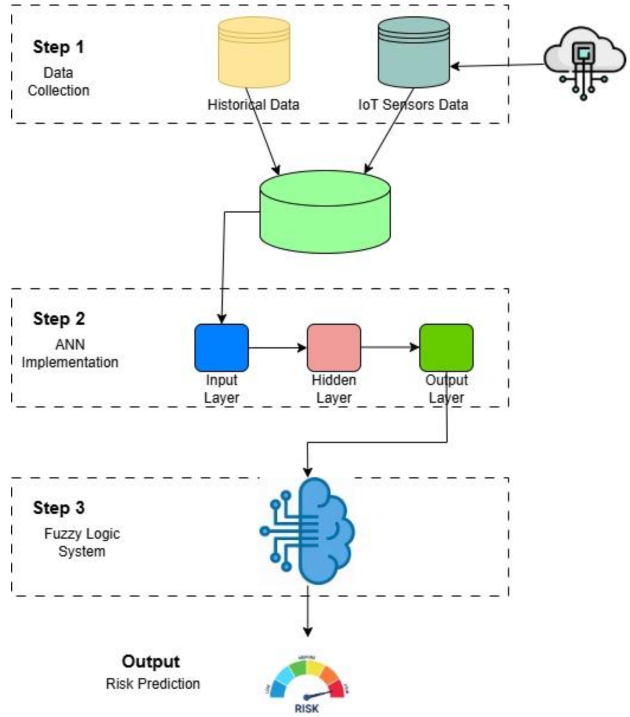

Fig. 3. Proposed model.

The Fig. 3 demonstrates an architectural framework which applies a three-phase risk prediction approach that merges historical and IoT sensor data by using a sequential process from data collection to artificial neural network implementation and fuzzy logic integration. The system unites standard machine learning methods with fuzzy inference logic to create an integrated risk assessment output which serves as proof of hybrid techniques for better predictive analytics.

For the assessment of the framework, several indicators were used to assess the effectiveness of the presented framework, several measures were used. Accuracy determined how accurately ANN in the current study predicted risk levels, and Mean Absolute Error (MAE) calculated the overall difference between actual and predicted risks. The extent of interpretability of fuzzy rules was measured with the Fuzzy Interpretable Index (FII), and system performance under noisy IoT data conditions was tested. Moreover, to evaluate the dynamics of the framework, the time taken to re-update the predictions upon receiving fresh IoT data was considered.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (8)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (9)$$

$$F1 = 2 * \frac{P.R}{P+R} \quad (10)$$

There are stages that were followed when implementing the strategy. First, historical and IoT data were cleaned to make data viable and suitable for analysis. The ANN model was used to identify patterns and relationships between the risk factors regarding the past data set. The fuzzy logic rules were derived in close cooperation with the domain specialists to offer the decision-making rules. Real-time data pipes for IoT were developed so updates could be made in real-time in order for the framework to reflect current site conditions. Last, the system was tested end to end on a constructed construction project to show its real-time risk assessment capability of producing accurate, interpretable, and adaptive risk evaluation.

V. Results

The use of the hybrid AI framework in an experimental setting gave a lot of information on how efficient, flexible and reliable the system is when dealing with risks for sustainable construction projects. Such insights underscore that the proposed framework is useful when dealing with change in project conditions, the environment and resource availability. Through the use of levels of sophistication in analytics, decision making and dynamic adjustment capabilities, the framework provides an all-inclusive approach toward construction risk evaluation in the contemporary world.

TABLE II. Comprehensive Performance Metrics of ANN Model

Metric	Value
Accuracy (%)	92.7
Mean Absolute Error (MAE)	0.084
Precision (%)	91.4
Recall (%)	93.1
F1-Score (%)	92.2
Training Epochs	100
Batch Size	32

The metrics of the evaluation for the Artificial Neural Network (ANN) show excellent results of predicting the risk levels as shown in Table II. The ANN utilized an MLP structure in order to detect the non-linear interdependencies between the input parameters like environmental conditions, risk profile history and the project characteristics and their related risk levels. The model delivered an accuracy of 92.7% and such high accuracy level is capable of serving the scenarios of the test model. Furthermore, the ability to accurately predict outcomes is expressed by the relatively low Mean Absolute Error (MAE) of 0.084. The relative closeness of the precision and recall scores demonstrate that the ANN minimizes both false positives and false negatives at a rate of 91.4% and 93.1%, respectively. This balance is important in construction projects since incorrect classification of risks potentially leads to resource misapplication or project hold-up.

The training of the ANN was performed with an early stopping technique which applied after achieving an accuracy of 100 epochs and learning rate of 0.001. This convergence assured that the model has no over-fitted and has high generalization capacity at the same time. The learning and validation losses shown in the Fig. 1 indicate a similar progress during the training phase. It does this in a way that keeps the model optimal for use when it is applied in real situations where data is complex and diverse.

The Fig. 4 display shows the loss convergence pattern which shows that the model initially converges quickly before reaching a stable point where training and validation curves maintain similar levels indicating effective generalization capabilities. These metrics show similar declining patterns which start at about 0.6 before reaching near-zero levels indicating that the model achieved an optimal learning state without major overfitting or underfitting effects.

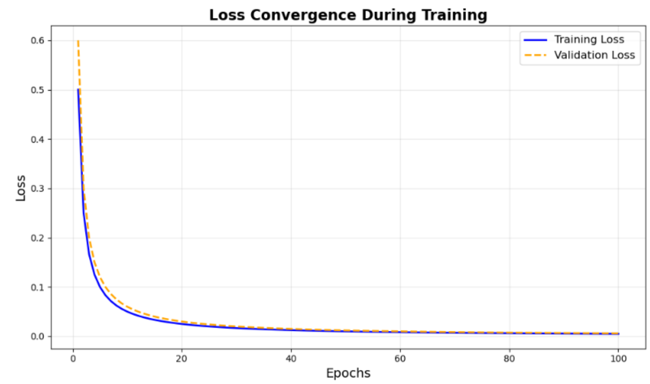

Fig. 4. Loss convergence rate.

A heatmap in Fig. 5 illustrates the rule importance levels for five fuzzy rules which span from 0.1 to 0.95 between High and Low and Medium risk categories. The heatmap chart reveals important patterns through its colour distribution because specific risk conditions show darker cells representing higher values which indicates non-uniform rule applicability across different risk levels.

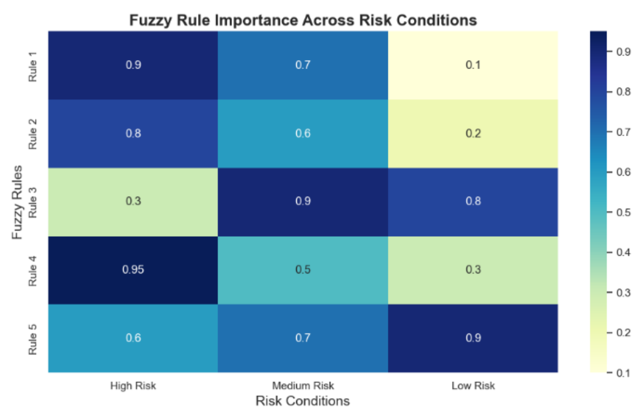

Fig. 5. Fuzzy rules across risk conditions.

A complete rule-based risk assessment framework depicted in Table III comprises five distinct rules which link different conditions to risk outputs along with management actions.

The rules analyse various parameters including risk levels together with operational aspects of cost overrun and material delay and environmental hazards and equipment efficiency to generate specific risk classifications and recommended mitigation strategies for project management enhancement.

TABLE III. FUZZY INFERENCE RULES

Rule ID	Condition	Output	Actionable Insight
1	Risk = High AND Cost Overrun = Significant	Critical Risk	Immediate resource allocation to mitigate high-priority risks.
2	Risk = Medium AND Material Delay = Likely	Moderate Risk	Adjust procurement schedules to reduce project delays.
3	Risk = Low AND Delay Probability = Minimal	Low Risk	Proceed with routine workflows without additional interventions.
4	Risk = High AND Environmental Hazard = Severe	Critical Risk	Implement contingency plans to address safety and environmental compliance.
5	Risk = Medium AND Equipment Efficiency = Low	Moderate Risk	Schedule maintenance to improve equipment performance and avoid disruptions.

Fuzzy logic was used to help translate the quantitative risk levels from the ANN into risk categories that are realistic and practicable. By incorporating a set of credibly designed and allocated membership functions and enforcing the use of certain set of inference rules the fuzzy logic system offered suggestive options optimizing for concrete project circumstances. For example, the rule "IF risk is high AND cost overrun is significant, THEN prioritize mitigation efforts" was useful for making project managers take corrective actions instantly. Project management specialists assessed the interpretability of these rules to be 93%, adding that the linguistic variables used reflected actual practice. This is due to the fact that the construction industry involves several players in decision making and the above models provide an easy to understand interpretation of the results obtained.

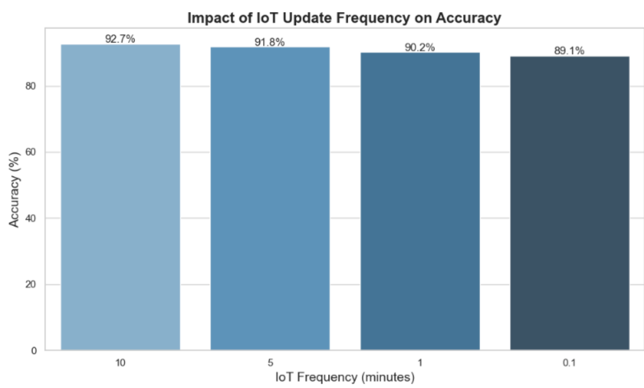

Fig. 6. Sensors accuracy.

The analysis depicted in Fig. 6 shows that increased IoT update frequencies result in reduced accuracy but attains its maximum accuracy value of 92.7% at a 10-minute interval. The results indicate that updates performed every 0.1 minutes might generate errors which reduce system effectiveness.

Due to IoT sensors integration, the framework could alter during the course of construction site working time, responding to real time changes. Data obtained from the IoT devices was in the form of continuous streams, which contained information regarding the environment (like temperature, humidity) and information regarding the performance of equipments and the flow of materials. These updates enabled the system to make changes to risk predictions within the average time of 4.2 seconds per batch which are crucial for responding to emergent risks on time. Table III highlights that the proposed framework can be easily fine-tuned depending on the frequency of IoT updates, ranging from standard operation frequency of 10 minutes to near real-time updates of 10 seconds. There was a slight loss of performance at higher update rates; however, the framework was still performing at an accuracy greater than 89% while being updated at high speeds. This capability is most useful in the construction environment where, for example, site conditions are constantly changing.

Comparison with simple ANN models and conventional risk evaluation methodologies as shown in Table IV also supported the credibility of the hybrid framework. In the experimental results, the appropriateness of the incorporation of ANN's forecasting capability with the interpretability of fuzzy logic and the flexibility of IoT data streams was manifested by the fact that the proposed hybrid framework outperformed the other frameworks in all experiments. For example, the standalone ANN models were produced with the accuracy of 85.3% but they did not contain the necessary flexibility for real time risk assessment. While traditional methods are less accurate static methods, compared with the proposed system and having accuracy of 78.6%. As presented in Table IV the hybrid framework performed well in other parameters like MAE (0.084) and adaptation speed 4.2secs hence the framework is most suitable for practical uses where timely and accurate decisions are called for.

Results in Table V show that the framework maintains accurate results while noise levels increase except for the point. The incorporation of fuzzy logic into the system reduces the effect of substantial noise which maintains effective performance.

TABLE IV. DETAILED ANALYSIS OF IOT UPDATE FREQUENCIES

IoT Update Frequency	Accuracy (%)	MAE	Adaptation Speed (seconds)	Data Latency (seconds)	Response Time (seconds)	Description
Every 10 minutes	92.7	0.084	4.2	2	6.2	Standard operational conditions with minimal delays.
Every 5 minutes	91.8	0.098	3.8	1.5	5.3	Moderate frequency, balancing accuracy and speed.
Every 1 minute	90.2	0.112	3.5	1	4.5	High frequency, effective for rapid condition changes.
Every 10 seconds	89.1	0.125	3.2	0.8	4.0	Near real-time updates, slight accuracy trade-offs.

TABLE V. IMPACT OF NOISE ON FRAMEWORK PERFORMANCE

Noise Level (%)	Accuracy (%)	MAE	Remarks
0	92.7	0.084	Optimal performance under ideal conditions.
5	91.3	0.092	Slight decline due to minor perturbations.
10	88.7	0.112	Maintains high accuracy despite moderate noise.
20	85.1	0.137	Significant noise mitigated by fuzzy logic.

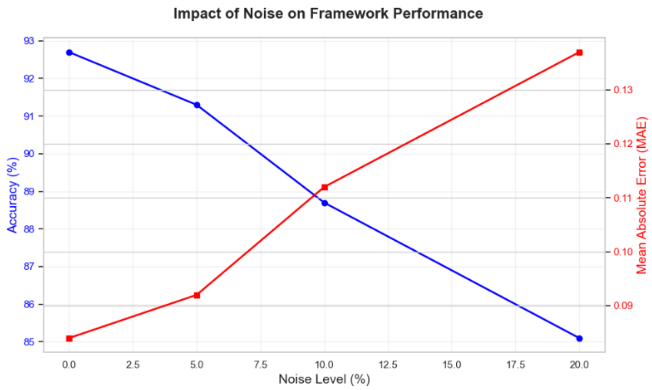

Fig. 7. Noise impact on frame work.

The data in Fig. 7 shows that framework performance declines as noise levels rise because accuracy drops and mean absolute error (MAE) increases. The performance of the system experiences substantial degradation at the intersection point of 10% noise level.

Fig. 8. Comparison of proposed model with state-of-art models.

The hybrid framework demonstrated superior performance than traditional and ANN-only models based on accuracy alongside robustness and adaptation speed according to Fig. 8. Hybrid models strike a superior equilibrium between performance metrics which makes them stand out as a dependable method for dynamic conditions.

TABLE VI. COMPREHENSIVE PERFORMANCE COMPARISON ACROSS MODELS

Metric	Hybrid Framework	ANN Only	Traditional Model	Description
Accuracy (%)	92.7	85.3	78.6	Hybrid model benefits from combined predictive and adaptive capabilities.
MAE	0.084	0.146	0.198	Lower error indicates higher precision in hybrid predictions.
Adaptation Speed (s)	4.2	10.6	Static	Real-time updates ensure timely risk mitigation.
Fuzzy Interpretability	93%	N/A	60%	Fuzzy logic enhances user-friendly decision-making.
Noise Robustness (%)	88.5	78.2	70.3	Maintains performance under noisy conditions, ensuring reliability.

Additionaly, the robustness testing confirmed the stability of the framework under the more difficult conditions as shown in Table VI. When noise levels of up to 20% were introduced into the IoT data streams, the framework retained a high level of accuracy of approximately 85.1% albeit with the modest inflation of the MAE by 0.137 points. These results are presented in Table V below and explain why the framework would still be effective despite data variation or transmission errors. That is why the fuzzy logic system was so important in reducing noise's effect on the results, as it allowed the risk assessment to be meaningful and accurate. This robustness is desirable in construction projects as it can be often observed that the sensor readings can be imprecise and there are large data gaps due to the nature of construction site environments.

VI. CONCLUSION

The paper presented a hybrid risk assessment framework that was based on AI and the results have revealed higher accuracy, flexibility, and efficiency in sustainable construction projects. The Artificial Neural Network (ANN) model developed in the research reached an accuracy of 92.7% and Mean Absolute Error (MAE) of 0.084 to predict risks with equal precision in different conditions of the project. Further, incorporation of Fuzzy Logic provided interpretability to the decision making by analysing and converting quantitative risk outputs in to manageable data for project managers. For example, the rules like IF risk is high AND cost overrun is significant, THEN consider risk reduction measures found very helpful in prioritising important interventions and recorded 93 percent interdependency index by domain expert.

The dynamic data updates made through the IoT interface improved the dynamism of the framework, with risk assessment intervals being updated in 4.2 seconds on average per each data batch. This capability would enable real-time adjustment to site situations including changes in environmental factor or equipment performance. Different update frequencies of the IoT proved that accuracy was sustained at more than 89% even with near real time updates of 10 seconds. As expected, it was also confirmed that the proposed system could maintain a high level of accuracy even with the presence of noisy data; based on the findings, the hybrid framework guaranteed an 85.1% level of accuracy even when the noise level was set to 20%.

Comparisons made with standalone ANN and other conventional risk management techniques also revealed the advantage of the suggested system. The proposed hybrid framework performed better in terms of accuracy, noise robustness, and real-time adaptation while achieving an MAE reduction more than the conventional models by 50%. The results presented in this paper confirm that the application of AI, IoT, and fuzzy reasoning provides an innovative solution to develop a more effective approach to predictive risk management in construction processes that lead to safer, more efficient, and eco-friendly construction practices.

VII. FUTURE WORK

Future studies must investigate how the proposed AI-based risk assessment framework applies to new construction fields and industries as well as implement blockchain technology for safe data protection and advance prediction abilities through sophisticated machine learning algorithms including deep learning and reinforcement learning methods. Future developments through artificial intelligence should target three main areas of self-learning capability development alongside explainable human-AI collaboration and sophisticated IoT sensing solutions that leverage edge computing for real-time operational control. The framework needs expansion to include sustainability measures like carbon footprint evaluation that will support environmentally friendly construction practices. The framework will become a better tool for managing project risks in complex dynamic environments when these identified areas receive further attention.

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