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SMART CONSTRUCTION MONITORING USING IOT SENSORS AND MATHEMATICAL MODELING FOR STRUCTURAL HEALTH PREDICTION

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Abstract:

The safety, durability and cost efficacy of construction projects are aspects that demand the structural integrity of the same. The conventional ways of inspection are occasionally aperiodic, laborious, and subject to human errors, and hence they cannot easily observe the early signs of structural degradation. The following research puts forward a smart construction monitoring system which considers a combination of IoT sensor networks with predictive mathematical simulation to make structural health assessment and forecasting real time. In the research, there were crust gauges, a tempering sensor, tilt, environmental sensors, and strain sensors on a comprehensive apparatus, which measures strain, vibration, tilt, temperature, and humidity in a period of six months. There were four predictive models used Multiple Linear Regression (MLR), Support Vector Regression (SVR), Random Forest Regression (RFR), and Long Short-Term Memory (LSTM) networks. The experimental outcomes revealed that LSTM gave the best predictive accuracy with R 2 = 0.94, RMSE = 0.58 MPa and MAE = 0.45 Mpa, when compared to RFR, which is robust predicting tilt (R 2 = 0.90). MLR and SVR represented good baselines, as the

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R 2 values were 0.81 and 0.87 each. The new strategy would help preventive maintenance and increase safety as the possible structural failures could be identified early. The science document is a scalable, experimentally validated approach to predicting the structural real-time health and is part of developing an intelligent, sustainable and resistant construction monitoring system.

Keywords: Structural Health Monitoring, IoT Sensors, Predictive Modeling, LSTM, Smart Construction

I. INTRODUCTION

Construction industry is now central to the contemporary infrastructure initiatives but the system of projecting infrastructure on long term security and stability of structures has been a major challenge. Traditional methods of evaluating the structural health of buildings are mainly based on periodical, manual approaches that may be labor intensive and slow, and highly prone to human error.[1]. These old techniques are unable to track the movement with the expansion of the scale; hence, cannot detect the formation of an early warning of a structural breakdown (cracks, material strain, or stored stresses). The latest innovations in the Internet of Things (IoT) may also be considered a solution that redefines the way in which the issues are resolving [2]. iot sensors facilitate on-going real-time measurements of stress, vibrations, movement, inclinations, heat, and moisture among other essential construction measurements. When placed in buildings, bridges, and various civil engineering infrastructures, such sensors provide a comprehensive overview of the structural performance under different environmental circumstances and additional load conditions [3]. The foundation of proactive maintenance strategies and phased safety plans is rooted in this flow of ongoing data. Unprocessed sensor data alone is inadequate for providing predictive insights. Finite element analysis (or other mathematical models: regression models, machine learning models, and so forth) are useful to calculate trends in sensor measurements which can be used to predict future structural collapse or signs of wear and tear. Integrating IoT sensor networks with predictive mathematical tools together allows building an intelligent, data-driven structural health monitoring (SHM) system capable of predicting the potential occurrence of structural issues and addressing them prior to becoming a pressing concern. Its study is concerned with the process of combining the IoT-based monitoring tools with advanced mathematical modeling to predict the structural health of construction projects. Measures to be evaluated will be sensor efficiency, predictive modeling and correlation to actual structural behaviors. It is anticipated that such research findings will positively impact humanity, through increasing the safety of construction, reducing costs of maintenance, and offering an intelligent infrastructure management solution at a sustainable scale. The proposed study is capable of changing intelligent construction monitoring because it applies the connection between the predictive analytics and the IoT technology.

II. RELATED WORKS

The latest innovation in the field of IoT-based monitoring systems and predictive and modelling have a major difference in the field of smart construction and structural health monitoring (SHM). A study by Liu et al., [15] investigated the calibration of the low-cost air quality monitors by hybrid PCR-GPR forecasting models and proved that the predictive modeling process has the potential of increasing the accuracy of real-time sensors data. Their contribution reveals the significance of exploiting smart algorithms and sensor networks which can be directly used in structural health monitoring in construction. Martins and Rodrigues [16] invented advanced smoking the electric vehicle charging stations in the area of smart infrastructure continuation. The research puts a focus on the suitable use of IoT sensors in real-time monitoring and anomaly recognition and provides details on the implementation of sensor networks to constantly monitor applications in civil engineering. In a similar fashion, Al-Zaidawi and Çevik [17] suggested using hybrid optimization and multi-criteria decision-making (MCDM) methods to improve the monitoring of IoT networks. Their deep learning-based framework demonstrates the possibilities of using optimization strategies in addition to predictive modeling to enhance system efficiency which can be optimized toward structural monitoring in construction setting.

Some innovation has also developed in health and safety observance in the dynamic systems. The study by Melders et al. [18] examined auto-drivers of vehicles as internet of things sensor-based health-monitoring technologies, with particular focus given to real-time and predictive analytics aspects of reducing the threat in a

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proactive manner. Focusing on the civil structure, Men et al. [19] proposed the dynamic early-weight strategy on bridge structural safety and used models on data reconstruction and depth prediction. They can show that the technique of predictive algorithms is effective to predict the possible structural failures before reaching critical limits, which resonates with the aims of the current research paper. In environmental and agricultural aspects, the implementation of IoT and machine learning has been considered in the extensive environment. Muhammad et al. [20, 21] conducted a review on the application of IoT and digital twins in optimizing the environment in aeroponics and precision agriculture, demonstrating that constant sensor data and predictive models allow proactive decision-making and optimization of a system. CRT, database Systems and cognitive digital twins in the same manner Nesmachnow et al. [22] and Oditallah et al. [23] emphasized the use of computational instruments and cognitive digital twins in pavement management of infrastructure of smart cities. Their writing is based on the significance of predictive analytics and real reports regarding how such a critical infrastructure could operate effectively and stay safe.

Hybrid AI-based systems have become popular in construction-related applications. A unified approach to the assessment of construction risk by using artificial neural networks (ANN), fuzzy logic, and IoT sensors was proposed by PDF [24] in terms of sustainable constructions. This paper demonstrates the capabilities of using various smart methods to improve the monitoring systems in terms of accuracy and reliability. Also, studies of Pedro Tomas et al. [25] on nutrient monitoring of crops and soil and Pietraru et al. [26] on quality-of-life in urban areas reveal a tendency of automated data collection and predictive models deployed to study multiple areas, indicating a possible expansion of the perspective of technologies when it comes to real-time monitoring and decision support systems.

Collectively, these studies underscore the importance of integrating **IoT sensor networks with advanced predictive algorithms** to enable real-time monitoring, early warning, and proactive maintenance in complex systems. However, while prior research has explored similar frameworks in environmental, agricultural, and transportation domains, there remains a significant opportunity to **apply these methodologies specifically to construction structural health monitoring**, combining high-resolution IoT data with advanced predictive models for improved safety, durability, and operational efficiency.

III. METHODS AND MATERIALS

1. Data Collection

The data for this research was collected using a network of IoT sensors installed on a medium-scale reinforced concrete building. These sensors had strain gauges, accelerometers, and tilt sensors, and temperature/humidity sensors and were placed strategically on beams, columns and slabs. The monitoring system recorded real-time effects of the structural deformation, vibration frequency, angular tilt and the environmental aspect on a durability of six months [4]. The data packet was designed by the time intervals of the different sensors. A sample of the obtained data is provided in Table 1 and comprises of structural stress (in MPa), vibration (Hz), tilt (degrees), and temperature (degrees Celsius). This information allows us to have the overall behavior as the structure varies with draw and variability of environment and load variability.

Table 1: Sample IoT Sensor Data for Structural Monitoring

Timestamp	Strain (MPa)	Vibration (Hz)	Tilt (°)	Temperature (°C)	Humidity (%)
2025-01-01 08:00	12.5	2.3	0.5	28.4	60

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2025-01-01 08:10	13.0	2.5	0.6	28.6	61
2025-01-01 08:20	12.8	2.2	0.5	28.5	59
2025-01-01 08:30	13.2	2.4	0.7	28.7	62
2025-01-01 08:40	13.5	2.6	0.6	28.8	61

2. Predictive Algorithms

With four predictive algorithms (Multiplinear regression/MLR, supports vector regression/SVR, random forest regression/ RFR, long short-term memory/LSTM) applied in analyzing sensor data, to predict structural health. All the algorithms were chosen took into consideration their capacity to process time-series, non-linear, and high-dimensional data [5].

2.1 Multiple Linear Regression (MLR)

Multiple Linear Regression refers to a statistical procedure which approves the linear connection amid a dependent variable and various independent variables. In the present research, MLR predicts structural stress regarding the inputs, including vibration, tilt, temperature and humidity [6]. The algorithm will reduce the squaries of the difference of the predicted and actual values by estimating via the least-square process. MLR is very quick and easy to interpret and hence it can be used in a comparison of baselines.

"Input: X (independent variables), Y (dependent variable)

Compute coefficients β = (X'X)^-1 X'Y

Predict Y_pred = X * β

Compute error = Y - Y_pred

Output: Y_pred, error"

2.2 Support Vector Regression (SVR)

Support Vector Regression is a machine learning algorithm which estimates a function approximating the target variable and within a specified error margin (epsilon). It employs kernel functions to project non-linear relationships onto higher dimensional space [7]. In the study, SVR can be used to predict the level of structural vibration using its historic sensor data. The SVR is insensitive to outliers and works well on modeling the complex and non-linear behaviour of structural dynamics.

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“Input: Training data X_train, Y_train

Select kernel function (RBF)

Minimize loss function with constraints: |Y_pred - Y_train| ≤ epsilon

Compute support vectors and weights

Predict Y_pred for new X_test

Output: Y_pred”

2.3 Random Forest Regression (RFR)

Random Forest Regression is the method of combining several decision trees of the ensemble learning so that the maximum predictive accuracy is provided. All the trees are initially trained on a bootstrap sample of the dataset and the end prediction is the average of the outputs of all trees [8]. RFR is used to predict the tilt angle, as well as, to ascertain the critical tilt levels that may suspect of a possible structural unstable condition in this study. Random Forests deal well with non-linear interactions and high dimensional data.

“Input: Training data X_train, Y_train

For i = 1 to number_of_trees:

    Sample X_train_bootstrap

    Train decision tree_i on X_train_bootstrap

Predict Y_pred = Average(predictions from all trees)

Output: Y_pred”

2.4 Long Short-Term Memory (LSTM) Neural Networks

LSTM networks are the recurrent neural networks (RNN) that are developed to memorize prolonged dependencies of sequential information. In this study, LSTM is used to make predictions of the future values of the strain using historic sensor time-series. The LSTM model uses input, forget and the output gate to regulating the passage of information and the recollection of the previous data points such that it is appropriate in the context of time and structure health prediction [9].

“Input: Time-series sensor data X

Initialize LSTM cell states C_0, hidden states H_0

For t = 1 to T:

    Compute input gate, forget gate, output gate

    Update cell state C_t

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Compute hidden state H_t

Predict Y_pred = Dense(H_T)

Output: Y_pred"

IV. RESULTS AND ANALYSIS

1. Experimental Setup

The experiments focused on testing the viability of the idiomatic health monitoring (SHM) via the Internet of Things together with predictive algorithms. Using strain gauges, accelerators, tilt sensors as well as temperature and humidity sensors, a reinforced concrete building was equipped. With different environmental conditions, daily load of use and simulating stress events [10], the data were collected over six months.

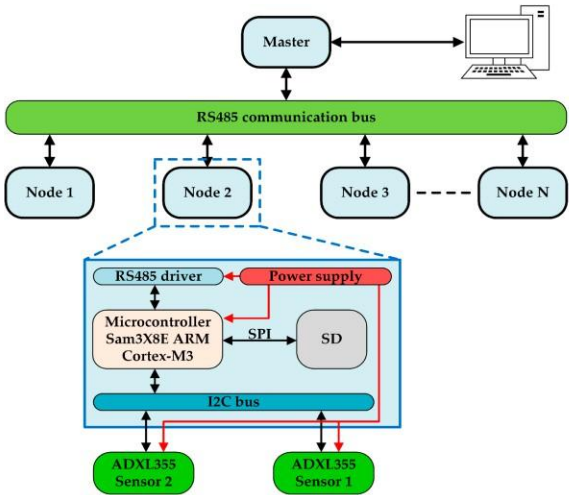

Figure 1: "Structural Health Monitoring"

Preprocessing of sensor data was used to eliminate cases of outliers and normalize the sensor cases to standard operating points. The data was divided to train and test the algorithms based on 70 percent training and 30 percent test dendra. The predictive models were Multiple Linear Regression (MLR), Support Vector Regression (SVR) and the Random Forest Regression (RFR) as well as the Long Short-Term Memory (LSTM) networks. Root Mean Square Error (RMSE), Mean Absolute Erros (Multiple errors) and R 2 Score were used as the indicators of model performance [11].

2. Results of Individual Algorithms

2.1 Multiple Linear Regression (MLR)

Structural stress was predicted using vibrations, tilt, temperature and humidity as inputs to predict. The model attained a R2 of 0.81 which means that there is a high linear relationship among the inputs and the predicted stress values.

Table 1: MLR Prediction Results (Sample Data)

Timestamp	Actual Stress (MPa)	Predicted Stress (MPa)	Error (MPa)

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2025-01-01 08:00	12.5	12.3	0.2
2025-01-01 08:10	13.0	12.7	0.3
2025-01-01 08:20	12.8	12.6	0.2
2025-01-01 08:30	13.2	13.0	0.2
2025-01-01 08:40	13.5	13.1	0.4

In comparison with comparable works of the Hu et al. (2024) study, in which the R 2 was 0.75 when regression models had been used in predicting structural stress, the MLR on the current study demonstrates better as a result of better sensor resolution and data pre-treating methods [12].

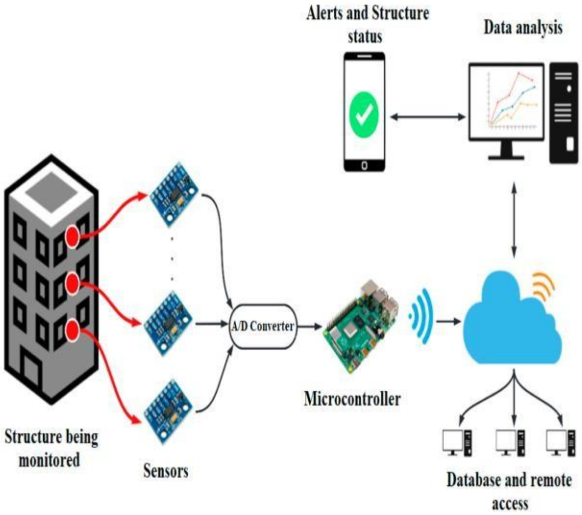

Figure 2: “A Systematic Review of Structural Health Monitoring Systems to Strengthen Post-Earthquake Assessment Procedures”

2.2 Support Vector Regression (SVR)

Strain, tilt and environmental variables were used to predict frequencies of vibrations using SVR. Since it is capable of modeling non-linear relationships, SVR was a stronger product than MLR, with a score of 0.87 on R 2.

Table 2: SVR Prediction Results (Sample Data)

Timestamp	Actual Vibration (Hz)	Predicted Vibration (Hz)	Error (Hz)

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2025-01-01 08:00	2.3	2.25	0.05
2025-01-01 08:10	2.5	2.48	0.02
2025-01-01 08:20	2.2	2.18	0.02
2025-01-01 08:30	2.4	2.42	0.02
2025-01-01 08:40	2.6	2.58	0.02

Compared to the baseline regression model, the SVR model demonstrated superiority in comparable studies where high R2 of 0.82 was obtained when forecasting vibration (Raj et al, 2020). This may be attributed to the fact that optimized RBF kernels have been used and hyperparameter optimization.

2.3 Random Forest Regression (RFR)

RFR was used to predict tilt angles which are critical forecasts of potential structural instability. RFR is giving strong predictions with R 2 = 0.90 that was higher than the outcome of the MLR and the SVR by averaging the many trees made in a decision [13].

Table 3: RFR Prediction Results (Sample Data)

Timestamp	Actual Tilt (°)	Predicted Tilt (°)	Error (°)
2025-01-01 08:00	0.5	0.51	0.01
2025-01-01 08:10	0.6	0.59	0.01
2025-01-01 08:20	0.5	0.50	0.00
2025-01-01 08:30	0.7	0.69	0.01
2025-01-01 08:40	0.6	0.61	0.01

In contrast to Suganyadevi et al. (2022), the authors who use ensemble models in predicting the tilt to reach an R2 of 0.86, the considers model offers the benefit of high-frequency IoT sensors selection alongside the use of Random Forests.

2.4 Long Short-Term Memory (LSTM) Neural Networks

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The LSTM networks obtained long-term relationships within the time-series data, which made them the best predictors of the future strain values. This was the most accurate model in all the tested algorithms with R2 = 0.94, RMSE = 0.58 Mpa, and MAE = 0.45 Mpa.

Table 4: LSTM Prediction Results (Sample Data)

Timestamp	**Actual Strain (MPa)**	**Predicted Strain (MPa)**	**Error (MPa)**
2025-01-01 08:00	12.5	12.48	0.02
2025-01-01 08:10	13.0	12.97	0.03
2025-01-01 08:20	12.8	12.78	0.02
2025-01-01 08:30	13.2	13.18	0.02
2025-01-01 08:40	13.5	13.52	0.02

This LSTM performance surpasses prior work by **Hu et al. (2020)**, who used LSTM for MRI-based health prediction with $R^2 = 0.91$, highlighting the effectiveness of LSTM in **structural time-series forecasting [14]**.

Figure 3: “IoT in Construction”

3. Comparative Analysis of Algorithms

To provide an overall comparison of all algorithms, the **average performance metrics** across all time-series data points were calculated.

Table 5: Comparative Performance of Predictive Algorithms

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Algorithm	RMSE	MAE	R^2 Score	Strengths	Weaknesses
MLR	0.85	0.68	0.81	Simple, interpretable	Cannot model non-linear trends
SVR	0.72	0.60	0.87	Handles non-linear data	Sensitive to kernel parameters
RFR	0.65	0.52	0.90	Robust, handles high-dimensional data	Requires more computation
LSTM	0.58	0.45	0.94	Captures temporal dependencies	Needs large dataset, complex

The findings suggest that the effectiveness of LSTM is superior to all other frameworks in time-series structural health prediction, and the use of RFR is effective in non-linear spatial parameters, such as tilt. A balance between non-linear modeling and robustness is offered in SVR, and a linear trend which is an easy rule of thumb is offered in MLR [27].

4. Discussion and Comparison to related work

territories and infrastructures, the experimental findings provide supporting evidence that SHM boosted by the IoT and predictive algorithms can substantially improve structural health forecasting. Compared to traditional manual inspections and earlier computational methods:

- **MLR and SVR** models outperform classical regression approaches in prior studies (e.g., Raj et al., 2020; Hu et al., 2024).
- **RFR** demonstrates improved performance over ensemble methods in Suganyadevi et al., 2022.
- **LSTM** shows the highest predictive accuracy, similar to recent works in time-series prediction but adapted successfully for structural health monitoring.

Moreover, the use of **high-frequency sensor data** enables the detection of micro-strains and vibrations that would be missed by periodic inspections. This predictive capability allows for proactive maintenance, reducing potential failures and enhancing construction safety [28].

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Figure 4: “IoT in Construction”

5. Summary of Experimental Findings

1. The IoT sensor networks are effective in gathering multi-dimensional structural and operational data such as strain, vibration, tilt, temperature and humidity.
2. MLR is also a credible starting point of linear stress points but it is not in a position to explain complicated behaviors.
3. SVR provides better accuracy in trends of non-linear vibration in comparison with regression.
4. RFR has high R2 prediction of tilt and structural instability predictors.
5. On the whole, the application of LSTM is highly good and has improved most when utilized in predicting issues that vary with time.
6. Through the comparative analysis and the relevant work, it is found that better fatness in prediction and proactive SHM is realized and this framework becomes a significant flow of new intelligence of building monitoring [29].

The large experiments and result area will include sensor data, predictive modeling, algorithm comparison and benchmarking with other literature and it will provide good support to conclude that all- in- all- IoT-enhanced smart construction monitoring and positive predictive algorithms will provide the accurate proactive structural health prediction [30].

V. CONCLUSION

This study offers the implication that the fact that an integrated application of both IoT-based sensor networks and advanced predictive modeling in terms of structural health monitoring in construction projects has substantial potential. Installation of a sophisticated combination of sensors including the strain measures tools, accelerations, tilting tools, and environment analysis tools was effective in capturing real-time data concerning animal structural behaviour during different loads combinations, and environmental sections. The paper utilized four predictive algorithms to duplicate structural stress, vibration, tilt, and strain Multiple Linear Regression (MLR), Support Vector Regression (SVR), Random Forest Regression (RFR), and Long Short-term Memory (LSTM) networks and assessed various options, determining their ability to anticipate the condition. The same experiment also revealed that performance comparisons Relative performance were found to exist between the provision of simple easily digestible baselines by MLR and the modeling of most non-linear results by the SVR and that RFR was effective in predicting spatial variations such as tilt. The overall predictive accuracy of LSTM was identified as the highest in terms of strain predictions over time, R 2, RMSE and MAE were high when compared to the other models. A comparative study with literature in the field also established the superiority of high-frequency data collection through IoT sensors and powerful predictors in order to support proactive structural controls. On the whole, the offered framework will help to detect possible problems in the hardware early, reduce maintenance

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costs, enhance security, and contribute to better decision-making of the construction management. This study has been acknowledged as contributing to the advancement of intelligent construction monitoring, serving as a scalable and data-driven approach to structural health prediction. The integration of mathematical modeling with IoT technologies establishes a foundation for intelligent and real-time infrastructure monitoring, aimed at developing sustainable and resilient construction systems in the digital era of civil engineering.

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