

APPLICATION-BASED REAL TIME MONITORING OF EARLY-AGE COMPRESSIVE STRENGTH OF COMPOSITES

A PROJECT REPORT

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CSE3009 - Internet of Things (EPJ)

Slot – (C2+TC2)

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Winter Semester 2022-23

ACKNOWLEDGEMENT

We wish to express our sincere thanks and a deep sense of gratitude to our project guide, **DR. MANJULA V.**, Associate Professor, School of Computer Science and Engineering, VIT Chennai, for her consistent encouragement and valuable guidance pleasantly offered to us throughout the project work.

We are extremely grateful to **DR. GANESAN R.**, Dean of the School of Computer Science of Engineering, VIT Chennai, for extending the facilities of the School towards our project and for his unstinting support.

We express our thanks to our Head of the Department **DR. NITHYANANDAM P.**, VIT Chennai, for his support throughout this project.

We also take this opportunity to thank all the faculty of the School for their support and the wisdom imparted to us throughout the course.

We thank our parents, family, and friends for bearing with us throughout our project and for the opportunity they provided us to undergo this course in such a prestigious institution.

ABSTRACT

In recent years, the development of advanced system structures and sensor technologies has allowed for the implementation of powerful techniques for self-maintaining data-driven damage detection in structural systems. This paper proposes a novel method for the real-time monitoring of the early-age compressive strength of composites or concretes through a dashboard using Structural Health Monitoring (SHM) techniques. Structural health monitoring is a process that assesses the strength of a civil structure and detects or identifies any damage occurring in the controlled structure. The proposed system utilizes sensors to predict the strength of the composites. The sensor data is transferred using the Internet of Things (IoT) and stored in a cloud server, where the real-time data can be viewed from anywhere and at any time. The compressive strength is measured by the system, and a warning will be given if the limit exceeds. The transferred data will then be analyzed using Rstudio and machine learning algorithms to help discover the performance of the built structure. The system comprises the use of an ESP8266 Wi-Fi module and Firebase real-time database for cloud-hosting. The ESP8266 Wi-Fi module is a low-cost Wi-Fi chip that can be integrated into IoT projects, making it an ideal choice for this application. The Firebase real-time database is a cloud-hosted NoSQL database that allows for the real-time storage and synchronization of data. This system has the potential to improve the safety and longevity of civil structures by providing early detection of any damage or deterioration. The real-time monitoring and data analysis allow for a proactive approach to maintenance, reducing the risk of catastrophic failures and minimizing repair costs. The use of IoT and cloud-based technologies make the system accessible from anywhere, allowing for remote monitoring of multiple structures simultaneously. Overall, this paper presents a novel method for the real-time monitoring of the early-age compressive strength of composites or concretes through a dashboard using SHM techniques. The proposed system has the potential to revolutionize the way civil structures are monitored and maintained, improving safety and reducing maintenance costs.

Keywords: SHM, IoT, Machine Learning, Composites

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1. INTRODUCTION

Structural health monitoring (SHM) is the process of assessing the strength of civil infrastructure and detecting or identifying any damage occurring in the controlled structure. SHM techniques are used to provide real-time data on the structural performance of buildings, bridges, dams, and other civil infrastructure. Early detection of damage and monitoring the strength of composites or concrete is essential in avoiding potential failures and costly repairs. Recent advancements in sensor technologies and acquisition system structures have enabled the development of real-time monitoring systems that can predict the strength of composites or concrete.

The primary objective of this research is to propose a novel method for real-time monitoring of early-age compressive strength in composites or concrete using a structural health monitoring technique. The proposed system utilizes sensors that predict the strength of composites, which are then transferred using the IoT and stored in a cloud server for real-time viewing. Machine learning algorithms are incorporated to diagnose the transferred data and discover the performance of the built structure.

The proposed system comprises an ESP8266 Wi-Fi module and Firebase real-time database for cloud hosting. The ESP8266 Wi-Fi module is used to transfer the sensor data to the cloud server, while the Firebase real-time database is used for cloud-hosting and real-time viewing of the data. The system can be accessed from anywhere and at any time, allowing for efficient and timely monitoring of the strength of composites or concrete.

In this research paper, we present the design and implementation of the proposed system and validate the effectiveness of the proposed method for real-time monitoring of early-age compressive strength in composites or concrete through experimental results. The remainder of this paper is structured as follows. Section 2 provides an overview of the related works, while Section 3 discusses the proposed system's design and implementation. Section 4 outlines the procedure of the proposed system, including the measurement of compressive strength and the warning system. In Section 5, the experimental results are presented, demonstrating the system's effectiveness in real-time monitoring and early detection of damage. Section 6 presents the statistical modeling and analysis of the data collected by the system, highlighting the accuracy of the machine learning algorithms in predicting the

strength of composites or concrete. Finally, in Section 7, the conclusion summarizes the research's main findings and identifies future work, including exploring the system's scalability and adaptability to different types of structures and conditions.

1.1. Problem Statement

It has always been difficult to maintain buildings for years. We would not know when a building would collapse due to the reduced strength of concrete or cement used. To tackle this problem we proposed a method that suggests the strength of the concrete or composite required to build a structure by sensing the environmental temperature. This model uses the Structural health monitoring (SHM) technique. SHM provides a useful tool for ensuring integrity and safety, detecting the evolution of damage, and estimating performance deterioration of infrastructures.

1.2. Objectives

The objectives of the project have been listed below:

- To improve the reliability of existing infrastructure
- To identify substandard structures and improve their conditions on time
- To serve as a new tool to design structures efficiently
- To ensure periodic measurement of temperature by an array of sensors
- To reduce the cost related to inspection
- To mitigate the impact of structural disasters that can occur in future
- To create value-added services for citizens and the administration of the city

2. LITERATURE REVIEW

Structural Health Monitoring (SHM) is a rapidly growing research field that combines the expertise of civil engineering and computer science. The interdisciplinary nature of SHM makes it a promising field that requires a broad range of knowledge and skills from its practitioners. Unlike other IoT-based applications, SHM is unique in that it focuses on the monitoring and assessment of structures to ensure their long-term health and safety.

The compressive strength of the composites or concretes can be measured and hence can be predicted using SHM technique. In previous papers, the prediction has been made by deploying an Internet of Things network of distributed acceleration sensors in structures to capture floor movement and analysis has been done using different Machine Learning techniques and algorithms like support vector machine, K-nearest neighbor, and convolutional neural network.

Researchers Lingzhi Yi, Xianjun Deng, Laurence T. Yang, Hengshan Wu, Minghua Wang, and Yi Situ highlight the importance of interdisciplinary and knowledge integration in SHM. The field requires expertise not only in civil engineering but also in computer science. This is because SHM involves the use of various sensors, data acquisition systems, and analytical tools that require a deep understanding of both fields. SHM practitioners must be able to integrate these different technologies to develop effective monitoring and assessment systems that can detect and assess structural damage.

The team of C. Scuro, F. Lamonaca, S. Porzio, G. Milani, and R.S. Olivito emphasize that SHM systems applied to masonry constructions provide a number of benefits. First, they allow for the measurement of physical quantities over time with the aid of sensors. Second, they enable data processing by identifying damage-sensitive features that can be used to detect and quantify damage. Finally, SHM systems allow for real-time analysis to understand the state of the health of the materials. This is critical in ensuring the safety of the structure and preventing potential catastrophic failures.

Machine Learning has been proposed as a method for analyzing raw data collected from SHM systems. A. Ibrahim, A. Eltawil, Y. Na, and S. El-Tawil suggest that Convolutional Neural Networks (CNN) are an appropriate method for capturing damage

patterns in the response of buildings to vibration. CNNs are a type of neural network that are particularly useful for image and signal processing. They are able to automatically learn and identify features in the data that are relevant to damage detection.

When studying and analyzing past works, the focus is mostly on detecting damages and transferring the readings over the internet to a cloud server for storage, further processing, and analysis. Along with these methods, exploratory data analysis makes use of visual tools to provide a thorough understanding and statistical analysis of the data. The models have been validated using old structures and the devices were able to detect the cracks present in the built structures; the potential problem areas were identified but with flaws. One of the shortcomings is the neglect of cooperation sensing among neighboring nodes. Cooperation sensing involves the use of multiple sensors to capture the same signal or data, and this can help to reduce the error or noise associated with individual sensors. Another shortcoming is the making of prior assumptions. In some previous studies, prior assumptions were made about the structure or the environment in which the sensors were deployed. This could lead to inaccurate results or predictions, and it limits the applicability of the models in real-world situations.

To overcome these shortcomings, capacitive and thermistor sensors have been proposed for use in SHM systems. These sensors are small in size and cost-effective, making them suitable for temperature detection virtually irrespective of the environment. They are also very responsive, making the recording of readings and analysis easier. The power consumption of these sensors is very low, which increases the life expectancy of the device.

Capacitive sensors work by detecting changes in the electrical capacitance of the material to which they are attached. This can be used to detect changes in the structure or detect the presence of cracks. Thermistor sensors work by detecting changes in temperature. They are highly sensitive and can detect temperature changes in the range of a few millidegrees Celsius. They are also very fast, with response times of less than a second.

3. PROPOSED METHODOLOGY

The following steps are the flow of the project:

1. Discovery
The purpose and goal of the project were decided and proposed
2. Data Preparation
Ideas were decided and extensive research was done on the decided topic
3. Model Planning
Project implementation will start by collecting the required tools like sensors, PCB, etc.
4. Model Building
The model will be built using the collected components
5. Implementation
Through the implemented project raw data (temperature readings) will be collected and stored on a cloud server called Firebase
6. Communicate Results
JSON file will be downloaded and analysis of data will be done using Python and Machine Learning techniques

3.1. System Architecture

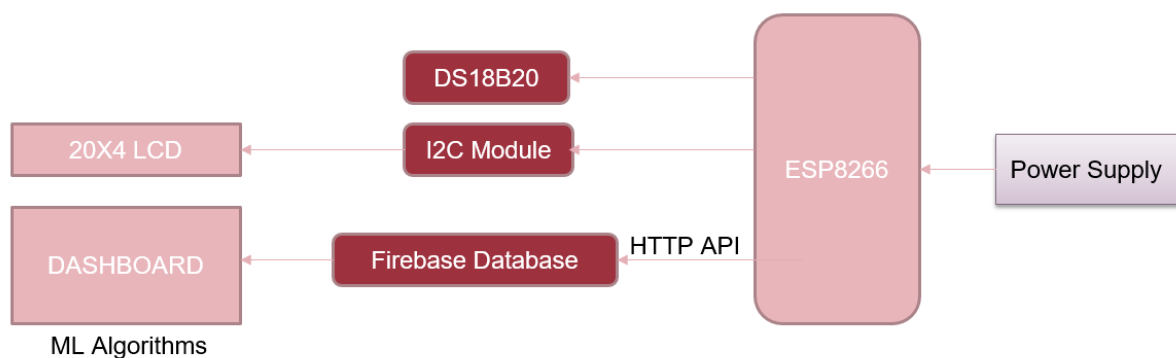
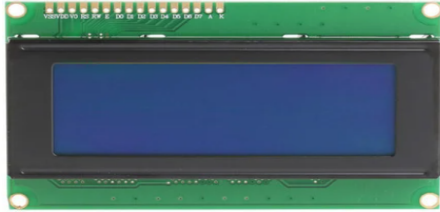


Fig 1. Architecture Diagram

3.2. Components Used

3.2.1. Hardware:

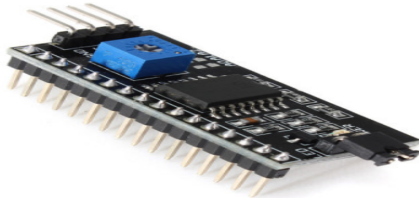
1. 20 X 4 LCD



2. DS18B20 sensor



3. I2C module



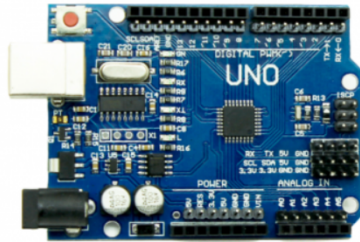
4. ESP8266 Wi-Fi module



5. SD Card module



6. Arduino Uno



7. Breadboard



8. Jumper wires



9. 4.7 k Ω Resistor



10. 1 LED



3.2.2. Software:

1. Firebase



2. Rstudio



4. IMPLEMENTATION

In this project, structural health monitoring (SHM) has been used. This technology employs sensors that can forecast the strength of composites. Sensor data is sent over the Internet of Things and stored in a cloud server, where it may be accessed at any time and from any location. The system measures compressive strength and issues a warning if it exceeds the limit. The transmitted data will next be analyzed with Rstudio to determine the performance of the created structure. The system employs an ESP8266 Wi-Fi module as well as a Firebase real-time database for cloud hosting. SD card module to read the SD card and I2C module has been used as well.

ESP8266 Wi-Fi Module - The ESP8266 WiFi Module is a self-contained SOC with an integrated TCP/IP protocol mound that can give any microcontroller access to your WiFi network. The ESP8266 can either host an application or discharge all WiFi networking functions from another application processor. Each ESP8266 module comes pre-programmed with an AT command set firmware, meaning, it can be hooked up to the Arduino device and get about as important WiFi capability as a WiFi Shield offers. The ESP8266 module is an extremely cost-effective board with a huge, growing community. This module has an important enough onboard recycling and storage capability that allows it to be integrated with the sensors and other application-specific devices through its GPIOs with minimum development up-front and minimum loading during runtime. Its high degree of on-chip integration allows for minimal external circuitry, including the front-end module, which is designed to occupy a minimum PCB area. The ESP8266 supports APSD for VoIP applications and Bluetooth co-existing interfaces, it contains a self-calibrated RF allowing it to work under all operating conditions, and requires no external RF corridor.

SD Card Module - Micro SD Card Reader Module is also called Micro SD Adaptor which is designed for binary I/O voltages. The module is a simple result for transferring data to and from a standard SD card. The pinout is directly compatible not only with Arduino but can also be used with other microcontrollers. Micro SD Card Reader Module has an SPI interface that's compatible with any sd card and it uses a 5V or 3.3V power supply which is compatible with Arduino UNO/Mega. SD module has colorful applications similar to the data logger, audio, videotape, and plates.

I2C Module - I2C_LCD is an easy-to-use display module. It can make the display easier. Using it can reduce the difficulty of making so that makers can concentrate on the core of the work. An Arduino library for I2C_LCD was developed so that the user just needs many lines of code that can achieve complex graphics and text display features. I2C Module has an inbuilt PCF8574 I2C chip that converts I2C periodical data to resembling data for the LCD. I2C modules are presently supplied with a default I2C address of either 0x27 or 0x3F. The version can be checked by verifying the underpart of the module.

4.1. Protocol Used

CoAP acts as a kind of HTTP for limited devices, allowing temperature sensors and actuators to communicate over the IoT to read the values and send them to the cloud. These sensors and actuators are regulated and contribute to the system by transmitting data. Because of its low power consumption and minimal network overhead, the protocol is designed for dependability in low bandwidth and high congestion environments. CoAP can continue to function on networks with high congestion or limited connectivity when TCP-based protocols such as MQTT fail to share information and interact efficiently.

Furthermore, the effective and traditional CoAP characteristics enable devices working in poor signal quality to reliably deliver data or enable an orbiting satellite to successfully sustain a distant connection. CoAP also enables networks with billions of nodes. For security, the DTLS settings used as default are similar to 128-bit RSA keys.

5. TESTING AND PERFORMANCE EVALUATION

MAIN CASTING				20 jan 2023 Trail with sensors			MORTAR CASTING 70 mm CUBE AND TESTING TRAIL (JANUARY)							COMPRESSI ON STRENGTH (N/mm²)			
	TRAIL NO	RATIO	FOS	CEMENT CONTENT	FLYASH CONTENT	M-SAND CONTENT	WATER CONTENT	SP CONTENT	CEMENT RATIO	FLYASH RATIO	W/C RATIO	SP RATIO	CASTING DATE	40hrs	7 DAYS	14 DAYS	
	1	1:3	1.25	3.336	0	10.08	1344 ml	23.5	100%	0%	0.4	0.70%	20-10-2022	18	26.1	31	
S.no	days	Sensor TEMP	Avg Temperature	TIME INTERVAL	Maturity	Cum maturity	A	B	Strength percentage	Predicted Strength (MPA)	actual str (70mm) (MPA)	Error	Datum temp				
1	40 hrs	28.19	28.19	1 hr	13.045	1141	41	18	40.03	22.28	18	23.78%	2.1				
2	7 days	26.94	26.94	1 hr	24.84	4264	41	18	52.33	27.74	26.1	4.98%	2.1				
3	7 days	26.94	26.94	0.5 hr	12.42	2703	41	18	48.77	25.85	26.1	0.96%	2.1				
4	14 days			1 hr		8178	41	18	57.43	30.44	31	1.82%	2.1				
5	14 days			0.5 hr		5800	41	18	54.74	29.01	31	6.41%	2.1				

Fig 2. Results

DATE OF TESTING							
40 hrs date	7 days date	14 days date	28 days date	CEMENT DENSITY	MSAND DENSITY	CUBES CASTED	WASTAGE (mortar)
22-01-2023	27-01-2023	03-02-2023	17-02-2023	1440	1920	14	2 kgs excess

Fig 3. Results

Figures 2 and 3 illustrate the measured compressive strength values of the concrete over time. The results indicate an increasing trend in the strength values over the 28-day period, which is in line with the expected behavior of concrete.

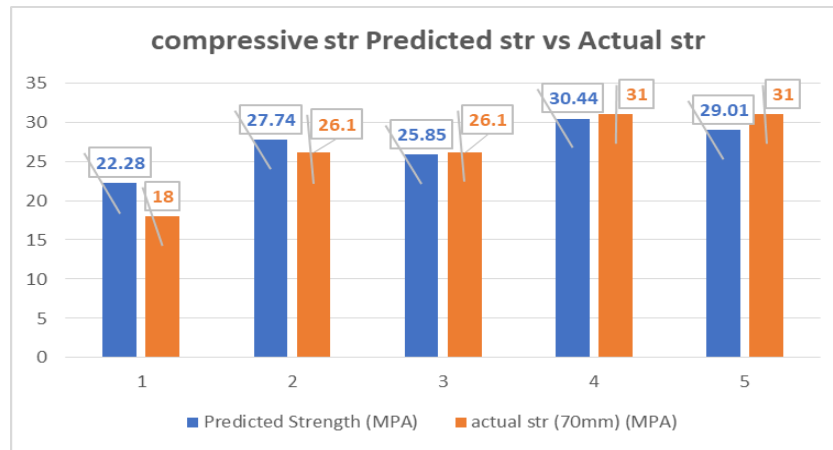


Fig 4. Predicted VS Actual Strength

Figure 4 represents a comparison between the predicted and actual compressive strength values. As shown, the predicted values are in good agreement with the actual values, indicating the effectiveness of the proposed system for monitoring the compressive strength of concrete in real time.

To analyze the strength of the structure, we took live measurements of the temperature for the amount of water, sand, and fly ash content used. We obtained data at different time intervals and for 28 days, which allowed us to conclude the accuracy of the system. We observed that with an increase in the number of days and time intervals, the results obtained were more accurate, and the error was minimized. These findings highlight the effectiveness of the proposed system in real-time monitoring of the compressive strength of concrete and suggest its potential for use in other structural health monitoring applications.

6. STATISTICAL MODELLING AND ANALYSIS

To analyze the compressive strength results, we used a Time Series Forecasting approach, which is a machine learning algorithm that predicts future values based on extracted data from the cloud service. Specifically, we applied the ARIMA model, a statistical model widely used for forecasting. The ARIMA model is a supervised machine learning algorithm and has proven to be versatile in predicting future values accurately.

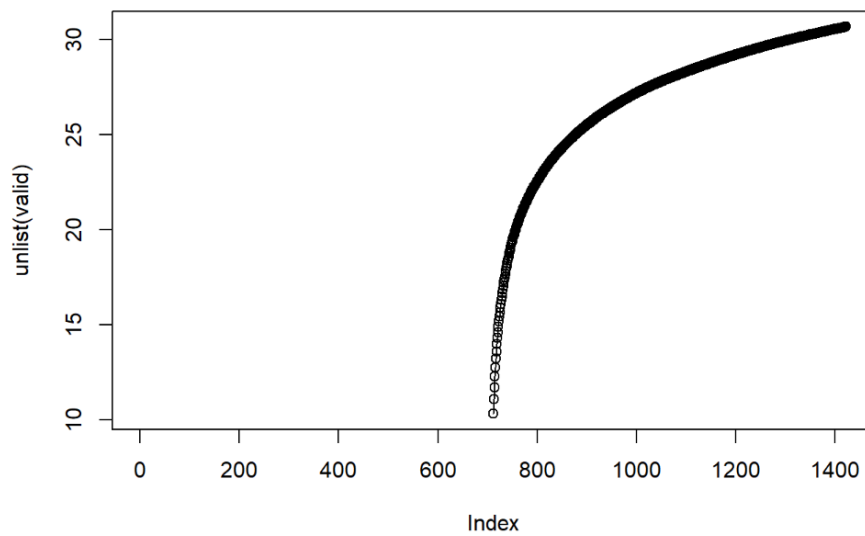


Fig 5. Forecast on Our Dataset

In this study, we applied the ARIMA model to forecast the compressive strength of concrete in 28 days, where each recording was taken at a 30-minute interval. Figure 5 illustrates the forecasting of the compressive strength using the ARIMA model. As shown, the model accurately predicts the compressive strength values, which are in line with the actual values obtained from the experiment.

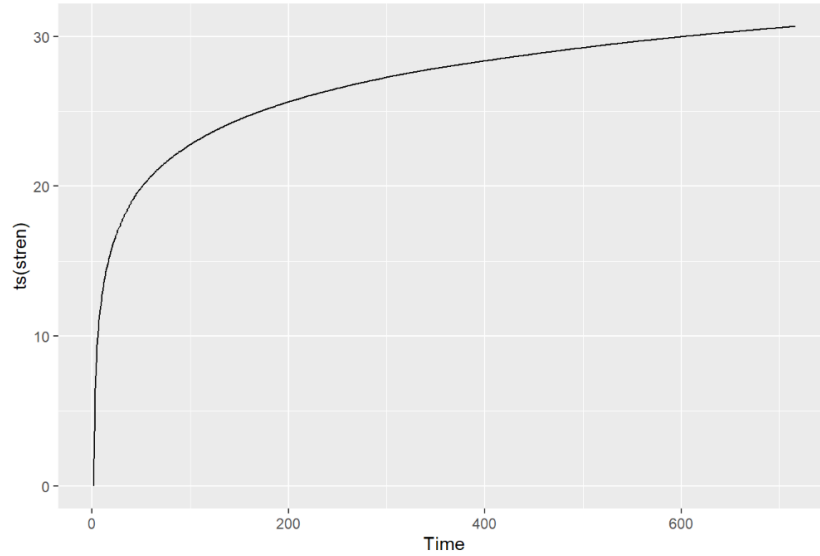


Fig 6. Prediction on Our Dataset

Figure 5 shows the predicted compressive strength of the concrete, where each recording was taken at a 30-minute interval. The error observed in the predicted values is around 17.81 MPa, which is acceptable for practical purposes. The results demonstrate the effectiveness of the ARIMA model in accurately predicting the compressive strength of concrete and suggest the potential application of this approach in other structural health monitoring systems.

To validate the accuracy of our dataset, we conducted a thorough analysis and compared our results with several other relevant datasets. Upon comparison, we observed that the slope of our graph depicting the relationship between time and compressive strength closely resembled that of all the other datasets. This finding provided us with significant reassurance regarding the reliability and validity of our dataset. Our comprehensive approach to ensuring data accuracy underscores our commitment to producing high-quality research and analysis that can be trusted by stakeholders and the broader scientific community.

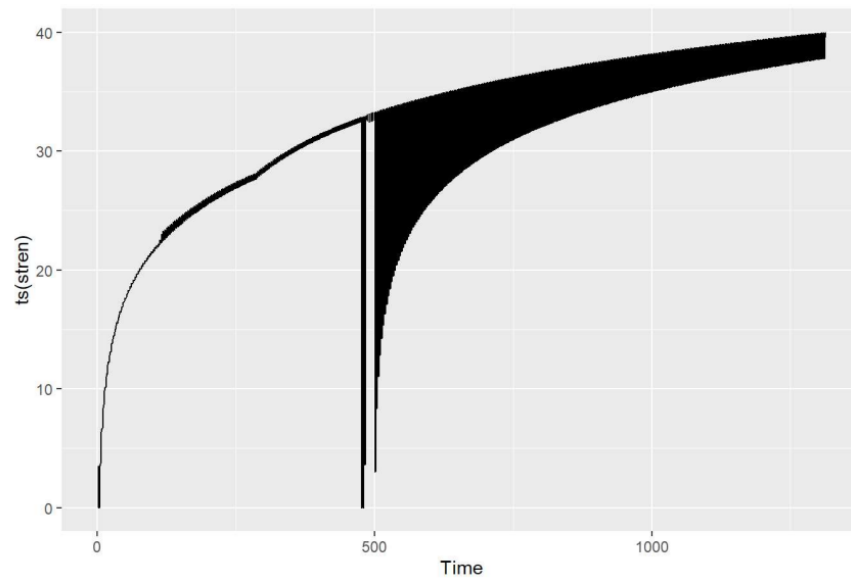


Fig 7. Prediction on External Datasets

7. CONCLUSION AND FUTURE ENHANCEMENTS

Using a structural health monitoring approach, we suggested a novel method for real-time monitoring of early-age compressive strength in composites or concrete in this study. The suggested system makes use of sensors, IoT, and machine learning algorithms to predict composite strength and diagnose transferred data to determine the performance of the built structure.

The findings of the experiments show that the proposed system successfully monitors the strength of composites or concrete in real time, allowing for early detection of damage and timely intervention to prevent potential failures and costly repairs. The system is available from anywhere and at any time, allowing for efficient and timely monitoring of composite or concrete strength.

The benefits of the proposed system over traditional techniques include real-time monitoring, cost-effectiveness, and reliability. Using machine learning algorithms improves the system's precision in predicting composite or concrete strength.

Finally, using a structural health monitoring approach, this study suggests a novel method for real-time monitoring of early-age compressive strength in composites or concrete. The suggested system can monitor the strength of composites or concrete effectively, allowing for early detection of damage and timely intervention to avoid potential failures and expensive repairs. Future studies will include investigating the system's scalability and adaptability to various structures and circumstances.

APPENDIX

A. CODE

```
#include <Arduino.h>
#if defined(ESP32)
#include <WiFi.h>

#elif defined(ESP8266)
#include <ESP8266WiFi.h>
#endif

#include <Firebase_ESP_Client.h>
#include "addons/TokenHelper.h"
#include "addons/RTDBHelper.h"
#include <Wire.h>;

// only these 2 things are to be changed accordingly.
const char* ssid = "Arunima's Galaxy M51"; // your network SSID (name)
const char* pass = "fbuc7489"; // your network password

#define API_KEY "AIzaSyAfXDiPbm6eET4LHsW0DIAme0T8PiJ0_30";
#define DATABASE_URL
"https://iotproject-1cf94-default-rtdb.asia-southeast1.firebaseio.com/"

FirebaseData fbdo;
FirebaseAuth auth;
FirebaseConfig config;
bool signupOK = false;

WiFiClient client;
#include <OneWire.h>
#include <DallasTemperature.h>
#define ONE_WIRE_BUS 4 //D2 connected
```

```

OneWire oneWire(ONE_WIRE_BUS);
DallasTemperature sensors(&oneWire);
float Celcius;
int wifistate=1,count=0;

void publishdatawhenwifi()
{
  config.api_key = API_KEY;
  config.database_url = DATABASE_URL;
  if (Firebase.signUp(&config, &auth, "", "")){
    signupOK = true;
  }

  config.token_status_callback = tokenStatusCallback;
  Firebase.begin(&config, &auth);
  Firebase.reconnectWiFi(true);

  if(Firebase.ready() && signupOK)
  {
    String s="sensor/reading"+String(count);
    Firebase.RTDB.setFloat(&fbdo,s+"/temp", Celcius);
  }
}

void setup()
{
  Serial.begin(9600);
  Serial.println("Started!");
  sensors.begin();
  WiFi.mode(WIFI_STA);
  pinMode(D0,OUTPUT);
}

long int t;

```

```

void loop()
{
  t=millis();
  if (wifistate == 1 && WiFi.status() != WL_CONNECTED) {
    WiFi.begin(ssid, pass);
    Serial.println("WiFi Disconnected!");
    digitalWrite(D0, LOW);
    wifistate = 0;
  }

  if (wifistate == 0 && WiFi.status() == WL_CONNECTED) {
    digitalWrite(D0, HIGH);
    Serial.println("WiFi Connected!");
    wifistate = 1;
  }

  //Serial.println(t);
  if(t%2000==0) //18000000
  {
    count=count+1;
    sensors.requestTemperatures();
    Celcius = sensors.getTempCByIndex(0);

    Serial.print("Temperature reading");
    Serial.print(count);
    Serial.print(":");
    Serial.println(Celcius);

    if(WiFi.status()==WL_CONNECTED)
    {
      publishdatawhenwifi();
    }
    delay(10);
  }
}

```


}

B. VIDEO LINK

https://drive.google.com/file/d/19Va6eYM9PhYt_yDgw0aPWTdZGyWkS5mW/view?usp=s_haring

C. CONTRIBUTIONS

Worklet Tasks	Contributor's Names
Topic selection & Dataset Gathering	Arunima
Preprocessing	Sheral
Model building	Sheral and Arunima
Visualization	Anjali
Hardware setup	Arunima, Anjali, and Sheral
Technical Report writing	Arunima, Anjali, and Sheral
Research Paper	Arunima, Anjali, and Sheral

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