

High-Level Design Document

CONCRETE COMPRESSIVE STRENGTH PREDICTION USING RANDOM FOREST REGRESSOR AND LINEAR REGRESSION

Domain: Infra

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Abstract

The concrete compressive strength prediction system is a machine learning-based model with the objective to predict the compressive strength of concrete based on the different quantities of materials used. Based on predictions we can determine the best combination of quantities of each material to achieve the best result. This model is more beneficial than regular concrete crash testing for determining the best set of material measurements by which the manufacturers can save time and expenses of equipment maintenance.

1. Introduction

1.1 Why High-Level Design Document?

This High-Level Design Document adds necessary detail to the forest cover classification project to represent a suitable model for coding. This document is also intended to help detect contradictions prior to coding and can be used as a reference manual for how the modules interact at a high level.

The HLD will:

- Present all of the design aspects and define them in detail
- Describe the user interface being implemented
- Describe the hardware and software interfaces
- Describe the performance requirements
- Include design features and the architecture of the project
- List and describe the non-functional attributes like:
 - Security
 - Reliability
 - Maintainability
 - Portability
 - Reusability
 - Application compatibility
 - Resource utilization
 - Serviceability

1.2 Scope

The HLD documentation presents the structure of the system, such as the database architecture, application architecture (layers), application flow (Navigation), and technology architecture. The HLD uses non-technical to mildly technical terms which should be understandable to the administrators of the system.

1.2 Definitions

IDE: Integrated Development Environment

Heroku: A cloud platform for deployment

Docker: A tool to containerize our system

2. General Description

2.1. Product Perspective

The concrete compressive strength prediction system is a machine learning-based model with the objective to predict the compressive strength of concrete based on the different quantities of materials used.

2.2. Problem Statement

The quality of concrete is determined by its compressive strength, which is measured using a conventional crushing test on a concrete cylinder. The strength of the concrete is also a vital aspect in achieving the requisite longevity. It will take 28 days to test strength, which is a long period. So, what will we do now? We can save a lot of time and effort by using Data Science to estimate how much quantity of which raw material we need for acceptable compressive strength.

2.3. Proposed solution

The system will predict the compressive strength of concrete from different combinations of materials using Random Forest Regressor and Linear Regression algorithms.

2.4. Data Requirements

Data requirements completely depends on the problem statement

| Name | Data Type | Measurement | Description |
|-------------------------------------|--------------|--------------------|--|
| Cement (component 1) | quantitative | kg in a m3 mixture | Input Variable |
| Blast Furnace Slag (component 2) | quantitative | kg in a m3 mixture | Input Variable-- Blast furnace slag is a nonmetallic coproduct produced in the process. It consists primarily of silicates, aluminosilicates, and calcium-alumina-silicates |
| Fly Ash (component 3) | quantitative | kg in a m3 mixture | Input Variable- it is a coal combustion product that is composed of the particulates (fine particles of burned fuel) that are driven out of coal-fired boilers together with the flue gases. |
| Water (component 4) | quantitative | kg in a m3 mixture | Input Variable |
| Superplasticizer (component 5) | quantitative | kg in a m3 mixture | Input Variable-- Superplasticizers (SP's), also known as high range water reducers, are additives used in making high strength concrete. Their addition to concrete or mortar allows the reduction of the water to cement ratio without negatively affecting the workability of the mixture, and enables the production of self-consolidating concrete and high performance concrete |
| Coarse Aggregate (component 6) | quantitative | kg in a m3 mixture | Input Variable-- construction aggregate, or simply "aggregate", is a broad category of coarse to medium grained particulate material used in construction, including sand, gravel, crushed stone, slag, recycled concrete and geosynthetic aggregates |
| Fine Aggregate (component 7) | quantitative | kg in a m3 mixture | Input Variable—Similar to coarse aggregate, the constitution is much finer. |
| Age | quantitative | Day (1~365) | Input Variable |
| Concrete compressive strength | quantitative | MPa | Output Variable |

2.5 Tools Used

- Programming Languages : Python, HTML, CSS
- Libraries : Pandas, NumPy, scikit-learn, matplotlib
- API Framework: Flask
- IDE : VSCode
- Deployment: Heroku, Docker, GitHub



2.6 Constraints

Model training takes large memory and longer time. The accuracy of the prediction depends upon the quantity and quality of data.

2.7 Assumption

Machine learning based concrete compressive strength prediction system predicts the compressive strength of concrete based on input data. It is assumed that all aspects regarding data and models of this project have the ability to work together in the way the developer is expecting.

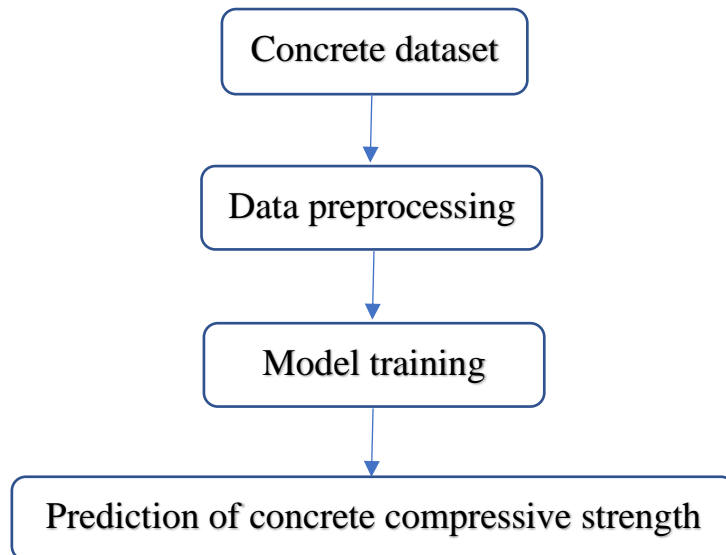
3. Design Details

3.1. Process flow

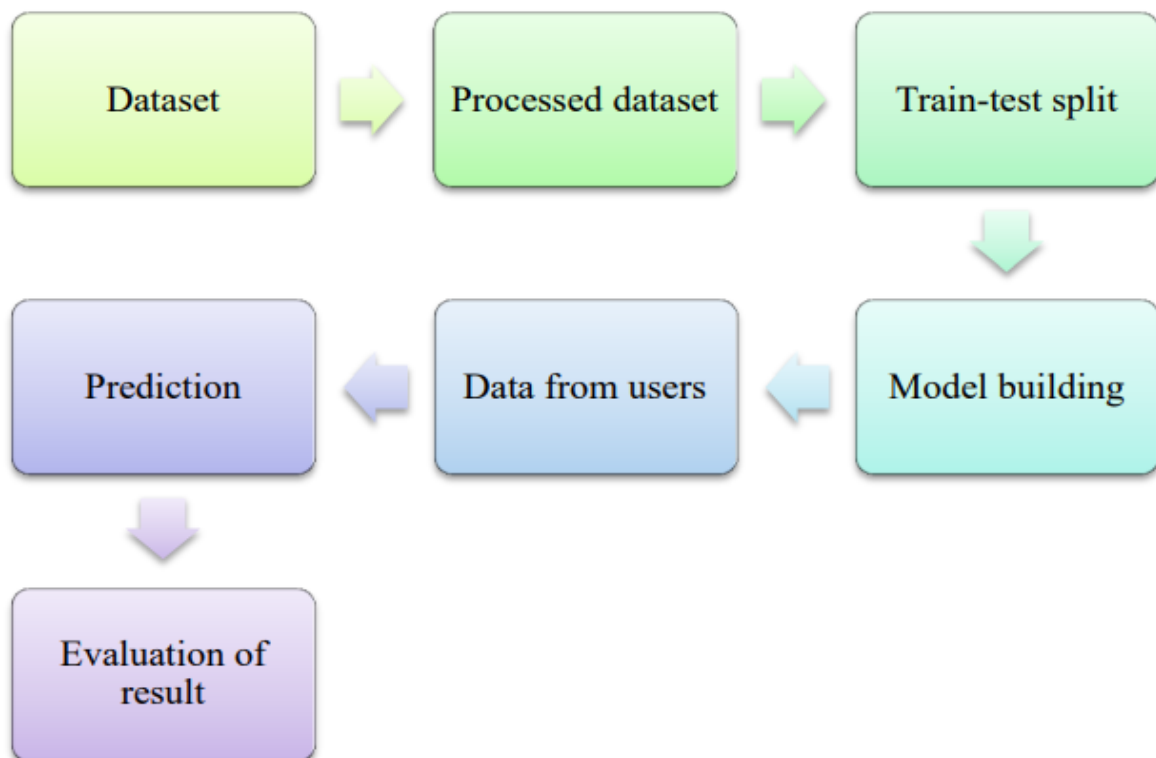
For predicting concrete compressive strength, we will use machine based model. Below is the process flow diagram as shown below.

3.1.1 Proposed methodology

Concrete Compressive Strength Prediction



3.1.2 Model Training and Evaluation



3.2 Event log

The system logs every event so that the user will know what process is running internally.

- Initial Step-By-Step Description
- The system identifies at what step logging is required
- The system logs each and every system flow.
- System handles many loggings. Logging allows easy debugging so logging is mandatory to do.

3.3 Error Handling

An explanation will be displayed as to what went wrong.

3.4 Performance

The system will predict the compressive strength of concrete.

3.5 Reusability

The code written and the components used have the ability to be reused with no problems.

3.6 Application Compatibility

The different components for this project will be using Python as an interface between them. Each component will have its own task to perform, and it is the job of Python to ensure the proper transfer of information.

3.7 Resource Utilisation

When any task is performed, it will likely use all the processing power available until that function is finished.

3.8 Deployment

The application will be containerized using Docker and deployed to Heroku using GitHub actions.

4. Conclusion

Hence, the concrete compressive strength prediction system will predict the compressive strength of concrete and will be able to determine the best set of approximate quantities of materials that the user can use to determine combinations by which he/she will be able to make the product with good strength.