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Python Implemented AI based Machine Learning Approach for the Prediction of Optimum Location of Building using Structural Response with Self Learning using ANN

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Abstract: The construction industry faces growing demands for faster, safer, and cost-effective building designs. Traditional methods are no longer sufficient, prompting the use of AI and ML for data-driven optimization. This study analyzes 10 multistory building cases with varying soil stiffness (K) using structural analysis software. A Python-based ML model focuses on predicting optimal configurations using column axial force data. An ANN is developed to minimize axial forces, with outputs visualized using Matplotlib. Data preprocessing is done using Pandas and NumPy, and models are built with scikit-learn and TensorFlow. Both Linear Regression and ANN are applied, with an 80:20 train-test split. The ANN outperforms with an MSE of 0 and R^2 of 1 after 150 training epochs. The model identifies optimal designs, improving cost efficiency and structural stability. This approach enhances design accuracy and reduces manual effort in structural engineering tasks.

Keywords: AI based Prediction, Machine Learning, Python Programming, Multistory Buildings, Optimization, Structural Design, Data Analysis, Model Training, Computational Efficiency

I. INTRODUCTION TO AI AND ML

Artificial Intelligence (AI) refers to the branch of computer science focused on creating systems or machines that can simulate human intelligence. These systems are designed to perform tasks typically requiring human cognition, such as learning, reasoning, problem solving, understanding natural language, and perceiving the environment.

Machine learning is a subset of artificial intelligence (AI) that focuses on developing algorithms and statistical models enabling machines to learn from and make decisions or predictions based on data without explicit programming for specific tasks. Machine learning involves feeding large amounts of data into algorithms that analyze and find patterns. Once trained, the models can make predictions, recognize patterns, or automate decision making for new, unseen data.

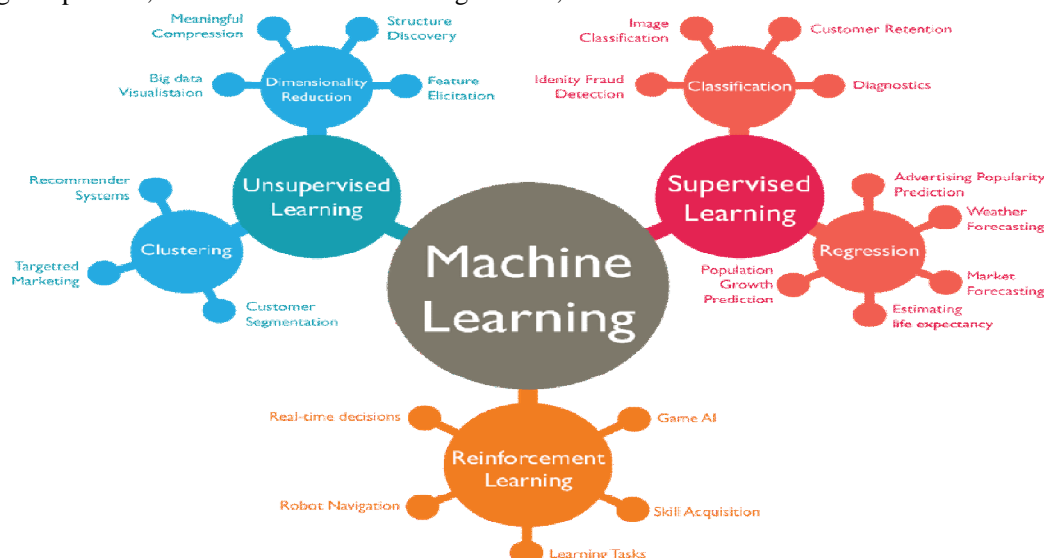


Fig. 1: Typical machine learning interaction with different industries

II. IMPORTANCE OF SITE LOCATION IN MULTI STOREYED BUILDING

Selecting the best soil location for a foundation involves a balance between natural soil properties, foundation type, and construction requirements. The extra load carrying capability of a multi storeyed building is crucial for several reasons, primarily concerning structural resilience, safety, and flexibility for future modifications. Here are some key points on its importance:

- 1) **Increased Safety Margins:** Buildings are typically designed to carry more load than they will regularly encounter. This additional capability is a safety margin, ensuring that the structure can handle unexpected loads due to environmental factors (e.g., heavy snow, wind, or seismic forces), temporary live loads, or human error in load estimations.
- 2) **Durability and Longevity:** Extra capacity allows the building to withstand wear and tear over time. It protects against structural degradation due to prolonged loading, fatigue, or potential corrosion in the materials, thus increasing the lifespan of the building.
- 3) **Resistance to Dynamic and Impact Loads:** Multi storeyed buildings may encounter dynamic loads (e.g., from elevators, machinery, or seismic activity) and impact loads (e.g., during renovations or unexpected events). The additional capability ensures the structure remains stable and safe under these variable loads.
- 4) **Flexibility for Future Modifications:** As buildings age, they may need to be repurposed, renovated, or expanded. The extra load carrying capability allows architects and engineers to make adjustments, like adding partitions, equipment, or even entire floors, without compromising the original structural integrity.
- 5) **Enhanced Performance under Extreme Events:** For areas prone to extreme conditions like earthquakes, high winds, or floods, extra load capability is essential for resilience. It helps the structure remain functional, even if it undergoes extreme lateral or vertical forces during these events.
- 6) **Reduced Maintenance Costs:** Buildings that operate near their maximum load capacity experience faster wear and require more frequent maintenance. Extra capacity minimizes strain, leading to fewer repairs and lower maintenance costs over the building's life.

III. LITERATURE REVIEW

The following literature articles have been selected for the current research study based on machine learning over AI architecture on different realistic problems. The individual summaries are as follows:

Alexandrina-Elena C. Pandelea et. al. (2014) In this research, Artificial neural networks are described as systems capable of solving complex problems for which no sequential algorithms exist, relying solely on examples of solutions has discussed. These systems are known to generate their own learning rules based on provided examples. Over the years, specific research addressing various problems has been undertaken in all areas of Civil Engineering using artificial neural networks, yielding varying degrees of success. Problems in the fields of building materials behavior, geotechnical engineering, structural engineering, structural identification and control, heat transfer, transport infrastructure, management, and technology in construction and installation have been studied extensively.

Somshubra Majumdar et. al. (2016) In this research, Sorting algorithms and their implementations in modern computing require ongoing improvements to efficiently handle large data sets, particularly in terms of time and memory consumption has discussed. This paper aims to review various adaptive sorting algorithms, focusing on selecting the appropriate algorithm based on the characteristics of the data set. Machine Learning facilitates the construction of adaptive algorithms by analyzing experimental data. A review of algorithms developed using Systems of Algorithmic Algebra and Genetic Algorithms was conducted. These methods are designed to address different use cases. Systems of Algorithmic Algebra represents pseudocode that can be converted into high-level code using an Integrated Toolkit for Design and Synthesis of Programs, while the Genetic Algorithm works by optimizing its fitness function to generate the most effective sorting algorithm.

Hongyan Zhang et. al. (2021) This paper presents a robot multi-object sorting system for unstructured scenes, focusing on efficient, stable, and accurate sorting. A rotating target detection model is trained using placement data of common objects, enabling detection of object position, rotation, and category. An optimized Mask R-CNN instance segmentation model segments object surfaces, and the normal vector of the upper surface is calculated to determine object attitude. Grasping order is determined by surface depth. The fused object posture, category, and grasping sequence are tested on an experimental platform. Experiments on object capture success rate show that the proposed system can efficiently sort stacked objects in unstructured environments.

Frank Jesús Valderrama Purizaca et. al. (2020) In this research, Artificial neural networks (ANNs) have become crucial in various fields due to their ability to solve complex problems with many constraints, outperforming traditional methods has discussed. This research conducts a systematic review of the literature to explore the use of ANNs in civil engineering.

A total of 41 articles were reviewed, sourced from Scopus, ScienceDirect, ProQuest, Google Scholar, DialNet, and SciELO. It was found that ANNs are widely used for predicting variables related to civil engineering, with applications in concrete properties, soil properties, seismic analysis, hydraulics, real estate valuation, and bridge design. The multilayer perceptron was identified as the most commonly used ANN model. An average R^2 of 0.99 was achieved, demonstrating its effectiveness in solving problems with precision and reducing error, even with missing data.

Pallavi U. Patil et. al. (2021) In this research, climate change-induced environmental stresses and limited agricultural land are addressed through sustainable agriculture intensification via crop diversification strategies. Dragon fruit, known for its nutraceutical benefits, is being promoted as a potential crop for resource-poor degraded lands. The understanding of consumer acceptability and the maintenance of high quality for marketing and processing are considered essential. Grading and sorting techniques for dragon fruit have been developed using machine learning algorithms (CNN, ANN, and SVM), based on a comprehensive review of available methods for detecting and classifying fruit quality through various features of fruits and vegetables. These algorithms are applied to analyze the shape, size, weight, color, and diseases of dragon fruits. Raspberry functionality is used to count the total number of fruits in a bucket, and sorting is carried out based on maturity levels using the machine learning algorithms.

IV. CRITIQUE AND IDENTIFICATION GAP OF RESEARCH PAPERS

- 1) Extensive research exists on AI/ML in building engineering, focusing on structural health monitoring and damage detection.
- 2) Most studies isolate specific components and lack integrated frameworks combining response data with optimization.
- 3) Current ML models rely on limited or synthetic datasets, restricting realworld applicability.
- 4) Generalized algorithms fail to account for customized structural configurations and design needs.
- 5) Few efforts directly integrate AI within Python-based structural design platforms.
- 6) Real structural response data under various loads is rarely used for model training.
- 7) Multi-variable optimization across structural factors is inadequately addressed.
- 8) Existing models are mostly static and lack adaptive or selflearning capabilities.
- 9) This research aims to bridge these gaps via a Pythonbased AI model for optimized multistory building design.

V. OBJECTIVES

With the aforementioned problem statement in mind, the following outline for new research work is proposed, emphasizing the conclusive outcomes detailed below in different sections:

- 1) To create the building cases using building analysis software over different bore holes.
- 2) To calculate spring stiffness using soil investigation report.
- 3) To analyse and obtain the axial force output parameter.
- 4) To create an AI and ML based code on python language and conduct value treatment, data normalization and cleaning.
- 5) To make a relationship of data from input values.
- 6) To select the technique for validation of selected datasets.
- 7) Evaluation of mean square error and R^2 score.
- 8) To study, evaluate and compare the the optimum structural case having least value among them using learning model of AI and ML based learning code.

The main and foremost objective is to create and use the AI and ML based coding that will be used for fast building analysis and fast prediction and recommendation of economic case among different soil scenario. From this dissertation, it has essential to find out the practical application in construction area and in the parallel field.

VI. METHODOLOGY

A. Data collection and preprocessing

Data collection involved sourcing structured and unstructured datasets from publicly available repositories and domain specific databases. Emphasis was placed on data quality, completeness, and relevance. Preprocessing steps included handling missing values, normalizing numerical features, encoding categorical variables, and performing feature selection or dimensionality reduction where necessary. Techniques such as Z score normalization and Principal Component Analysis (PCA) were applied to ensure the dataset was optimized for model training. Geotechnical soil investigation data has been used of a particular soil of seismic zone III, so that the structure will behave as it actually exists on the actual soil strata.

Table 1: Net safe bearing capacity obtained for all Bore Holes

Bore Hole Nos.	Type of Structure	Depth of Foundation (metres)	Size of Footing (metres)	Net Safe Bearing Capacity (Tonne/sqm.)	Settlement Produced (mm)	Safe Allowable Pressure /Permissible Settlement (Tonne/sqm.)
1	FOR CONSTABLE BLOCK	2.00	48.00X28.00	20.49	215.60	9.72/125.00
2		2.00	48.00X27.00	18.57	178.20	11.34/125.00
4		2.00	48.00X27.00	19.34	198.50	10.38/125.00
5		2.00	48.00X27.00	18.50	175.40	11.63/125.00
6		2.00	48.00X27.00	20.15	211.10	9.86/125.00
7		2.00	48.00X27.00	15.16	185.00	9.02/125.00
8		2.00	48.00X27.00	16.73	202.60	8.84/125.00
10		2.00	48.00X27.00	16.48	207.00	8.45/125.00
11		2.00	48.00X27.00	13.70	192.20	7.85/125.00
3	FOR NGO BLOCK	2.00	48.00X48.00	24.06	215.40	11.02/125.00
9		2.00	48.00X48.00	21.56	246.20	8.52/125.00

B. Output result parameter used - Axial Forces

Axial force refers to the internal force acting along the longitudinal axis of a structural member due to applied loads. It plays a key role in understanding how forces are distributed within elements under various conditions, typically resulting in either tension or compression. Monitoring axial forces helps detect stress concentrations, potential failure zones, and supports evaluation of structural integrity. These values are also vital for training AI models like ANN, enhancing their ability to predict structural behavior accurately.

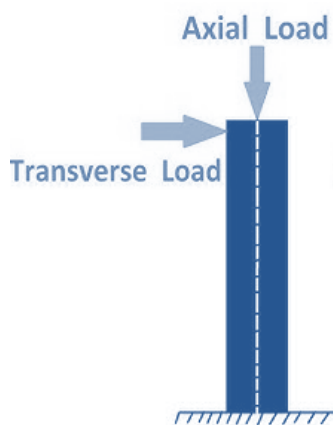


Fig. 2: Axial Forces in Column

C. Horizontal spring stiffness and its significance

Horizontal Spring Stiffness refers to the resistance offered by a structural or mechanical element such as spring, base isolator, or foundation system against horizontal (lateral) movement or deformation. It is usually denoted by K and measured in kN/m. Horizontal Spring Stiffness is defined as the ratio of the force P applied to an element to the resulting displacement Δ:

$$K = \frac{P}{\Delta} \dots \dots \dots \text{Eq. 1}$$

Table 2:Horizontal Spring Stiffness for selected 10 Bore Holes

Bore Hole No.	Soil Resistance (P) (Ton/Sq. m.)	Soil Resistance (P) (KN/Sq. m.)	Deflection (mm)	Deflection (m)	Horizontal Spring Stiffness (K = P/Delta)
1	20.49	20490	215.6	0.2156	95037.10575
2	18.57	18570	178.2	0.1782	104208.7542
3	24.06	24060	215.4	0.2154	111699.1643
4	19.34	19340	198.5	0.1985	97430.73048
5	18.5	18500	175.4	0.1754	105473.2041
6	20.15	20150	211.1	0.2111	95452.39223
7	15.16	15160	185	0.185	81945.94595
8	16.73	16730	202.5	0.2025	82617.28395
9	21.56	21560	246.2	0.2462	87571.08042
10	16.48	16480	207	0.207	79613.52657

Machine Learning

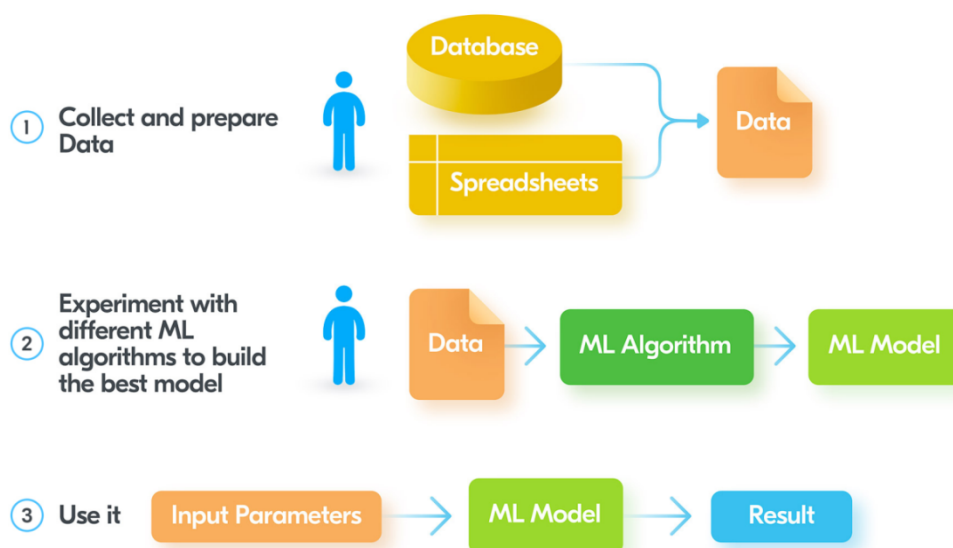


Fig. 3: Flow diagram for building a solution with machine learning

Table 3: Steps of structural response for prediction

Step	Purpose
Data Cleaning	Ensures high quality input by removing or filling missing values
Feature Selection	Uses structural response (Column Axial Force) as predictor and outcome
Model Training	Learns patterns from the data to generalize future predictions
Model Testing	Validates prediction accuracy on unseen data
Evaluation Metrics	Measures how well the model predicts using MSE and R ²

1) Step 1: Prepare input and target features for modeling

target = 'Column Axial Force'

df = df.dropna(subset=[target]) {Remove rows where target is missing}

df = df.fillna(df.mean()) {Fill remaining missing values with column }mean

X = df[['Column Axial Force']] {Input feature(s) can be expanded}

y = df[target] {Target variable (same in this case for prediction pattern learning)}

2) Step 2: Split data into training and testing sets

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

3) Step 3: Train a regression model (Linear Regression used here)

```
from sklearn.linear_model import LinearRegression
```

```
model = LinearRegression()
```

```
model.fit(X_train, y_train)
```

4) Step 4: Make predictions on unseen (test) data

```
y_pred = model.predict(X_test)
```

5) Step 5: Evaluate the model performance

```
from sklearn.metrics import mean_squared_error, r2_score
```

```
mse = mean_squared_error(y_test, y_pred)
```

```
r2 = r2_score(y_test, y_pred)
```

```
print(f'Mean Squared Error: {mse:.2f}')
```

```
print(f'R-squared: {r2:.2f}')
```

Table 4: List of buildings framed with assigned abbreviation

S. No.	Buildings framed for analysis	Abbreviation
1	Optimum Building Model supposed to be constructed at location 1	OBM1
2	Optimum Building Model supposed to be constructed at location 2	OBM2
3	Optimum Building Model supposed to be constructed at location 3	OBM3
4	Optimum Building Model supposed to be constructed at location 4	OBM4
5	Optimum Building Model supposed to be constructed at location 5	OBM5
6	Optimum Building Model supposed to be constructed at location 6	OBM6
7	Optimum Building Model supposed to be constructed at location 7	OBM7
8	Optimum Building Model supposed to be constructed at location 8	OBM8
9	Optimum Building Model supposed to be constructed at location 9	OBM9
10	Optimum Building Model supposed to be constructed at location 10	OBM10

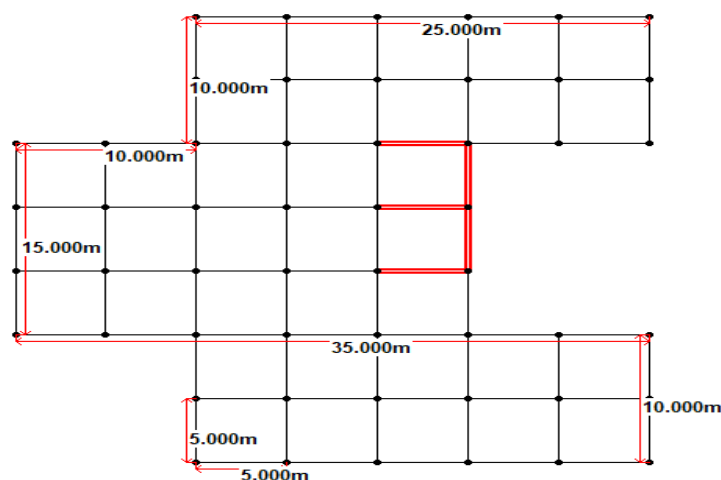


Fig. 4: Plan of all cases

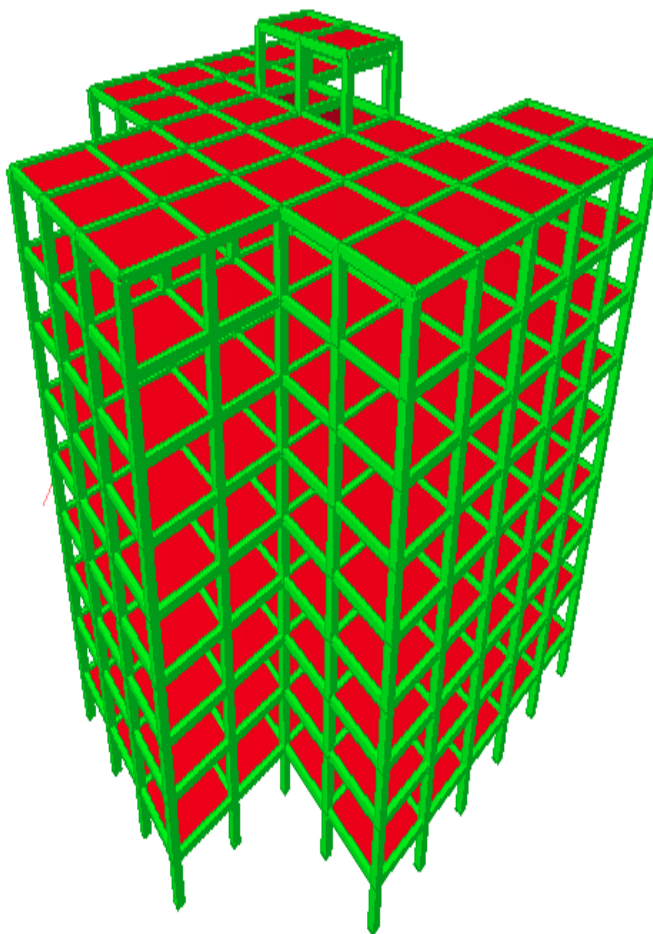


Fig. 5: 3D view of all cases

STAGES OF ML PROGRAMMING

PREPARE - TRAIN - PREDICT - REPEAT

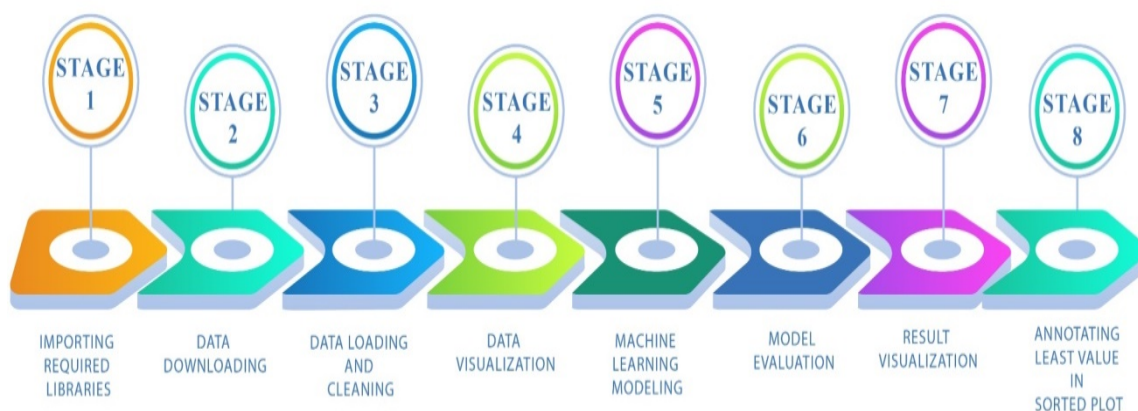
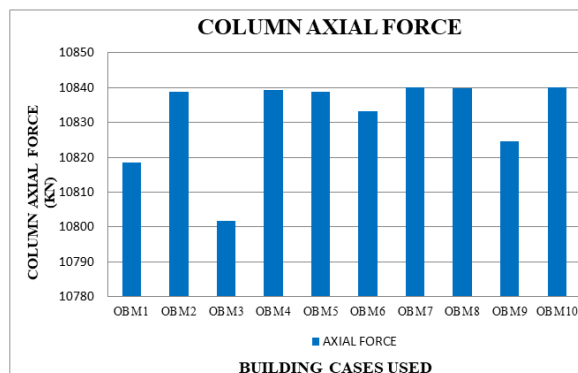


Fig. 6: Stages of ML programming

VII.RESULT AND DISCUSSION

Table 5: Maximum axial forces in column for all bore holes parameters using general intelligence

Model Case	Column Axial Force (KN)
OBM1	10818.425
OBM2	10838.891
OBM3	10801.749
OBM4	10839.218
OBM5	10838.829
OBM6	10833.294
OBM7	10839.970
OBM8	10839.937
OBM9	10824.666
OBM10	10840.082



Optimum case determination using artificial intelligence and machine learning approach

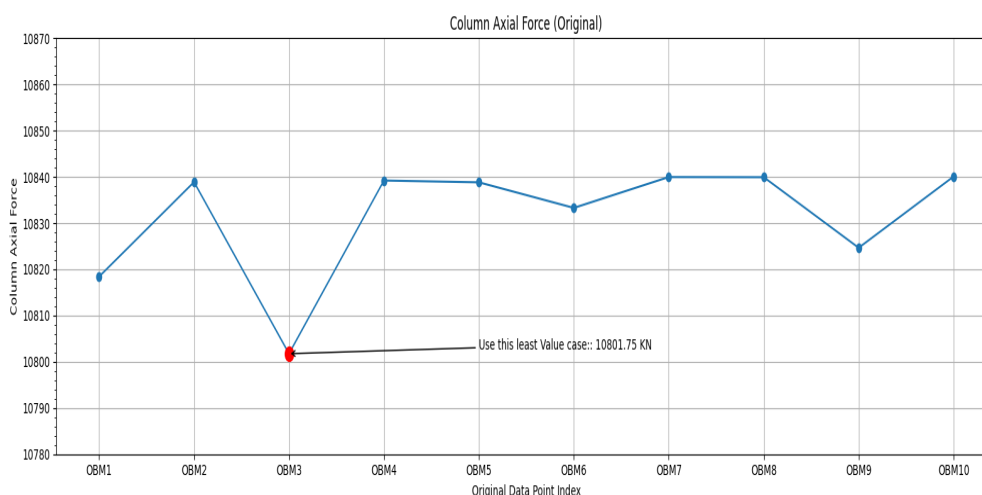


Fig. 7: General graphical plot of axial forces using matplotlib.pyplot and marking least value with matplotlib.ticker

In above figure, the general graphical plot of axial forces showed by importing the values and marked the least value within the plot.

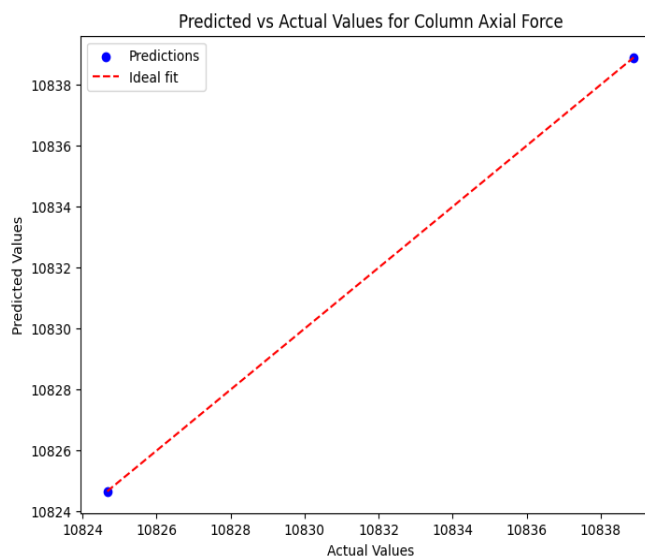


Fig. 8: Graphical plot of predicted value v/s actual value

In above figure, the graphical plot of predicted value v/s actual value has created and checked using mean square error and R^2 value come out to be 1. This represents the predictions are ideally fits the actual values.

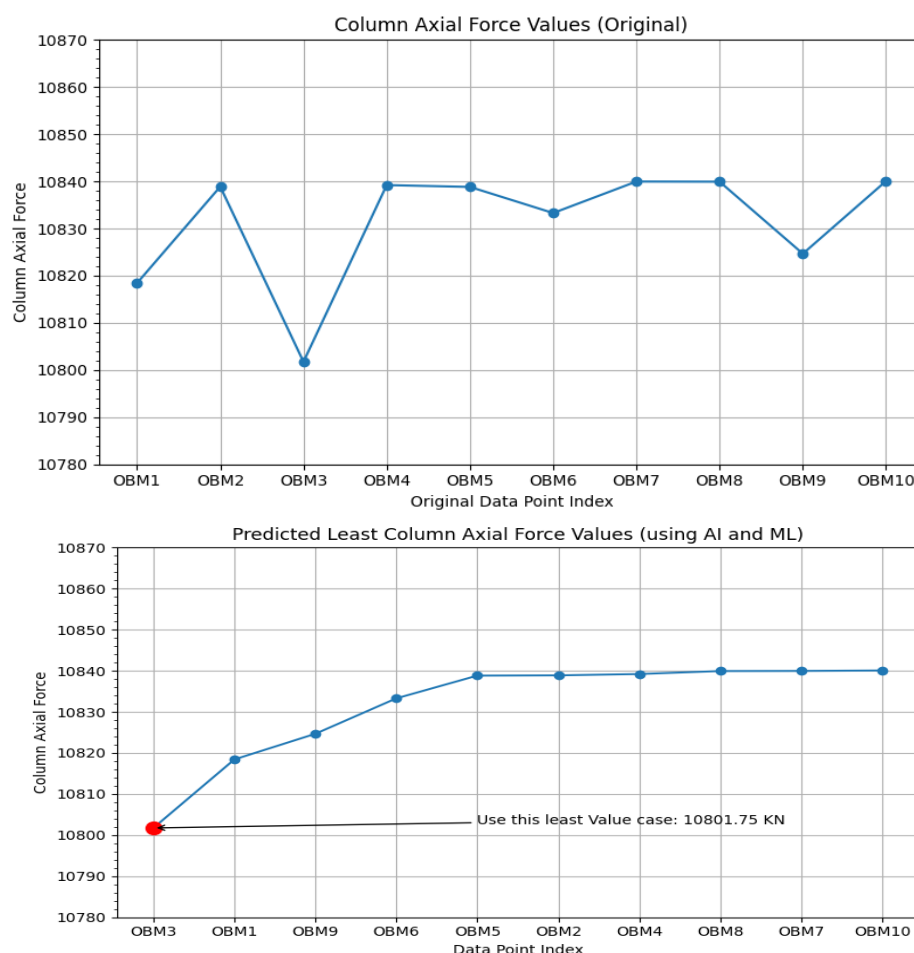


Fig. 9: Graphical plot of original column axial forces values and predicted least column axial force values using AI and ML

In above figure, the graphical plot of original column axial forces values and predicted least column axial force values using AI and ML has created and the machine learning programming has automatically predicts and arrange the least value according to artificial intelligence.

VIII. CONCLUSION

With the aforementioned problem, the following conclusions have drawn mentioned below:

- 1) Building case creation: Multiple structural models were successfully created using building analysis software, incorporating varied subsurface conditions represented by different borehole data. This enabled a realistic evaluation of the influence of geotechnical variability on structural performance. Total 10 distinct building cases created abbreviated as OBM1 to OBM10.
- 2) Spring stiffness calculation: Spring stiffness values were accurately derived from the soil investigation reports, allowing realistic simulation of soil structure interaction and the incorporation of subgrade response in the structural models. It has basically denoted by K and the obtained value used as input for analysis software to provide a pretend scenario over actual soil.
- 3) Axial force analysis: Structural analysis yielded axial force values as key output parameters. These results formed the basis for evaluating the structural loading behavior under varying soil conditions and served as critical input data for AI-ML model training.
- 4) AI-ML based code development: A Python based machine learning model was developed incorporating essential pre processing steps such as missing value treatment, data normalization and data cleaning to ensure high quality and reliable input data. This has achieved using Pandas v2.0.3 and NumPy v1.26.4.

- 5) Selection of techniques for data relationship: The AI-ML based linear regression and feed forward Artificial Neural Network model established using meaningful relationships between the input parameters (e.g., soil properties, stiffness, load cases) and output responses (axial force), demonstrating strong predictive capability.
- 6) Validation technique selection: Suitable validation techniques such as scikit-learn (sklearn) v1.3.0 and TensorFlow v2.16.1 used that train test split data and conduction of cross validation to ensure robust evaluation of model performance. An 80:20 train test split was applied to the dataset, and the models were trained and validated using scikit-learn (sklearn) v1.3.0 and TensorFlow v2.16.1 respectively.
- 7) Model evaluation (MSE and R^2): Model performance was assessed using Mean Squared Error (MSE) and R^2 score. The results indicate that ANN trained over 150 epochs (time) with two hidden layers of 64 and 32 neurons, produced an MSE of 0 and an R^2 of 1, thereby demonstrating improved predictive accuracy and reliability.
- 8) Optimum case comparison: Among all structural cases, the model successfully identified the optimum configuration i.e., the case with the least axial force highlighting the effectiveness of AI-ML in optimizing structural design based on soil and structural parameters.

The main and foremost objective has achieved, all the model cases have created over selected bore hole cases, applied K value, analyzed and results obtained by using analysis software. Results are then used as input for obtaining the best possible location. Also, the AI and ML based code snippets has proved for fast building site prediction with larger dataset with recommendation of economic case among different soil scenario and will recommend to use this self learning approach for practical application in building engineering which significantly minimized manual effort while improving the speed and accuracy of structural assessments.

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REFERENCES

- [1] Pandelea, A.-E. C., Budescu, M. Gh., Covatariu, G. M., & Gheorghe Asachi Technical University of Iași, Faculty of Civil Engineering and Building Services. (2014). Applications of artificial neural networks in civil engineering. In 2nd International Conference for PhD Students in Civil Engineering and Architecture.
- [2] Sasnauskas, R., SES Engineering, Chen, Y., Nvidia, Inc., Collingbourne, P., Google, Inc., Ketema, J., Embedded Systems Innovation by TNO, Lup, G., Microsoft, Inc., Taneja, J., University of Utah, Regehr, J., & University of Utah. (n.d.). A Synthesizing Superoptimizer. Conference Paper.
- [3] Shazeer, N. & Google. (2019). Fast Transformer Decoding: One Write-Head is All You Need. Conference Paper.
- [4] Evaluating Large Language Models Trained on Code. (2021). In arXiv [Journal-article]. <https://arxiv.org/pdf/2107.03374>
- [5] Pearce, H., Tan, B., Ahmad, B., Karri, R., New York University, & University of Calgary. (2022). Examining Zero-Shot Vulnerability Repair with Large Language Models [Journal-article]. arXiv. <https://arxiv.org/abs/2112.02125v3>
- [6] Andon, A., & Covatariu, G. (2022). A Study on Image Processing Using Artificial Neural Networks in Civil Engineering. Buletinul Institutului Politehnic "Gheorghe Asachi" Din Iași. Secția Construcții. Arhitectură, 67(3), 85–94. <https://doi.org/10.2478/bipca-2021-0027>
- [7] Majumdar, S., Jain, I., & Kukreja, K. (2016). AdaSort: Adaptive Sorting using Machine Learning. International Journal of Computer Applications, 145(12), 12–17. <https://doi.org/10.5120/ijca2016910726>
- [8] Shaikh, A., Sawant, S., Patil, A., Bhandare, A., & International Research Journal of Modernization in Engineering, Technology and Science. (2024). RAISIN SORTING USING MACHINE LEARNING ALGORITHM. International Research Journal of Modernization in Engineering Technology and Science, 06. <https://www.irjmets.com>
- [9] Fuchsguber, D., Poštuvan, T., G. Unnemann, S., Geisler, S., Department of Computer Science & Munich Data Science Institute, TU Munich, & EPFL. (2024). GRAPH NEURAL NETWORKS FOR EDGE SIGNALS: ORIENTATION EQUIVARIANCE AND INVARIANCE.
- [10] Zhang, H., Liang, H., Ni, T., Huang, L., & Yang, J. (2021). Research on Multi-Object Sorting System Based on Deep Learning. Sensors, 21(18), 6238. <https://doi.org/10.3390/s21186238>
- [11] Purizaca, F. J. V., Barturen, D. a. C., Pérez, S. P. M., Tuesta-Monteza, V. A., & Mejía-Cabrera, H. I. (2020). Importance of artificial neural networks in civil engineering: a systematic review of the literature. ITECKNE Innovación E Investigación En Ingeniería, 18(1). <https://doi.org/10.15332/iteckne.v18i1.2542>
- [12] Anjum, A., Hrairi, M., Shaikh, A. A., Yatim, N., & Ali, M. (2024). Integrating AI and statistical methods for enhancing civil structural practices: current trends, practical issues, and future direction. Frattura Ed Integrità Strutturale, 19(71), 164–181. <https://doi.org/10.3221/igf-esi.71.12>
- [13] Li, X., Garzaran, M. J., & Padua, D. (2007). Optimizing Sorting with Machine Learning Algorithms. Conference Paper, 1 2, 1–6. <https://doi.org/10.1109/ipdps.2007.370499>
- [14] Patil, P. U., Lande, S. B., Nagalkar, V. J., Nikam, S. B., & Wakchaure, G. (2021). Grading and sorting technique of dragon fruits using machine learning algorithms. Journal of Agriculture and Food Research, 4, 100118. <https://doi.org/10.1016/j.jafr.2021.100118>
- [15] Research and applications of artificial neural network in pavement engineering: A state-of-the-art review. (2021). In Journal of Traffic and Transportation Engineering (English Edition). <http://doi.org/10.1016/j.jtte.2021.03.005>
- [16] Faster sorting algorithms discovered using deep reinforcement learning. (2023). Nature, 618, 257–258.



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