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An Ensemble Machine Learning-Based Decision-Support Framework for Predicting Construction Labour Productivity

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ABSTRACT

The construction sector is currently recognised as a highly innovative industry, where sustained monitoring of labour efficiency has accelerated project expansion. Nevertheless, addressing performance constraints requires optimising workforce productivity, accurately estimating task durations, and improving output rates to minimise labour expenses and project timelines. This study examines enhancements to conventional site practices, where professionals such as contractors, engineers, and managers typically rely on theoretical productivity approximations that often result in time and cost inefficiencies. Within the Egyptian context, standardised benchmarks for forecasting construction labour productivity remain absent. Accordingly, this research identifies the principal determinants affecting column formwork productivity through a structured questionnaire. Variables demonstrating high relative importance index (RII) values were selected as independent predictors influencing the dependent variable, labour productivity, within the proposed model. Empirical productivity observations were recorded at two-hour intervals across three sites, Smouha, Beheira, and Moharam-Bek, enabling the assessment of time and cost loss ratios and the establishment of baseline metrics for each location. Furthermore, an artificial intelligence model was implemented using the Python programming language within Visual Studio Code to estimate short-term productivity, thereby supporting improved scheduling and managerial decision-making for enhanced efficiency and cost reduction. The findings indicate that the developed ensemble machine learning approach achieved a performance accuracy of 97.66% with a validation error of 0.015. A web-based platform was also created as a baseline system, offering practitioners and planners a dependable and precise tool for forecasting column formwork labour productivity at two-hour intervals prior to project execution.

1. Introduction

Poor labour productivity remains a critical challenge in construction, as it elevates project costs and extends completion timelines [11]. Consequently, the measurement of labour productivity has

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gained considerable importance, particularly in relation to time and cost efficiency [19]. Empirical evidence indicates that methodological limitations constrain accurate productivity assessment in construction contexts, although the sector continues to demonstrate strong value generation per labour hour [2]. Furthermore, numerous determinants influencing labour productivity have been identified, enabling the modelling of interrelationships among key factors to enhance performance outcomes within the industry [4]. Analytical approaches, including index number techniques and econometric estimation of production or cost functions, highlight the necessity of integrating multiple methodologies for reliable evaluation [24]. The selection of appropriate formwork systems in high-rise construction has also been shown to significantly influence both project duration and cost, with the relative importance index method widely applied to determine critical factors [14]. Observational studies reveal that only a limited proportion of working time is utilised productively, with approximately 30% of total time contributing to effective output [3]. Process control techniques have further been employed to establish baseline productivity under standard conditions, alongside quantifying associated time and cost loss ratios [1].

Despite continuous advancements, improving productivity modelling remains a persistent concern, driven by the increasing demand for more accurate and practical predictive frameworks [12]. Statistical regression approaches, supported by extensive historical datasets, have demonstrated high predictive capability in estimating project cost and duration [8]. The literature further confirms the availability of diverse techniques for forecasting labour productivity, with multiple studies validating the accuracy of these approaches [5; 10; 13; 23]. Direct observational methods combined with neural network models have been utilised to estimate production rates with minimal error margins [20]. In parallel, advancements in artificial intelligence have transformed construction engineering practices through the integration of machine learning and digital technologies, enhancing design optimisation, automation, and quality management processes [16; 17]. Recent developments in deep learning have also improved predictive accuracy in control chart applications [22], while ensemble-based approaches, such as random forest algorithms, have strengthened predictive robustness through the aggregation of multiple decision trees [6]. These methods have demonstrated significant potential in monitoring and forecasting labour productivity [13; 21].

Ensemble machine learning techniques have shown superior performance in predicting labour productivity and project delays compared to individual models [7]. Hybrid approaches, including stacking and voting algorithms, have achieved enhanced predictive precision in construction environments. Additionally, the integration of multiple neural networks has proven effective in evaluating labour efficiency in reinforcement activities [15]. Emerging non-destructive monitoring methods, such as ultrasonic wave reflection, have enabled accurate assessment of concrete hardening, supporting optimal decision-making for formwork removal based on material stiffness development [18]. Comparative analyses indicate that both random forest and deep neural network models can reliably estimate formwork and shoring removal times, with the former demonstrating higher accuracy and forming the basis for web-based decision support systems [25].

2. Research Methodology

The comprehensive flowchart (Fig. 1) outlines the methodological framework adopted for developing the ensemble learning model, presenting a sequential depiction of procedures from data pre-processing to model evaluation in the context of analysing labour efficiency in formwork activities.

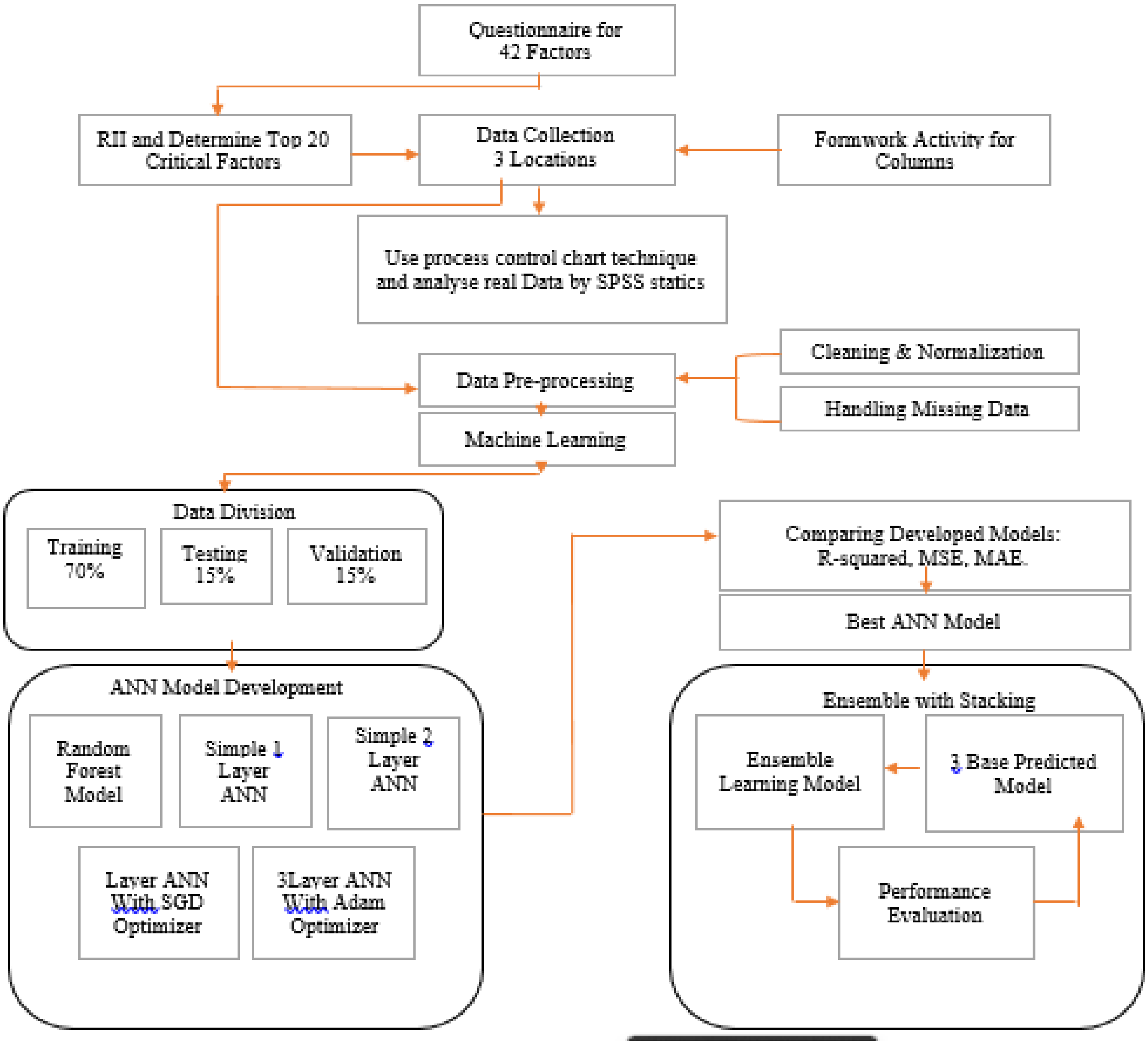

Fig. 1: Flowchart of Labour Productivity Prediction

3. Data Collection and Results

3.1 Survey Questionnaire

In this study, a structured questionnaire was employed to identify the most significant factors affecting labour productivity through the calculation of the RII, as presented in Equation (1). A total of 42 key variables relevant to labour productivity in Egypt were incorporated into the survey, with 700 questionnaires distributed and 450 valid responses obtained. Factors with RII values exceeding 0.75, as illustrated in Fig. 2, were selected as independent input variables influencing the single dependent variable, labour productivity. The analysis of responses enabled the identification of the 20 most critical factors impacting labour productivity in column formwork activities within the Egyptian construction context.

$$RII\ (\%) = \sum_{i=1}^{i=5} \left(\frac{i}{15}\right) \times \left[\frac{\sum_{k=k}^{k=1}[(K \times RII_K^i]}{\sum_{k=1}^{k=k}(k)}\right] \quad (1)$$

Where: i = response category index, and N = is the total number of respondents [9].

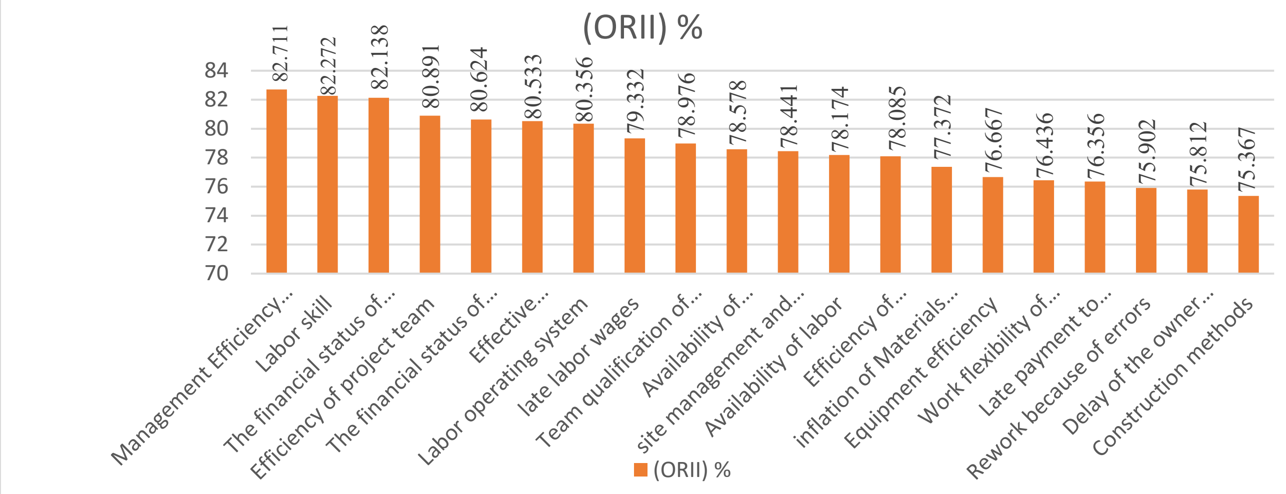

Fig. 2: Overall Ranking of the Top Twenty Most Influential Variables on Productivity

3.2 Productivity Data Collection

Real-time productivity observations were gathered at two-hour intervals from multiple construction sites to evaluate labour performance. Site selection was based on defined criteria, including geographical location (Smouha, Beheira, and Moharam-Bek) and project type, ensuring access to detailed records on workforce performance, scheduling, and other variables influencing productivity. The dataset supported a robust and adaptable environment for model development, validation, and deployment. Empirical data were derived from daily column formwork operations over varying durations. The first case involved three residential buildings in Smouha, each comprising 12 floors with an approximate area of 1000 m² per building, where data were recorded over one year. The second case covered a single five-storey residential building in Beheira, with data collected at two-hour intervals across a six-month period. The third case included two residential buildings in Moharam-Bek, each with 11 floors, where productivity data were obtained over two months. The dataset was categorised into independent and dependent variables. Independent variables represented critical influencing factors affecting labour productivity, whereas the dependent variable corresponded to productivity output measured as cubic metres per two hours ($m^3/2h$), serving as the target for prediction. These variables were selected based on their direct impact on variations in daily labour performance. Although data collection occurred between 2022 and 2023, the identified factors remain consistently relevant across contemporary construction environments. Given the dynamic nature of productivity and its determinants, measurements were systematically recorded at two-hour intervals to capture short-term fluctuations accurately.

3.3 Baseline Productivity Assessment

Real-time productivity measurements were obtained at two-hour intervals, followed by the application of process control chart techniques to detect inefficiencies, including time and cost loss ratios, and to establish baseline values. The implementation of control charts involved a sequence of procedures to ensure data reliability and analytical validity. Initially, the dataset was pre-processed through the treatment of missing values and the elimination of outliers. Subsequently, statistical parameters, including the mean and standard deviation, were computed to define the upper and lower control limits (UCL and LCL). Identified outliers were either corrected or excluded, ensuring that the control charts accurately represented inherent process variability. This procedure resulted in refined control limit charts capable of effectively monitoring process stability and deviations.

For the Smouha site, the average proportion of time utilised to complete the full scope of column formwork activities under standard operating conditions was approximately 84% of total working time, with an associated time loss of about 15.3% for the activity. At the Beheira site, the corresponding productive time averaged 79%, indicating a time loss of nearly 20.8%. In contrast, the Moharam-Bek site demonstrated higher efficiency, with approximately 88% of time contributing to productive work and a reduced time loss of around 11.5%. These loss estimations were confined to the column formwork activity rather than the overall project. Baseline productivity values were established on a two-hour basis for each location, where the central line (C.L) values were recorded as 11.462 $m^3/2h$ for Smouha, 11.133 $m^3/2h$ for Beheira, and 15.171 $m^3/2h$ for Moharam-Bek, as presented in Table 1.

Table 1

Process Control Chart Summary for Three Locations

Metrics	Smouha	Beheira	Moharam-Bek
Productivity Per Two Hours/ Labour	0.72	0.56	0.64
Actual Accumulated Hours	1298 H	1290 H	2024 H
Cumulative Baseline Hours	1098.99 H	1021.1 H	1795.2 H
Loss of Hours	199.01 H	268.93 H	227.8 H
Percentage of Loss in Time and Cost	15.3%	20.8%	11.5%

3.4 Initial Statistical Analysis

Following the identification of productivity declines and associated time and cost losses, the dataset was further examined using the Statistical Package for the Social Sciences (SPSS) to manage these variations. This analysis facilitated the formulation of predictive equations for each site, delivering high-accuracy forecasts of labour productivity, particularly for column formwork activities. The developed model supports more effective workforce allocation, minimises time inefficiencies, enhances cost control, and ultimately improves overall project performance. The R^2 values for all three models indicate strong predictive capability, confirming their effectiveness in estimating labour productivity. Although the Smouha, Beheira, and Moharam-Bek models all demonstrate high performance, the observed differences among them are not practically significant. However, based on the F-statistic, the Moharam-Bek model exhibits a superior fit (81.472) compared to Beheira (39.785) and Smouha (28.357). A higher F-statistic reflects improved model robustness, suggesting that the Moharam-Bek model is more reliable, particularly given its relatively moderate time and cost loss level of 15.3%. Furthermore, the significance level (Sig. F) for all models is identical (0.001), indicating that each model is statistically significant and equally reliable, as presented in Table 2.

Table 2

The Key Summary Statistics of the Three Models

Model	R2 (Predictive Power)	F-Statistic (Model Fit)	Sig.F (Statistical Significance)	Std. Error of the Estimate
Smouha	0.931	28.357	.001	1.67104
Beheira	0.957	39.785	.001	1.01548
Moharam-Bek	0.966	81.472	.001	1.36212

Figure 3 presents the statistical outcomes for the Smouha site, illustrating the relationship between observed and predicted values produced by the regression model. The black line represents the ideal prediction, and the dense clustering of points around this line indicates the model's high predictive accuracy. Most data points align closely with the line, demonstrating that the predicted values correspond well with actual measurements. Overall, the graph confirms the strong performance of the regression model.

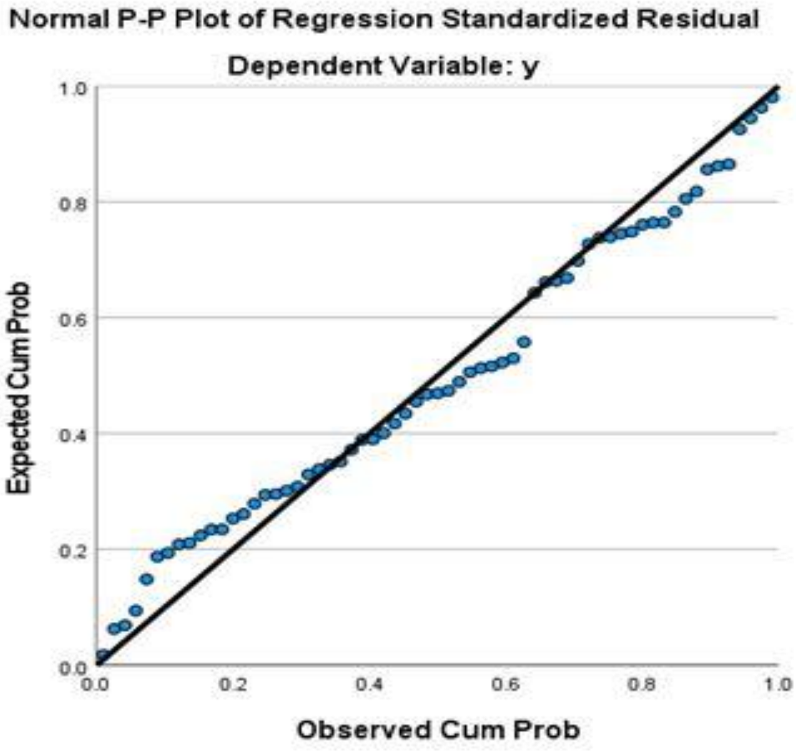

Fig. 3: Overall Ranking of the Top Twenty Most Influential Variables on Productivity

3.5 Data Pre-Processing

During the pre-processing phase, the dataset underwent several steps to prepare it for model training. Initially, data cleaning was performed by addressing missing values and removing outliers to ensure input quality. To achieve consistent model performance across sites, all variables were normalised using the Standard Scaler, aligning them to a common scale and enhancing prediction accuracy. Feature selection and extraction were then applied to optimise the input data, improving model precision and minimising overfitting. Finally, the dataset was divided into training, testing, and validation subsets (70%, 15%, and 15%, respectively) to assess the model's ability to generalise and accurately predict unseen data.

3.6 ANN Model Development

Initially, a model was created by combining datasets from the three sites; however, its performance was limited, achieving an R^2 value of only 75.6%. This result indicated that the model failed to adequately capture the unique factors influencing labour productivity at each individual site. A portion of the implementation code is presented in Fig. 4 to illustrate the procedure.

To improve predictive accuracy, the methodology in this study was revised. Rather than using a combined dataset model, five separate models were developed in Python for each location (Smouha, Beheira, and Moharam-Bek) to identify the most effective predictive approach. Data analysis at each site revealed the key positive factors influencing productivity, enabling more precise forecasts. Each model incorporated a combination of traditional machine learning, deep learning, and hybrid architectures.

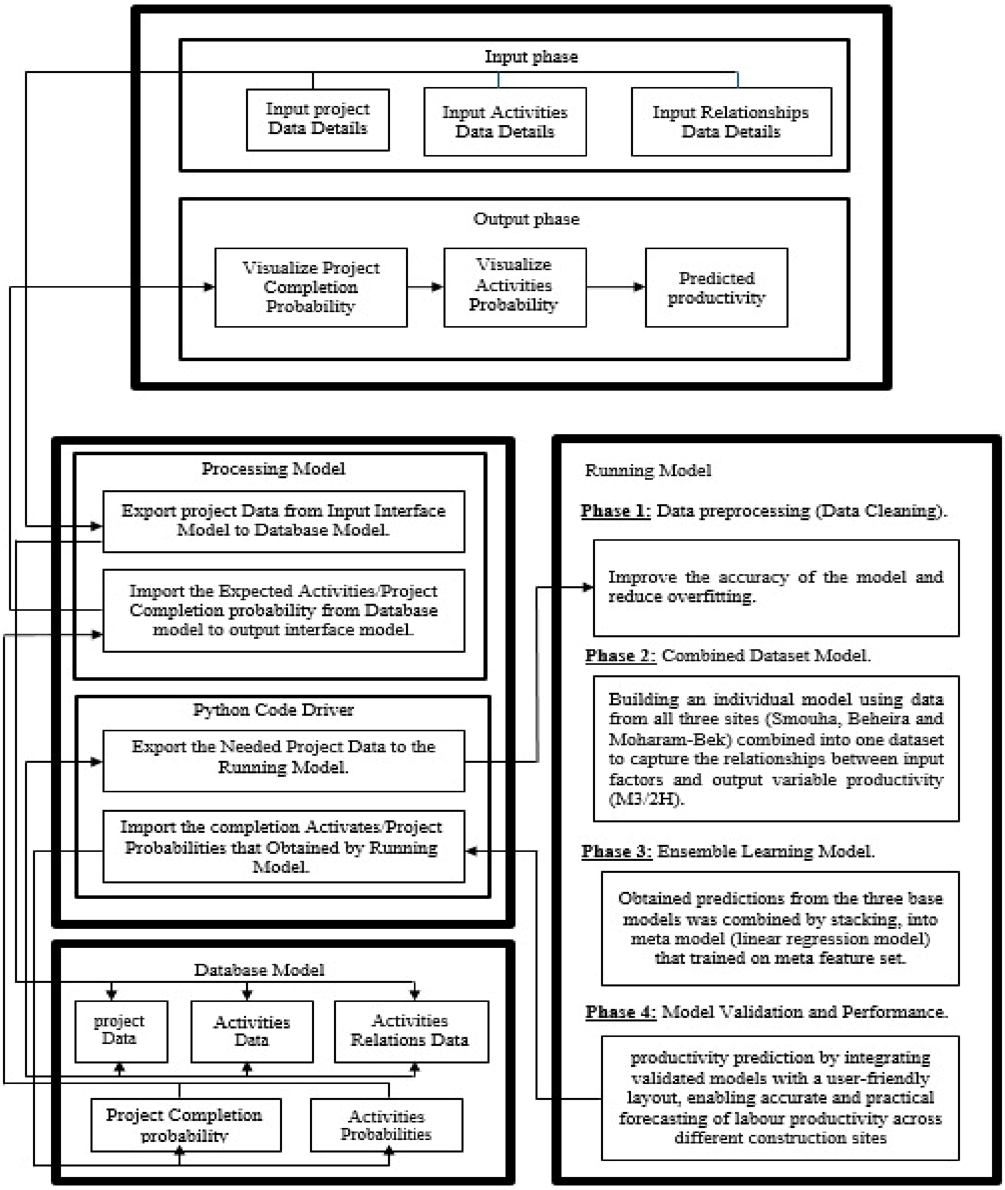

Fig. 4: Python Code Snippet Used for Training the Ensemble Model

Comparative evaluation indicated that a three-layer artificial neural network (ANN) with the Adam optimizer achieved the highest performance, as shown in Table 3. Additionally, three high-performing individual deep learning models were selected for each construction site to predict labour productivity in column formwork activities.

Table 3

Evaluation Metrics for Five Models Applied to Each Site

Architectures	Smouha Model			Behierh Model			Moharam Bek Model		
	MAE	MSE	R2	MAE	MSE	R2	MAE	MSE	R2
Random Forest Model	2.12	7.14	0.75	1.71	4.70	0.69	2.73	11.25	0.71
Simple 1-Layer ANN	0.59	1.19	0.95	0.40	0.46	0.96	0.90	2.21	0.94
Simple 2-Layer ANN	0.74	1.60	0.94	0.51	0.60	0.96	1.18	2.94	0.92
Layer ANN with SGD Optimizer	0.69	1.44	0.95	0.44	0.48	0.96	1.01	2.38	0.93
3 Layer ANN with Adam Optimizer	0.5001	1.0860	0.9628	0.3740	0.4594	0.9701	0.7408	1.6458	0.9594

3.7 Developing the Ensemble Machine Learning Productivity Model

For each site, the highest-performing model among the five developed was selected, and their predictions were combined into a meta-feature set using the stacking technique. A linear regression model was then trained on this meta-feature set to form the final ensemble model. Subsequently, a web-based platform was created to predict labour productivity at two-hour intervals. This website functions as a baseline tool that engineers, project managers, and consultants can utilise to monitor and enhance productivity performance.

3.8 Stacking Technique

The ensemble learning approach using the stacking technique is designed to optimise the integration of predictions from the selected deep learning models, enhancing overall predictive performance by leveraging the strengths of each algorithm. As illustrated in Figure 5, the two-level stacking method involves training the base-level (level 1) models and collecting their predictions. The second level then utilises these outputs, combining the advantages of the different models trained on diverse datasets to produce the final prediction.

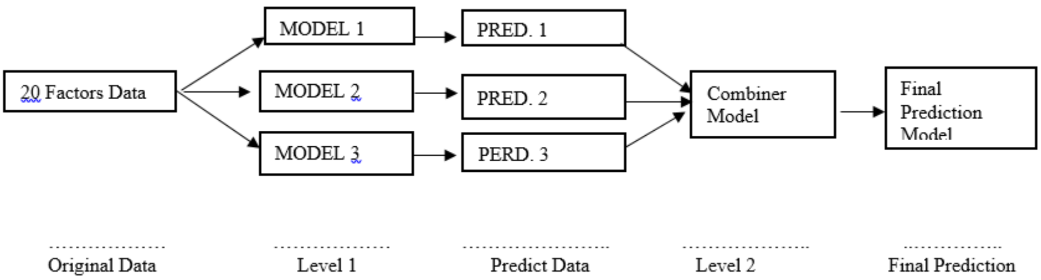

Fig. 5: Stacking Ensemble Model Structure

3.9 Software Implementation

This sequence of technical illustrations presents the software implementation of an advanced ensemble machine learning workflow developed in Python. The process begins with structured data ingestion and preprocessing, including the scaling of site-specific datasets such as Smouha and Moharam-Bek, followed by the deployment of three specialised pre-trained neural network models.

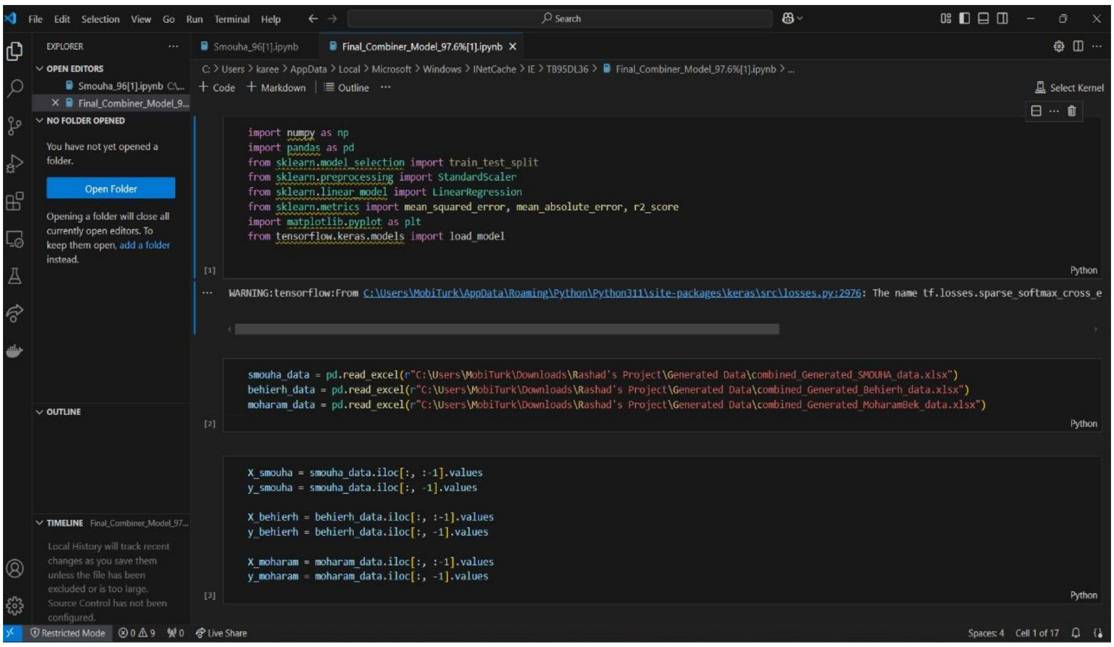

Fig. 6: Import Data smouha_data, behierh_data, moharam_data

A linear regression meta-model is then employed to integrate these individual outputs, achieving a high predictive accuracy with an R^2 of 0.9766 and a low mean squared error (MSE) of 0.687. The implementation concludes with a comparison of actual versus predicted values, confirming the model's reliability and robust performance in practical applications.

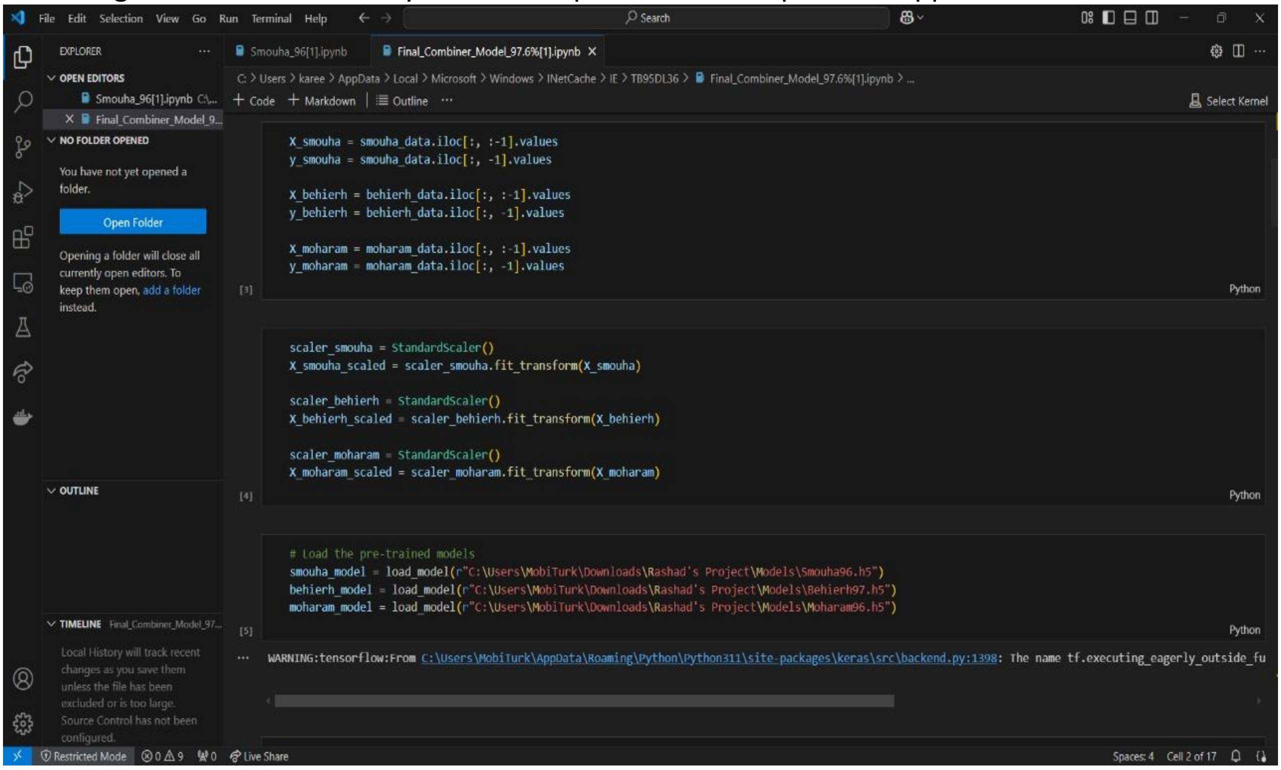

Fig. 7: Load the Pre-Trained Models

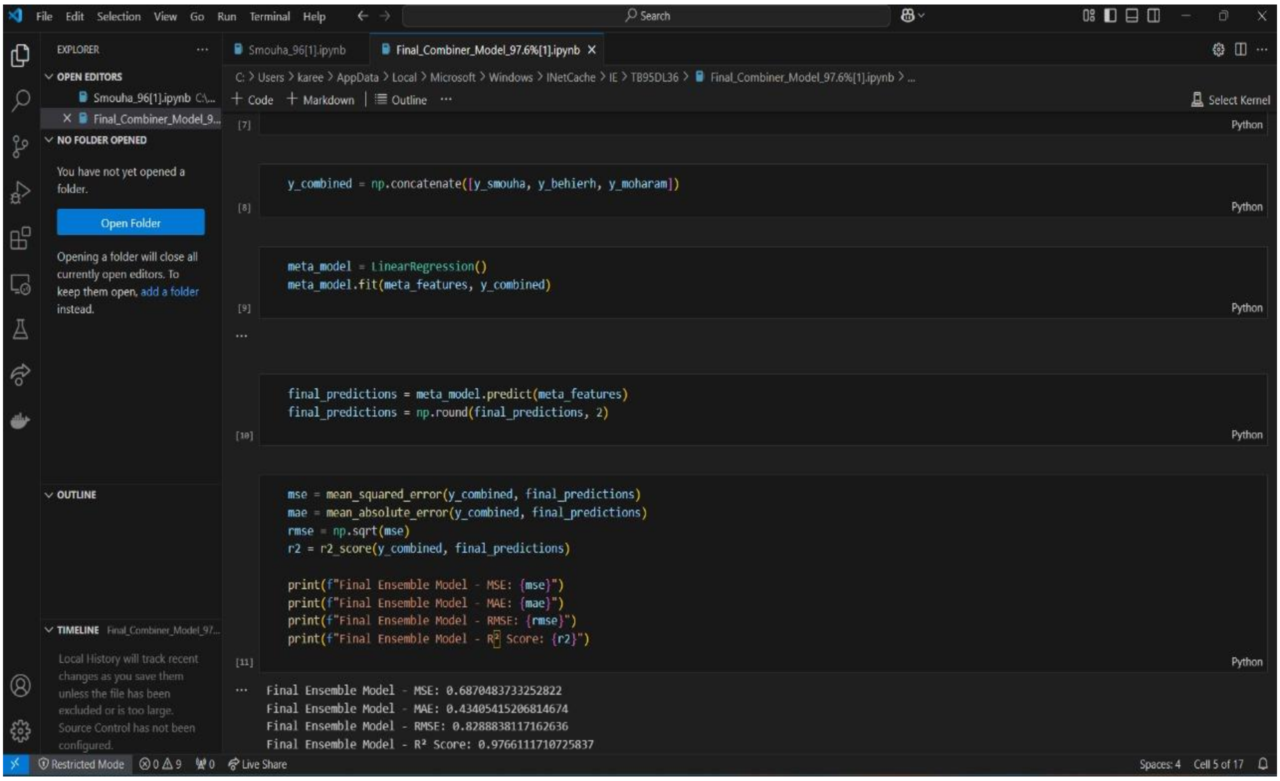

Fig. 8: Model Linear Regression Fit and Calculate r^2 and MSE

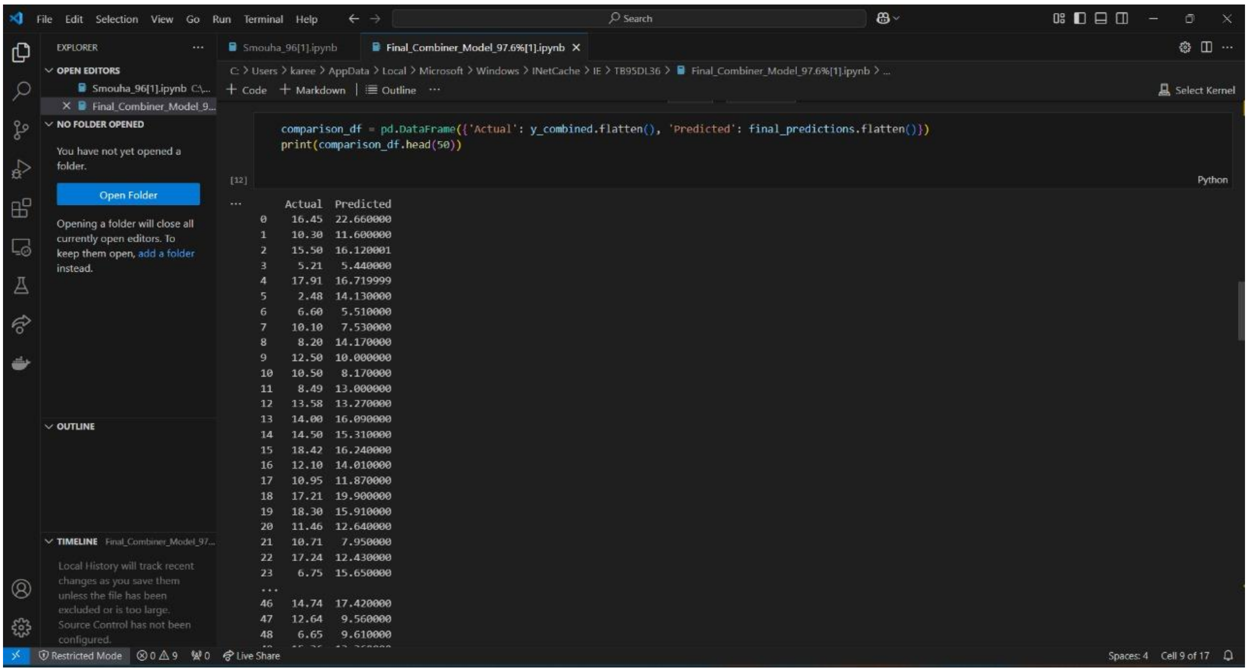

Fig. 9: Actual Predicted for LP

3.10 Model Evaluation Metrics

In this study, multiple performance evaluation metrics were employed to assess the suitability of the model, including MSE, root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2), as presented in Equation (2). The MAE quantifies the average absolute difference between predicted and actual values, with values closer to zero indicating higher predictive accuracy. Similarly, the MSE is calculated by squaring these differences, where lower values correspond to improved model performance, as shown in Equation (3). The RMSE, derived as the square root of the MSE, provides another measure of predictive accuracy; like MSE and MAE, smaller RMSE values indicate better model fit, as illustrated in Equation (4). RMSE is particularly useful because it retains the same units as the dependent variable, making it more interpretable compared to MAE and MSE when evaluating regression models. The coefficient of determination, R^2, ranges from 0 to 1, with values approaching 1 indicating a stronger model fit. R^2 represents the proportion of variance in the dependent variable explained by the model, as calculated in Equation (5). The relevant equations are presented as follows.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{2}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{5}$$

Where:

n = The number of total observations in the dataset

y_i = Actual value.

$\hat{y}_i$ = Predicted value.
$\overline{y_i}$ = Mean value of actual values.

4. Results and Discussion

The AI model was developed to predict labour productivity at two-hour intervals, supporting improved scheduling and decision-making to enhance performance and reduce project costs. For each of the three sites, datasets were used to train five different model architectures to determine the highest-performing model. This procedure enabled the selection of the most accurate model for each location, providing site-specific predictions for column formwork productivity. Predictions from the three base models (pred_smouha, pred_beheira, and pred_moharam) were then combined into a meta-feature set using the stacking technique. A linear regression model (meta_model) was trained on this set to produce the final ensemble model. By employing stacking, the ensemble model integrates the strengths of multiple base models, improving the overall accuracy of labour productivity predictions.

The comparison results indicate that the ensemble model outperformed the individual base models, achieving higher accuracy and lower error rates across all performance metrics, as illustrated in Fig. 6. By integrating the strengths of models trained separately on datasets from the three different locations, the ensemble approach demonstrated superior generalisation and predictive capability, making it highly suitable for multi-site productivity prediction in construction. This highlights the effectiveness of stacking in ensemble learning as a straightforward method to enhance model performance when combining diverse data sources. The highest predictive performance was achieved by merging the three deep learning algorithms, as shown in Table 4.

Table 4
The Key Summary of Evaluation the Ensemble Model Performance Compared to Individual Models

MODEL	MSE	MAE	RMSE	R^2 SCORE	Error Validation
SMOUHA	1.0860	0.5001	1.0421	96.28%	0.3271
BEHIERA	0.3978	0.3618	0.6777	97.41%	0.6686
MOHARAM-BEK	1.2562	0.7408	1.02562	95.94%	1.7879
Ensemble MODEL	0.6870	0.4341	0.8289	97.66%	0.015

As illustrated in Fig. 10, a portion of the code demonstrates the successful implementation of the ensemble machine learning model, which achieved the highest predictive accuracy.

```
pred_smouha = smouha_model.predict(X_smouha_scaled)
pred_behierh = behierh_model.predict(X_behierh_scaled)
pred_moharam = moharam_model.predict(X_moharam_scaled)

96/96 [==============================] - 0s 1ms/step
96/96 [==============================] - 0s 1ms/step
97/97 [==============================] - 0s 1ms/step

meta_features = np.concatenate([pred_smouha, pred_behierh, pred_moharam])

y_combined = np.concatenate([y_smouha, y_behierh, y_moharam])

meta_model = LinearRegression()
meta_model.fit(meta_features, y_combined)

▾ LinearRegression
LinearRegression()
```

```
final_predictions = meta_model.predict(meta_features)
final_predictions = np.round(final_predictions, 2)
```

```
mse = mean_squared_error(y_combined, final_predictions)
mae = mean_absolute_error(y_combined, final_predictions)
rmse = np.sqrt(mse)
r2 = r2_score(y_combined, final_predictions)

print(f"Final Ensemble Model - MSE: {mse}")
print(f"Final Ensemble Model - MAE: {mae}")
print(f"Final Ensemble Model - RMSE: {rmse}")
print(f"Final Ensemble Model - R² Score: {r2}")
```

```
Final Ensemble Model - MSE: 0.6870483733252822
Final Ensemble Model - MAE: 0.43405415206814674
Final Ensemble Model - RMSE: 0.8288838117162636
Final Ensemble Model - R² Score: 0.9766111710725837
```

```
comparison_df = pd.DataFrame({'Actual': y_combined.flatten(), 'Predicted': final_predictions.flatten()})
print(comparison_df.head(50))
```

Fig. 10: Python Code Snippet Used for the Final Ensemble Model

Table 5

Sample of Actual vs. Predicted Productivity from the Best Ensemble Model

Record.NO	Actual Productivity	Predicted Productivity
1	16.45	22.66
2	10.30	11.6
3	15.50	16.12
4	5.21	5.44
5	14.5	15.31
6	12.1	14.01
7	10.95	11.87
8	11.46	12.64
9	6.03	7.42

Furthermore, the ensemble algorithm achieved the highest predictive accuracy, as reported in Table 5. Based on the evaluation of the stacking model, the performance metrics MAE, MSE, RMSE, and R^2 were 0.4341, 0.6870, 0.8289, and 0.9766, respectively, as derived from the code presented in Fig. 6. Visual assessment through comparison graphs, R^2 score plots, and scatter plots illustrates the relationship between actual and predicted values, with a red line indicating the ideal prediction. These graphical representations were utilised to examine data distribution and detect outliers that deviate from expected patterns, as shown in Fig. 11 (11a, 11b, and 11c).

The R^2 plot in Fig. 11(a) shows a strong clustering of points around the red line, indicating high predictive accuracy of the model. The scatter plot in Fig. 11(b) demonstrates a close alignment between actual and predicted values, reflecting a good model fit, while the residual plot in Fig. 11(c) shows points distributed near zero, indicating minimal prediction errors. Some variance is observed at higher productivity values, suggesting potential areas for further refinement. Overall, the plots confirm that most predicted values closely match the actual measurements, demonstrating the ensemble model's robust performance and reinforcing its predictive reliability. Finally, a web-based platform was developed to predict labour productivity at two-hour intervals. This website functions as a baseline tool that engineers, project managers, and consultants can use to monitor performance and enhance productivity management.

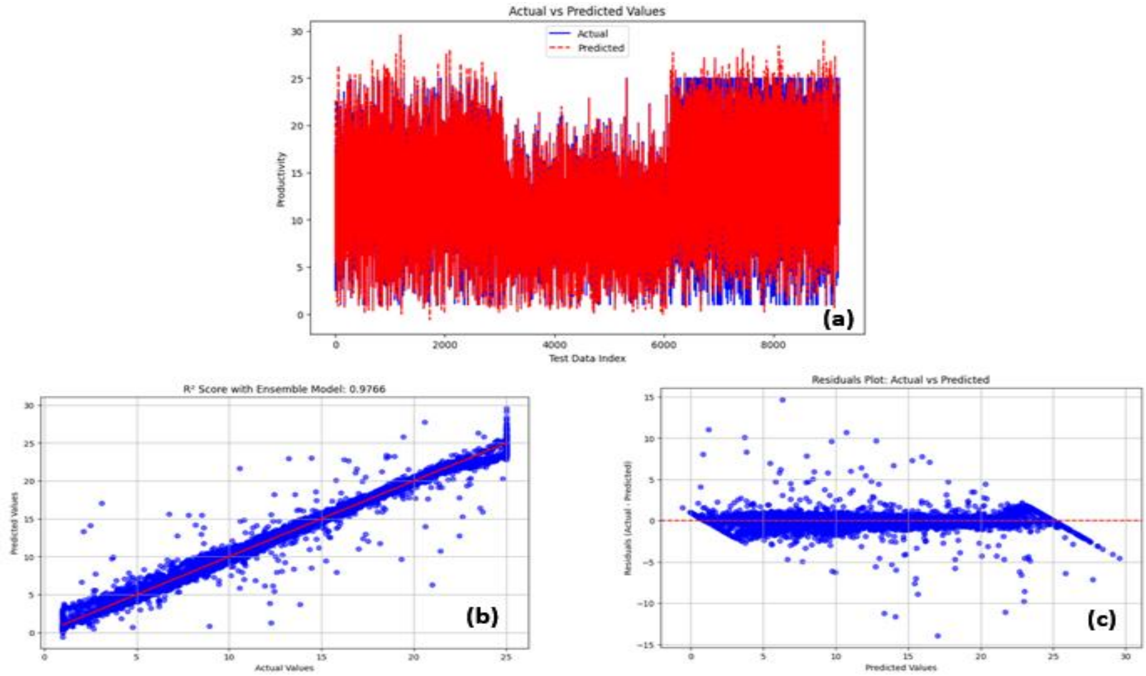

Fig. 11. Displaying Actual Productivity Versus Predicted Productivity for Three Graphs (a) Actual vs. Predicted Values, (b) R2 Score Plot, and (c) Residual Plot

5. Conclusion

This research successfully developed a comprehensive ensemble machine learning model to forecast labour productivity for column formwork during the initial phases of construction projects in Egypt. The study commenced by identifying the factors most significantly influencing productivity, reducing an initial list of 42 potential variables to 20 critical determinants. To construct the predictive model, two-hourly productivity measurements were gathered from projects across three locations: Smouha, Beheira, and Moharam-Bek, executed between 2022 and 2023. A process control chart technique was applied to detect inefficiencies and establish site-specific productivity baselines. Subsequent statistical analysis using SPSS facilitated the identification of correlations and the development of predictive equations tailored to each location. The generated models demonstrated strong predictive capability, yielding R^2 scores of 93.1% for Smouha, 95.7% for Beheira, and 96.6% for Moharam-Bek. The AI model was implemented in Visual Studio, chosen for its efficiency and user-friendly interface. The datasets were encoded, organised in MS Excel, and used to train three deep learning models. Each model incorporated an input layer of 23 neurons, followed by two hidden layers comprising six and four neurons, respectively. This predictive framework has proven highly effective in enhancing construction project planning and operational efficiency. By integrating data from multiple sites, the ensemble model improves generalisation and adaptability, offering a reliable instrument for labour management across multi-site construction projects. This method optimises resource allocation and strengthens operational performance by combining the strengths of individually trained models while mitigating their individual limitations.

Key findings and contributions of this research include:

- Identification of Critical Factors: Analysis of 42 potential variables led to the selection of 20 primary factors that most strongly impact the productivity of column formwork.
- Data Collection and Analysis: Two-hourly productivity data were systematically collected from projects executed between 2022 and 2023. Process control charts were applied to detect inefficiencies, quantify time and cost losses, and establish baseline productivity for each

location.

- High-Accuracy Predictive Models: Statistical analysis using SPSS was conducted to formulate predictive equations for each site, achieving high performance. R^2 scores were 93.1% for Smouha, 95.7% for Beheira, and 96.6% for Moharam-Bek.
- Ensemble Model Development: A deep learning ensemble model was constructed in Visual Studio. The model included an input layer with 23 neurons and two hidden layers of six and four neurons, respectively. Encoded datasets were used to train individual models, which were later combined using a stacking technique.
- Enhanced Prediction and Generalization: The ensemble model combines the outputs of the three individual models, reducing weaknesses while leveraging their strengths. This strategy enhances predictive reliability, adaptability, and generalisation across multiple sites, providing a dependable tool for labour management in multi-site construction projects.

The successful application of this methodology demonstrates its potential to improve labour productivity forecasting, contributing to better project planning, optimised allocation of resources, and heightened operational efficiency in the construction sector.

6. Limitation

This study has several limitations. The predictive performance of the model depends heavily on the quality and representativeness of the collected site data, which may restrict the generalisability of the findings due to the limited number of construction sites examined. Furthermore, certain qualitative factors influencing labour productivity are challenging to quantify and were not comprehensively incorporated into the analysis. Although the ensemble machine learning model exhibits strong predictive capability, it remains sensitive to small datasets and may be susceptible to overfitting, limiting its applicability to smaller-scale or atypical construction sites. Lastly, the model does not explicitly consider dynamic changes in site conditions over time, which could affect productivity and levels of operational waste.

List of Abbreviations

ANN	Artificial Neural Network
RII	Relative important Index
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence
UCL	Uper Control Limit
CL	Control Limit
LCL	Lower Control Limit

Competing interests

The authors declare that they have no competing interests.

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References

[1] Abdel-Hamid, M., & Abdelhaleem, H. M. (2022). Impact of poor labor productivity on

construction project cost. *International Journal of Construction Management*, *22*(12), 2356-2363. https://doi.org/10.1080/15623599.2021.1877243

[2] Ahmad, S. B. S., Mazhar, M. U., Bruland, A., Andersen, B. S., Langlo, J. A., & Torp, O. (2020). Labour productivity statistics: a reality check for the Norwegian construction industry. *International Journal of Construction Management*, *20*(1), 39-52. https://doi.org/10.1080/15623599.2018.1484859

[3] Alinaitwe, H., Mwakali, J., & Hansson, B. (2006). Labor productivity in the building construction. https://itc.scix.net/pdfs/w65-2006-85.pdf

[4] Almamlook, R., Bzizi, M., Al-Kbisbeh, M., Ali, T., & Almajiri, E. (2020). Factors affecting labor productivity in the construction industry. *American Journal of Environmental Science and Engineering*, *4*(2), 24-30. https://doi.org/10.11648/j.ajese.20200402.11

[5] Aswed, G. K. (2016). Productivity estimation model for bricklayer in construction projects using neural network. *Al-Qadisiyah Journal for Engineering Sciences*, *9*(2), 183-199. https://journal.qu.edu.iq/index.php/engineering/article/view/283

[6] Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, *16*(3), 199-231. https://doi.org/10.1214/ss/1009213726

[7] Budak, A., & Karataş, İ. (2022). Impact of the BIM system in construction management services in developing countries; Case of Turkey. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, *28*(6), 828-839. https://doi.org/10.5505/pajes.2022.12352

[8] Dozzi, S. P., & AbouRizk, S. M. (1993). *Productivity in construction*. https://nrc-publications.canada.ca/eng/view/object/?id=8b3c3a61-6d06-4c58-b5a2-0c0b7e5b8e1c

[9] El-Gohary, K. M., & Aziz, R. F. (2014). Factors influencing construction labor productivity in Egypt. *Journal of management in engineering*, *30*(1), 1-9. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000168

[10] El-Gohary, K. M., Aziz, R. F., & Abdel-Khalek, H. A. (2017). Engineering approach using ANN to improve and predict construction labor productivity under different influences. *Journal of Construction Engineering and Management*, *143*(8), 04017045. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001342

[11] Golnaraghi, S., Moselhi, O., Alkass, S., & Zangenehmadar, Z. (2020). Modelling construction labour productivity using evolutionary polynomial regression. *International Journal of Productivity and Quality Management*, *31*(2), 207-226. https://doi.org/10.1504/IJPQM.2020.110418

[12] Golnaraghi, S., Zangenehmadar, Z., Moselhi, O., & Alkass, S. (2019). Application of artificial neural networks in predicting formwork labour productivity. *Advances in Civil Engineering*, *2019*, 5972620. https://doi.org/10.1155/2019/5972620

[13] Heravi, G., & Eslamdoost, E. (2015). Applying artificial neural networks for measuring and predicting construction-labor productivity. *Journal of Construction Engineering and Management*, *141*(10), 04015032. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001006

[14] Jarkas, A. M. (2010). Buildability factors influencing formwork labour productivity of walls. *International Journal of Construction Management*, *10*(4), 101-117. https://doi.org/10.3763/ijcm.2010.0342

[15] Juszczyk, M. (2020). Analysis of labour efficiency supported by the ensembles of neural networks on the example of steel reinforcement works. *Archives of Civil Engineering*, *66*(1), 97-111. https://doi.org/10.24425/ace.2020.131789

[16] Kediya, S., Bhorkar, M., Deshpande, P., Jain, R., Puri, C., & Gudadhe, A. A. (2023). Review on the Significance of Artificial Intelligence in Construction Engineering and Management. https://doi.org/10.1109/ICCSAI58935.2023.10291173

[17] Mohapatra, A., Mohammed, A. R., & Panda, S. (2023). Role of Artificial Intelligence in the Construction Industry—A Systematic Review. https://ijarcce.com/wp-content/uploads/2023/01/IJARCCE.2023.120105.pdf

[18] Ospitia, N., Jaramani, R., Remy, O., & Aggelis, D. G. (2022). Determination of concrete formwork removal time based on ultrasound reflection. *Applied Sciences*, *12*(3), 1221. https://doi.org/10.3390/app12031221

[19] Rojas, E. M., & Aramvareekul, P. (2003). Labor productivity drivers and opportunities in the construction industry. *Journal of Management in Engineering*, *19*(2), 78-82. https://doi.org/10.1061/(ASCE)0742-597X(2003)19:2(78)

[20] Sana, S. S. (2011). A production-inventory model of imperfect quality products in a three-layer supply chain. *Decision Support Systems*, *50*(2), 539-547. https://doi.org/10.1016/j.dss.2010.09.012

[21] Sonmez, R., & Rowings, J. E. (1998). Construction labor productivity modeling with neural networks. *Journal of Construction Engineering and Management*, *124*(6), 498-504. https://doi.org/10.1061/(ASCE)0733-9364(1998)124:6(498)

[22] Tayalati, F., Boukrouh, I., Azmani, A., & Azmani, M. (2024). Deep Learning-Based Intelligent X-Bar Control Chart for Monitoring Manufacturing Process. https://doi.org/10.1109/IICAIET60512.2024.10420465

[23] Tsehayae, A. A., & Fayek, A. R. (2016). Developing and optimizing context-specific fuzzy inference system-based construction labor productivity models. *Journal of Construction Engineering and Management*, *142*(7), 04016017. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001128

[24] Waters Ii, W. (2007). Productivity measurement. In *Handbook of Transport Modelling* (pp. 395-415). https://doi.org/10.1108/9781847200201-022

[25] Woldetsadik, E. T. (2025). *A Predictive Model for Estimating Formwork and Shoring Removal Time* The George Washington University]. https://hsrc.himmelfarb.gwu.edu/etd/