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Implementation of a deep neural network model to predict critical joint loads based on SAP2000 structural data

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ABSTRACT

This study proposes a Deep Neural Network (DNN) framework to predict joint reaction force ratios in structural analysis using datasets obtained from SAP2000 simulations. The datasets cover various load cases and geometrical parameters, ensuring the model is exposed to diverse structural scenarios. The DNN architecture comprises multiple fully connected layers, employing ReLU activation functions, dropout regularization, and batch normalization for stable training. Model performance was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 score, and prediction accuracy within a 5% error margin critical for civil engineering applications. The results demonstrate excellent predictive capabilities, achieving accuracy levels exceeding 98% across all datasets. Notably, the third dataset yielded the lowest accuracy at 98.97% and an R^2 score of 0.9915, with slightly elevated error metrics (MSE of 5.11, RMSE of 2.26, and MAE of 1.51). Despite these challenges, the DNN model consistently delivers robust predictions, showcasing its potential for practical structural health monitoring and design optimization. Future work should consider incorporating more diverse and experimental data to enhance model robustness further.

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1. INTRODUCTION

The main Accurate prediction of joint reaction forces is a fundamental aspect of structural analysis, as these forces represent how internal loads are transferred and distributed across the connectivity of a structural system. In civil engineering practice, joint reaction force ratios (JRFRs) offer critical insights into the proportion of forces carried by individual supports or connections, which is essential for design safety, structural optimization, and failure prevention. Finite element analysis (FEA) software such as SAP2000 is widely used to compute these values through comprehensive simulations of both simple and complex structural systems. However, repeated analyses under varying load conditions or for large-scale design iterations in SAP2000 can be computationally expensive and time-consuming, especially when dealing with high-fidelity models and dynamic loading scenarios (Ahmad et al., 2023), (Azanaw, 2024). Moreover, the identification of critical joints—such as those with the highest reaction forces—is typically performed manually in SAP2000 using visual post-processing tools. This step requires engineers to inspect each load case one by one to extract maximum values, which not only slows down the workflow but also introduces the potential for human error. When simulations are repeated across dozens or hundreds of scenarios, this manual process becomes a significant computational and operational bottleneck.

In recent years, advancements in artificial intelligence (AI), particularly deep learning, have shown substantial potential in enhancing structural engineering workflows through data-driven modeling and surrogate analysis. Deep Neural Networks (DNNs), as universal function approximators, have demonstrated superior capabilities in capturing complex nonlinear and multivariate relationships inherent in structural behavior (Kekez & Kubica, 2021), (Al-Gburi et al., 2025). Compared to shallow neural networks, DNNs offer improved feature extraction capabilities, enabling more accurate predictions of mechanical responses such as stress fields (Bhaduri et al., 2022), load capacities (Işık et al., 2023), and seismic performance (Bond et al., 2024), even in the absence of explicit analytical models.

Prior research has extensively focused on AI applications for predicting global structural performance, such as load-displacement behavior (Al-Gburi et al., 2025), material property estimation (Kekez & Kubica, 2021), and damage detection in full-scale structures (Bui-Ngoc et al., 2024), (Jia & Li, 2023). Furthermore, recent developments in physics-informed neural networks and hybrid AI models have enabled more robust modeling of dynamic systems (Djeumou et al., 2022), (Antonelo et al., 2024). Despite these advancements, there has been limited attention toward predicting localized structural responses such as joint reaction forces, especially when derived from high-quality finite element simulations. Most existing studies either oversimplify support conditions or treat them as deterministic boundary constraints, thereby neglecting their variability under real-world conditions.

Recent studies have demonstrated the effectiveness of surrogate modeling techniques, including deep learning, in reducing the computational burden of structural simulations. For instance, DNN-based surrogate models have been successfully applied to approximate FEA results with high accuracy, enabling rapid evaluation of structural responses under varying parameters (Zhang et al., 2020), (Haderbache et al., 2021). Additionally, the emergence of physics-informed neural networks (PINNs) as a method to integrate governing physical laws into data-driven models has significantly improved prediction reliability for complex structural phenomena, (Al-Adly & Kripakaran, 2024).

Specifically, the prediction of joint reaction forces has been explored in only a limited number of AI-based studies, where multilayer perceptrons and convolutional architectures demonstrated reasonable accuracy but often lacked scalability or interpretability for large-scale models (Honglan et al., 2020). The key challenge remains in developing DNN architectures that balance predictive accuracy and computational efficiency, particularly when applied to commercial structural software outputs like SAP2000. This research gap is especially evident considering that extensive simulation data from SAP2000 remains underutilized in the development of predictive AI models. While the integration of AI in structural health monitoring (SHM) and stress prediction has gained traction (Bhaduri et al., 2022), (Zhang et al., 2020), (Haderbache et al., 2021), little attention has been given to learning the underlying patterns of JRFRs using deep learning, especially in a supervised learning setting informed by SAP2000-generated data.

To address this challenge, this study proposes the implementation of a Deep Neural Network model to predict joint reaction force ratios based on structural input features derived from SAP2000 simulations. The main objectives of this research are to develop a predictive DNN model trained on a curated dataset of SAP2000 structural analyses, to evaluate the model's performance in terms of accuracy and generalization, and to demonstrate the model's applicability in reducing computational costs and accelerating structural design decisions. The contribution of this work lies in bridging the gap between finite element simulation outputs and modern AI-based predictive modeling. By leveraging DNNs for JRFR estimation, the proposed approach offers a data-driven surrogate tool to support engineers in early-stage design evaluations, sensitivity studies, and rapid decision-making under uncertainty.

2. RESEARCH METHOD

Data Acquistion and Preprocessing

This study uses structural joint reaction data obtained from finite element analysis (FEA), extracted from an Excel dataset. The dataset includes directional force and moment components (F1, F2, F3, M1, M2, M3) along with load combination identifiers labeled under the

"OutputCase" column. Following the procedures of (Wang et al., 2024) and (Jin et al., 2023), raw data were cleaned by removing null values (NaN) and converting relevant columns to numerical data types. Each data instance was then categorized into one of four structural load types: Non-Foundation, Serviceability, Nominal, and Ultimate, in accordance with the structural loading classifications proposed by (Do et al., 2025).

To prepare the dataset for model training, absolute values of the vertical force (F3) and bending moments (M1 and M2) were calculated and normalized against the maximum values in their respective groups, resulting in relative ratios. These ratios reflect the percentage contribution of each response compared to the peak structural response under similar load conditions. Categorical features such as CaseType, StepType, and OutputCase were transformed using one-hot encoding—a standard method for converting nominal features into machine-readable formats (Sorilla et al., 2024). This preprocessing pipeline was designed to ensure numerical consistency and interpretability, consistent with methods employed by (Kim et al., 2024) for deep learning-based structural defect classification.

The selection of F3, M1, and M2 as dominant target features was based on their structural importance. F3 (vertical force) is directly associated with gravity loads and support reactions, playing a critical role in assessing bearing capacity. M1 and M2 represent the major bending moments acting on joints, which are key indicators of structural performance under both service and ultimate limit states. In contrast, components such as F1, F2 (horizontal forces) and M3 (torsion) typically contribute less significantly to overall structural demand in typical building systems. By focusing on F3, M1, and M2, the model captures the most structurally relevant responses, resulting in more interpretable and practical prediction outputs.

Deep Neural Network

The predictive model developed in this study is a fully connected Deep Neural Network (DNN) constructed using TensorFlow and Keras. The architecture consists of an input layer, three hidden layers, and a single output layer. Specifically, the network includes a first dense layer with 256 units and ReLU activation, followed by a 30% dropout layer to prevent overfitting. This is followed by a second dense layer with 128 units (ReLU), another 30% dropout, and a third dense layer with 64 units (ReLU). The output layer consists of one neuron with a linear activation function to perform regression.

This structure is adapted from similar architectures applied in structural health monitoring by (Ahmadzadeh et al., 2024) and in 3D point-cloud analysis for unstructured environments by (Azhari et al., 2021). The use of ReLU ensures non-linearity in learning, while dropout layers enhance generalization by randomly deactivating nodes during training (Dong et al., 2024), (Do et al., 2025).

Model Evaluation Metrics

The dataset was split into training and test sets with an 80:20 ratio using the train_test_split method, consistent with best practices in supervised machine learning (Jin et al., 2023), (Bakshi & Chaudhary, 2024). Feature scaling was performed using StandardScaler from Scikit-learn to normalize input data to zero mean and unit variance (Dong et al., 2024), (Kim et al., 2024). The model was compiled using the Adam optimizer and Mean Squared Error (MSE) as the loss function, which is well-suited for continuous target prediction tasks.

Model training was conducted for a maximum of 200 epochs with a batch size of 64. To mitigate overfitting, early stopping was applied with a patience of 20 epochs based on validation loss monitoring, in accordance with recommendations from (Kim et al., 2024) and (Sorilla et al., 2024) Additionally, 20% of the training data was reserved for internal validation during model fitting.

Implementation Enviroment

All stages of data processing, model development, training, and evaluation were carried out in the Python programming environment. Key libraries include Pandas and NumPy for data manipulation, Scikit-learn for preprocessing and model evaluation, TensorFlow with Keras for neural network development and training, and Matplotlib for visualization.

This implementation setup is consistent with prior research in structural integrity prediction using deep learning, as demonstrated by (Dong et al., 2024), (Jin et al., 2023),and

(Ahmadzadeh et al., 2024), providing a robust and flexible platform for machine learning applications in structural engineering.

3. RESULTS AND DISCUSSIONS

This study utilized three distinct datasets derived from SAP2000 simulations to evaluate the performance of the proposed Deep Neural Network (DNN) model in predicting joint reaction force ratios. The results demonstrate that the DNN model consistently achieves high predictive accuracy across all datasets, highlighting its robustness and generalization capabilities.

For the first dataset, the model reached a prediction accuracy of 99.73% within an error tolerance of 5%, with an R^2 score of 0.9976 indicating excellent goodness-of-fit. The mean squared error (MSE) was recorded at 1.85, while the mean absolute error (MAE) and root mean squared error (RMSE) were 1.01 and 1.36, respectively. These metrics reflect a low average deviation between predicted and actual values, confirming the model's precision.

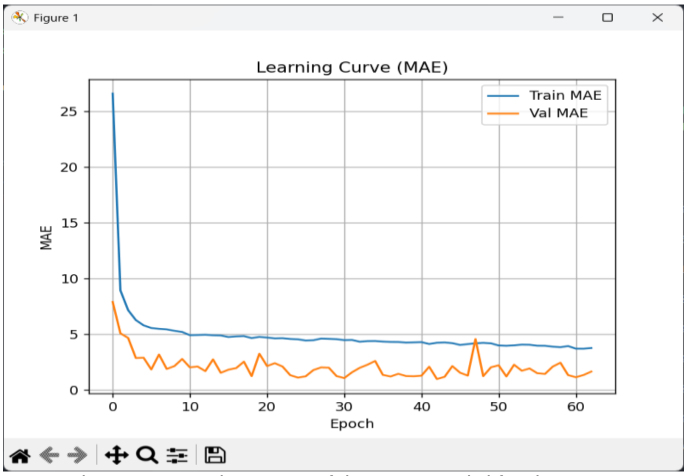

Figure 1. Learning curve of the DNN model for dataset 1

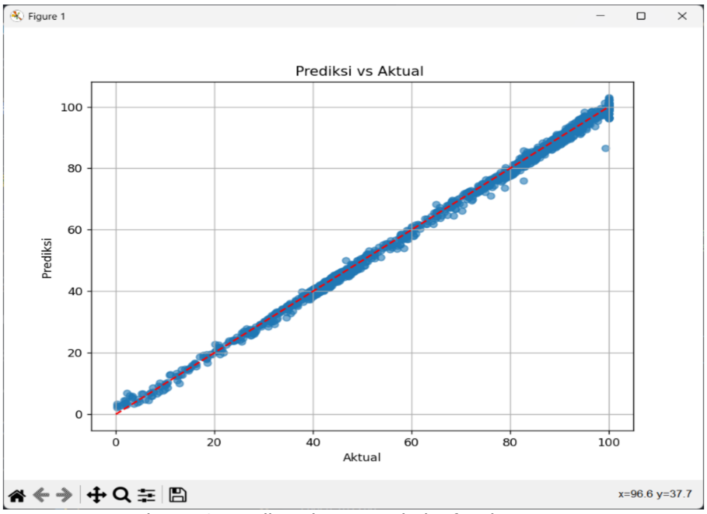

Figure 2. Pedicted vs actual plot for dataset 1

The second dataset yielded a slightly lower accuracy of 99.08%, with an R^2 score of 0.9961. The MSE increased to 2.89, while the MAE and RMSE values were 1.26 and 1.70, respectively. Despite the marginal decrease in performance compared to the first dataset, the model still demonstrated strong predictive ability, effectively capturing the nonlinear relationships within the data.

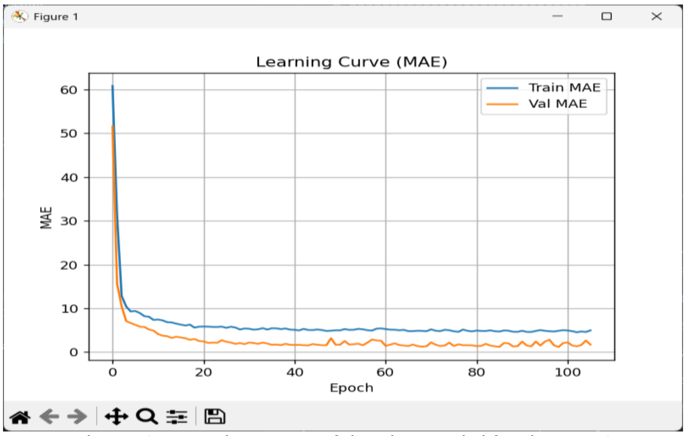

Figure 3. Learning curve of the dnn model for dataset 2

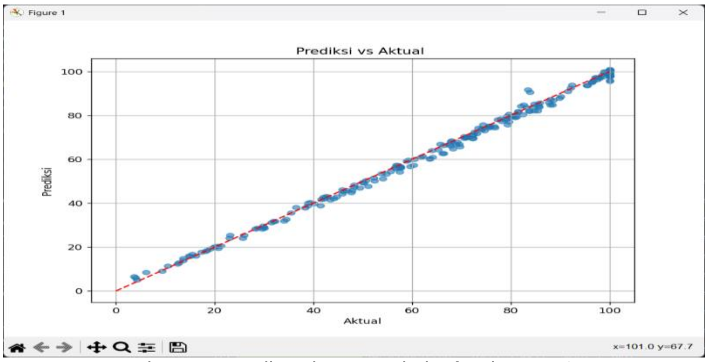

Figure 4. Pedicted vs actual plot for dataset 2

Notably, the third dataset produced the lowest accuracy among the three, achieving an accuracy of 98.97% and an R^2 score of 0.9915. The MSE rose to 5.11, with corresponding MAE and RMSE values of 1.51 and 2.26, respectively. These results suggest that the relatively low accuracy for the third dataset might be due to insufficient data quantity or an inadequate number of training epochs, preventing the DNN from fully learning the underlying patterns. Nevertheless, the prediction results still demonstrate excellent performance, with nearly 99% accuracy and relatively low errors, indicating that despite the limiting factors, the DNN model remains highly capable of producing accurate and practically acceptable predictions for structural analysis applications.

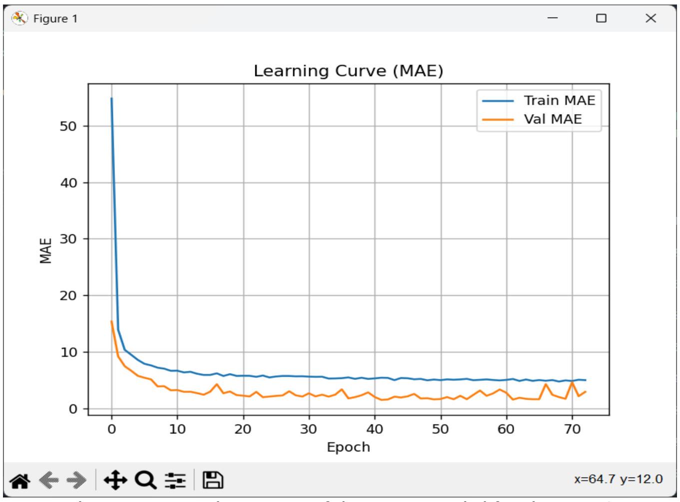

Figure 5. Learning curve of the DNN model for dataset 3

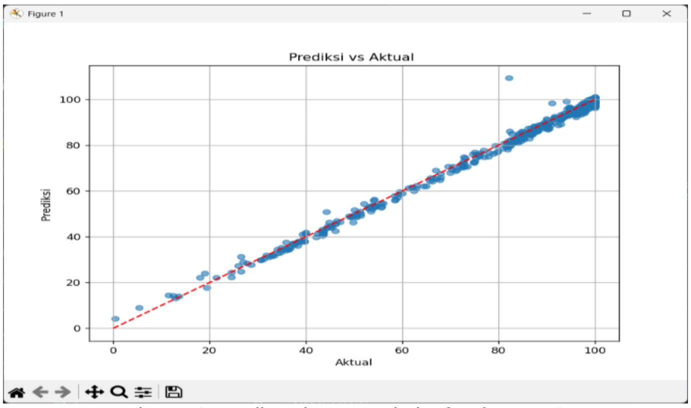

Figure 6. Pedicted vs actual plot for dataset 3

The following table summarizes the performance metrics of the proposed DNN model for each dataset tested:

Table 1. The performance of ...

Dataset	Accuracy	R Score	MSE	RMSE	MAE
Dataset 1	99.73%	0.9976	1.85	1.36	1.01
Dataset 2	99.08%	0.9961	2.89	1.70	1.26
Dataset 3	98.97%	0.9915	5.11	1.51	2.26

Based on the data presented in Table 1, the proposed DNN model consistently demonstrates high accuracy and strong predictive performance across all three datasets, with accuracy ranging from 98.97% to 99.73% and R^2 scores exceeding 0.99 in each case. The mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) metrics also indicate low prediction errors, confirming the model's robustness. Overall, these results confirm that the proposed DNN framework is highly effective for predicting joint reaction force ratios in structural analysis. The low error metrics and high coefficient of determination across varied datasets validate the model's reliability and its potential application in practical structural health monitoring and design optimization. Future work could focus on expanding dataset diversity and incorporating real-world experimental data to further enhance model robustness.

4. CONCLUSION

The Deep Neural Network (DNN) model developed in this study demonstrated excellent performance in predicting joint reaction force ratios within structural analysis tasks. Using three different datasets derived from SAP2000 simulations, the model consistently achieved high accuracy and low error metrics across all cases. The prediction accuracy remained above 98%, with strong R^2 scores indicating that the model effectively captured the underlying relationships in the data. Although the third dataset showed a slightly lower accuracy compared to the others, this difference was marginal and still within an acceptable range, likely influenced by factors such as limited data size or insufficient training epochs. These results highlight the model's robustness, generalization capability, and adaptability to datasets with varying complexities and noise levels, which are critical for real-world structural health monitoring and design optimization.

Overall, the findings confirm that the proposed DNN framework is reliable and effective for structural engineering applications, offering precise predictions that can support decision-making processes. Future research should focus on expanding the diversity of datasets, incorporating experimental and real-world data, and optimizing the training process to further enhance the model's performance and applicability. This continuous improvement will contribute to more accurate and dependable structural analysis tools in practical engineering scenario.

Importantly, the results of this study can be directly utilized by civil engineering practitioners who do not have expertise in machine learning. Since the DNN model operates on input data already familiar to structural engineers such as load combinations and joint force components it can be integrated into a simplified application or plugin. This allows engineers to benefit from rapid and accurate predictions without needing to understand or interact with the underlying algorithm. Thus, this research not only demonstrates the predictive potential of AI in structural design but also offers practical accessibility for day to day engineering decision making

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