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Machine Learning Applications in Structural Engineering: Prediction Models for Moment-Rotation Characteristics in Boltless Steel Connections

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Abstract

This article presents a study on the application of machine learning for predicting the moment-rotation behavior of boltless steel connections commonly used in pallet rack structures. Through extensive experimental data collection, Support Vector Machines (SVM) and Deep Learning (DL) models were developed to serve as predictive tools for these connections. The analysis demonstrates that these models enable engineers to accurately forecast structural characteristics, optimize boltless connection designs, and enhance the stability and functionality of pallet rack systems. The generalized model framework established here offers a robust foundation for future studies and design improvements, with SVM achieving the highest predictive accuracy among the models tested.

1. Introduction

Steel pallet racks (as shown in Figure 1) are indispensable components within warehouse and distribution centers, forming a critical foundation for modular storage solutions. Their effectiveness and operational safety are underpinned by their structural integrity and resilience, particularly in regions prone to seismic activity, where they must withstand dynamic forces and absorb impacts during seismic events [1-2]. Traditional structural analysis methods, however, often fall short in accurately capturing the complex interplay of forces, especially within boltless connections, where interaction forces between bolts, beams, and braces are difficult to elastically model [3-4]. This paper introduces an advanced analytical approach for assessing connection reliability based on moment-rotation relationships. This method leverages machine learning (ML) techniques to develop precise predictive models for these connections, offering a robust alternative to traditional approaches. By integrating ML into this design space, the study aims to quantify and explain the variability in materials, load distribution patterns, and seismic performance factors not fully addressed in conventional design models.

The integration of machine learning into structural engineering has grown increasingly valuable in recent years. ML's sophisticated computational and data-processing capabilities allow engineers to analyze extensive datasets and uncover latent structural patterns that would be difficult to capture through conventional methods. This capability becomes crucial for developing enhanced models for boltless connections, which exhibit unique behaviors under various loading conditions and seismic forces. Notably, prior research has highlighted the need for improved design tools to capture the dynamic behavior of boltless connections more accurately. Studies by Tsarpalis et al. [7] and Adamakos et al. [8] underscore the importance of rotational stiffness and the seismic behavior of steel racks, emphasizing the critical need for predictive tools that can address these specific challenges. This paper extends such foundational research by introducing ML-driven models that proactively simulate and predict connection performance across a range of conditions. By harnessing extensive simulation data, these ML-based models can improve the accuracy of connection design, providing engineers with proactive tools to predict performance under various scenarios, including seismic events. The significance of this approach is further underscored when considering existing standards, such as Chilean NCh2369 and ANSI RMI MH16, which offer regulatory guidelines for connection design but lack predictive capabilities when subjected to different operational and environmental conditions [9-11].

In this context, the research aims to bridge this gap by developing an ML-based predictive framework that not only aligns with regulatory standards but also provides enhanced insight into structural performance, even under non-standard conditions. This innovative approach to connection reliability has the potential to implement theoretical advancements directly into engineering practices, ultimately enhancing the safety and resilience of steel pallet racks in dynamic environments.

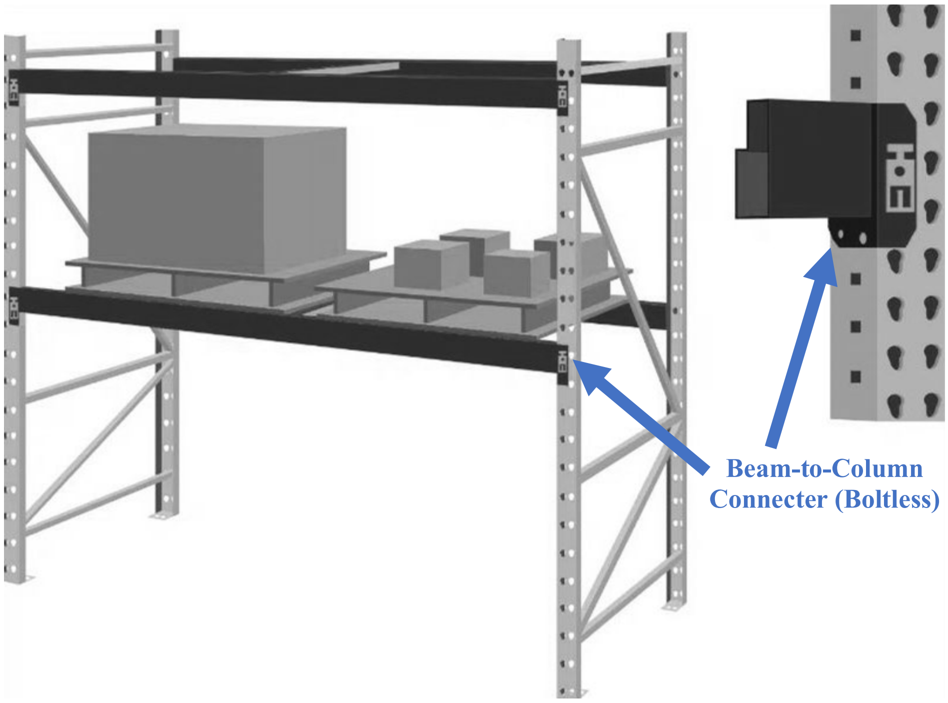


Fig. 1 *Boltless connection of typical steel pallet racks*

2. Literature Review

Steel pallet rack systems play an integral role in industrial storage, where they must meet both seismic and structural requirements to ensure safety and functionality, particularly in earthquake-prone regions. The design of such systems involves a complex interplay between stability, durability, and resilience, especially under dynamic loading conditions. This study delves into the most prominent international standards for pallet racks, evaluating their strengths and limitations, particularly in terms of predictive design capabilities. Below is an analysis of key standards, along with an exploration of how machine learning (ML) insights could enhance their predictive power and reliability [9-16];

1. Chilean Standard NCh2369 (Addressing High-Seismicity Zones): The Chilean Standard NCh2369 is specifically formulated to address the design requirements for structures situated in regions of high

seismicity. This standard emphasizes the necessity for structural redundancy, ensuring that construction elements have sufficient durability to withstand seismic excitation. An important feature of NCh2369 is its incorporation of P-delta effects, which account for stability changes during structural deformation. This is crucial in high-seismic regions where even minor displacements can affect a structure's integrity. NCh2369 mandates that members of the rack system must be proportionally reinforced to exceed durability expectations, even in situations where live loads surpass the rack's self-weight—a common occurrence during seismic events. Cold-formed rack sections, known for their susceptibility to local buckling, are given special consideration to ensure resilience under these loading conditions.

2. RMI ANSI MH16.1 and MH16.3 (U.S. Standards with Enhanced Seismic Provisions): The U.S. based standards, RMI ANSI MH16.1 and MH16.3, are comprehensive guidelines for the safe design and installation of rack systems. With the latest 2023 edition, these standards now incorporate enhanced seismic testing requirements, reflecting a growing recognition of the need for seismic resilience. Notably, the updated provisions introduce cyclic testing of beam-to-column connections, allowing engineers to better simulate seismic loads on these connections. Additionally, these standards recommend advanced software-based techniques for calculating response coefficients under various loading scenarios. This software-oriented approach not only improves the accuracy of design specifications but also provides a flexible framework for accommodating the wide array of seismic conditions across different geographic areas.
3. European Norm EN 16681 (Groundbreaking European Initiatives in Seismic Rack Design): The European Norm EN 16681, spearheaded by the European Racking Federation (ERF) in 2000, represents a significant advancement in the seismic design of steel storage rack systems. Inspired by Eurocode 8 and the Rack Manufacturers Institute (RMI) Specification, this standard has undergone continuous refinement. Initial development efforts received significant support from two European Union-funded initiatives, SEISRACKS and SEISRACKS 2, which provided extensive research and testing data on seismic performance. EN 16681's evolution exemplifies a rigorous approach to harmonizing seismic standards across Europe, enhancing compatibility and performance. This standard has served as a critical model for the integration of seismic-specific considerations in rack design, including guidelines for load distribution, structural flexibility, and reinforcement measures.
4. Chinese Standards CESC 23 and GBT 28576 (Tradition Meets Modern Seismic Considerations): China's standards, CESC 23 and GBT 28576, reflect a longstanding tradition of structural design standards that initially focused on general rack design. Recent updates in these standards, however, demonstrate a shift towards explicit seismic design criteria, acknowledging the critical importance of seismic resilience for rack structures in industrial and storage settings. This evolution underscores China's commitment to advancing structural safety measures in response to its own high-seismic-risk areas, especially by mandating design principles that prioritize structural endurance and stability under seismic stress.

While these standards address a comprehensive range of safety and durability factors, a notable limitation remains in their predictive capacity. Traditional engineering approaches often rely on prescriptive guidelines that, although effective, may lack the adaptability needed to respond dynamically to varying seismic conditions and structural configurations. This study proposes the integration of machine learning (ML) techniques as a supplement to these standards. ML can enhance predictive design by analyzing vast datasets of seismic events, material behaviors, and structural responses. This data-driven approach offers valuable insights that go beyond conventional design parameters, enabling engineers to predict rack performance under a wider array of conditions. By identifying patterns and correlations, ML can help refine load distribution models, optimize structural reinforcement, and anticipate failure points more accurately, thus bridging the gap between safety requirements and adaptive resilience. In nutshell, while standards like NCh2369, ANSI MH16.1 and MH16.3, EN 16681, and CESC 23/GBT 28576 lay essential groundwork for seismic resilience in steel pallet rack systems, the integration of ML insights represents a forward-looking enhancement. Machine learning holds the potential to refine these guidelines further, making them more responsive to complex and unpredictable seismic challenges. This study aims to leverage such predictive insights, adding value to existing frameworks and contributing to safer, more resilient rack system designs.

2.1 Finite Element Model and Experimental Testing

Finite element modelling (FEM) and experimental testing form a robust foundation for creating stable and reliable databases essential for training and validating machine learning (ML) models. By leveraging these approaches, predictive models gain a foundation grounded in precise data, reflecting real-world behaviours under complex loading conditions;

1. Experimental Approach: Predictions concerning moment-rotation stiffness, a critical aspect of structural response in steel pallet racks, were enabled by incremental static loading tests conducted in prior studies

[17] on boltless connections. These experimental setups, designed to replicate real-world stress conditions, provided a solid reference for current predictive models. Through rigorous testing, critical behaviours such as flexural response and deformation patterns were meticulously observed, delivering data that enhance the understanding of moment-rotation characteristics. In tandem, comprehensive laboratory tests verified the material properties, including tensile strength, yield stress, and flexural capacity, ensuring that the predictive models incorporate accurate material responses, further supporting the simulations' realism.

2. Finite Element Analysis (FEA): Advanced commercial FEA software, such as ANSYS, was utilized to simulate complex load types and configurations affecting boltless steel connections, focusing on both local buckling phenomena and overall structural deformation. The FEA models comprehensively represented load-bearing characteristics, from localized flexural deformations to the ultimate bearing capacity of cross-sectional elements. Through FEA, intricate structural behaviours under load were captured, particularly in the boltless connections, which are prone to unique deformation mechanisms due to the lack of rigid fasteners. The FEA outputs, alongside experimental data, enriched the dataset for ML model training, capturing a broader range of structural responses and potential failure modes.

By integrating FEM and empirical testing, a comprehensive dataset is assembled that not only aids in ML training but also allows the validation of predictive models across varied load conditions and connection types. These simulations and experiments are crucial in developing predictive capabilities that address specific challenges in structural engineering, especially in contexts like seismic design, where accurately predicting material and structural behaviour under static/dynamic loads is paramount. As such, the combined approach ensures that ML models are anchored in precise, realistic data, empowering them to support high-stakes decision-making in engineering design and safety analysis.

3. Methodology

In this study, regression analysis, SVMs, and DL were used for the development of bolts for boltless connections for constructing predictive models. FEA and boltless connection tests were used to construct three datasets. Key aspects of the methodology include;

1. Data Collection: Mechanical properties for tension and bending loads were investigated for components and the results provided the data basis for the machine learning models. Controlled settings were mimicries of natural conditions in a bid to obtain none or little manipulated results.
2. ML Model Development: Thus, SVM models, as well as DL models, were developed. DL models consisted of several hidden layers to capture rich input-output mapping while SVMs involved for nonlinear regression, efficient in moments-rotation mappings.
3. Model Training and Validation: Taking 1534 data sets, the data was divided into train/validation sets to adjust the performance of every single model; certain metrics were selected to judge the prediction ability of every ML model.

3.1 Machine Learning Model Development

The study's machine learning using RapidMiner model development emphasized regression, Support Vector Machines (SVM), and Deep Learning (DL) techniques for structural prediction [5, 18-20];

1. SVM (Figure 2), a powerful machine learning approach, was introduced and developed by Cortes and Vapnik, grounded in statistical learning theory. Unlike DL, SVM is a supervised learning model focused on classification and regression tasks. The strength of SVM lies in its robustness and reliability, making it a preferred choice for applications where data is limited, yet high accuracy is desired. One of its notable applications is in anomaly detection, as SVM can intuitively model data boundaries to identify outliers effectively. SVM differs from other machine learning algorithms by aiming to maximize the margin of separation between different classes, thus minimizing classification errors. Conceptually, SVM seeks a function f that maintains a maximum margin (denoted as ε) from the actual targets for all training samples while ensuring the function remains as flat as possible, balancing both precision and generalization.

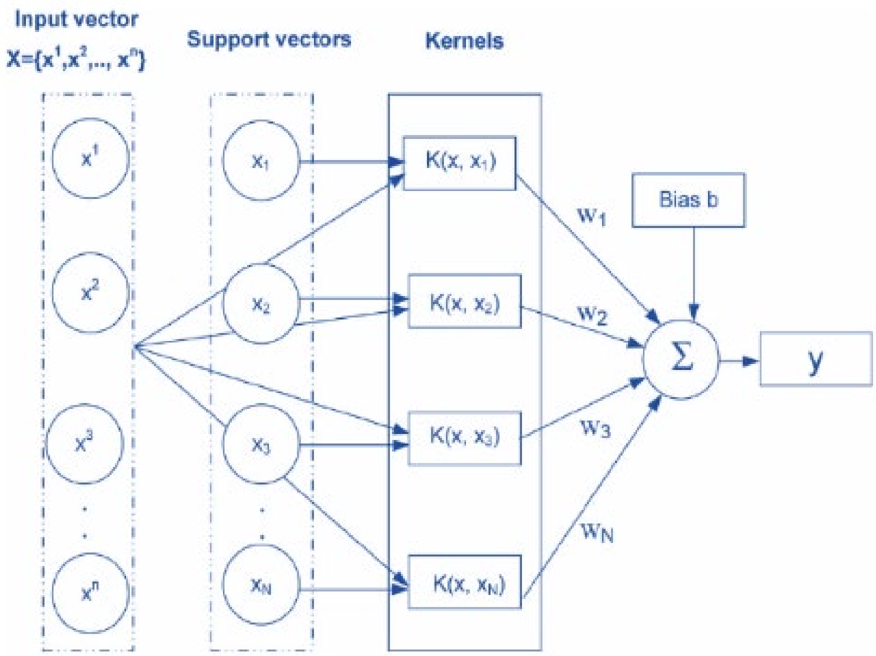


Fig. 2 *Typical algorithm of SVM*

2. Whereas, DL represents a sophisticated category of machine learning algorithms, designed to extract increasingly abstract and high-level features from raw data inputs by employing multiple hierarchical layers. Through a layered architecture, DL models progressively analyze input data, where initial layers typically detect basic patterns such as edges in images, while deeper layers identify more complex and meaningful patterns, such as shapes, digits, letters, or even facial features. This hierarchical feature extraction allows DL to model complex data representations effectively. The term "Deep Learning" was first coined by Rina Dechter in 1986, with significant contributions from Igor Aizenberg and colleagues in 2000, who implemented the concept using Boolean threshold neurons. Each hidden layer within a DL network (as shown in Figure 3) conducts intricate mathematical operations based on the input data and network structure. However, DL models have certain limitations where they require large datasets for effective training and are computationally intensive, demanding substantial processing power during both training and deployment phases. This resource intensity can limit their application in certain contexts or on devices with restricted computational capabilities.

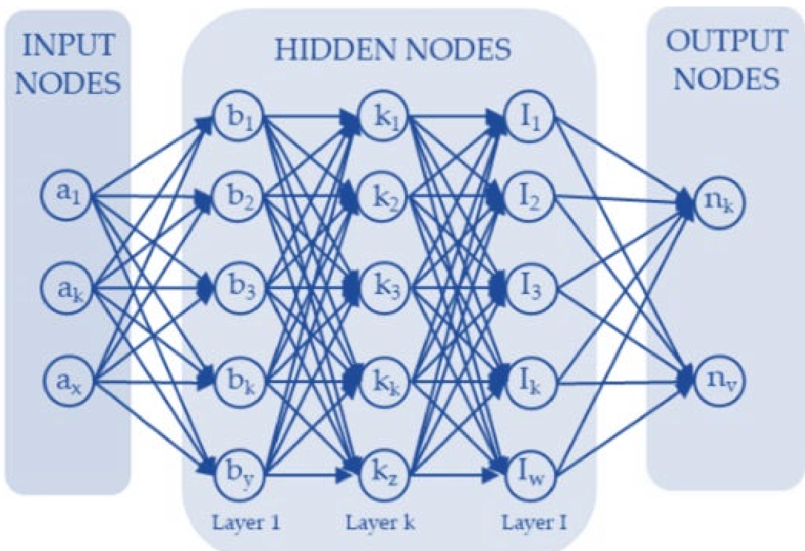


Fig. 3 *Typical algorithm of DL [5]*

The study employed a structured framework model, as illustrated in Figure 4, based on methodologies recommended in prior research [5]. To assess the model's predictive accuracy, regression performance metrics were used across all classification models. These models were evaluated using a labeled dataset, where input data attributes were assigned specific labeling roles, while a key attribute was designated for the prediction of moment-rotation characteristics. In this framework, the labeled attribute stored actual observed values, while the prediction attribute captured the anticipated values as estimated by the regression models. The model training process utilized a carefully curated collection of sample data, known as the training set, to develop and refine each model's predictive capacity. Once trained, these models were tested using a separate test set to estimate their prediction accuracy for the moment-rotation behavior in boltless connections, particularly in steel pallet racks. For consistency and validity, a 70:30 data split ratio was applied, assigning 70% of the data to the training set and the remaining 30% to the test set across all models. This ratio ensured a robust balance between model training and evaluation, aiming to yield an accurate reflection of each model's performance in predicting moment-rotation responses. This approach, grounded in rigorous data partitioning, allowed for a reliable assessment of the model's capability to predict the behavior of boltless connections under varying conditions.

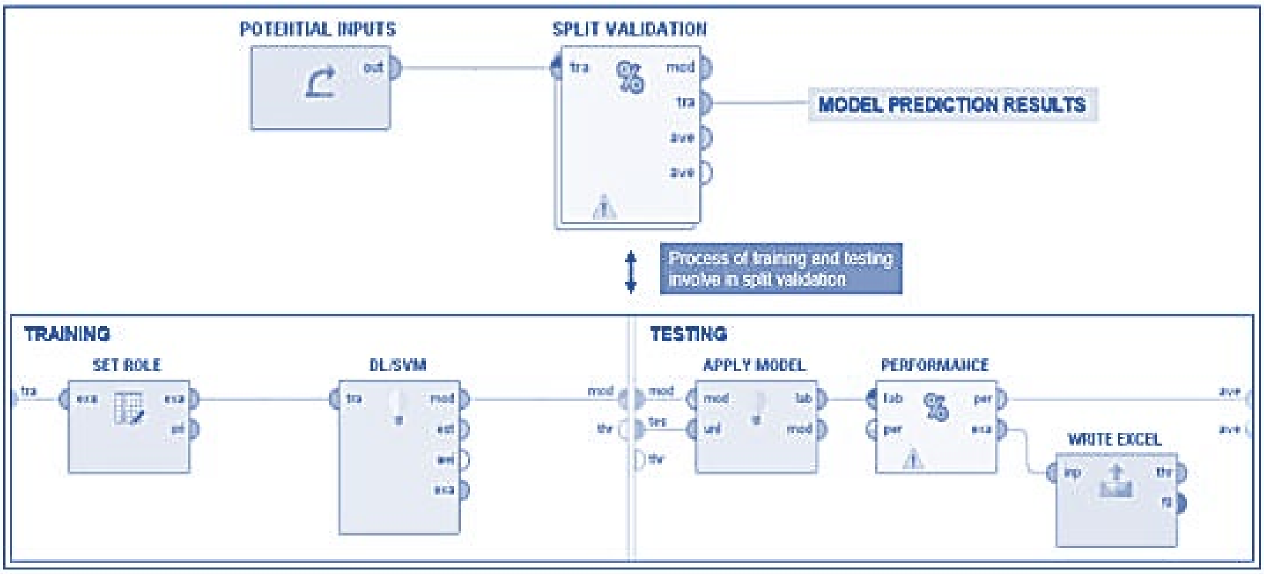


Fig. 4 *The framework model applied for both SVM and DL prediction models from RapidMiner machine learning as recommended in previous research [5]*

4. Results and Discussions

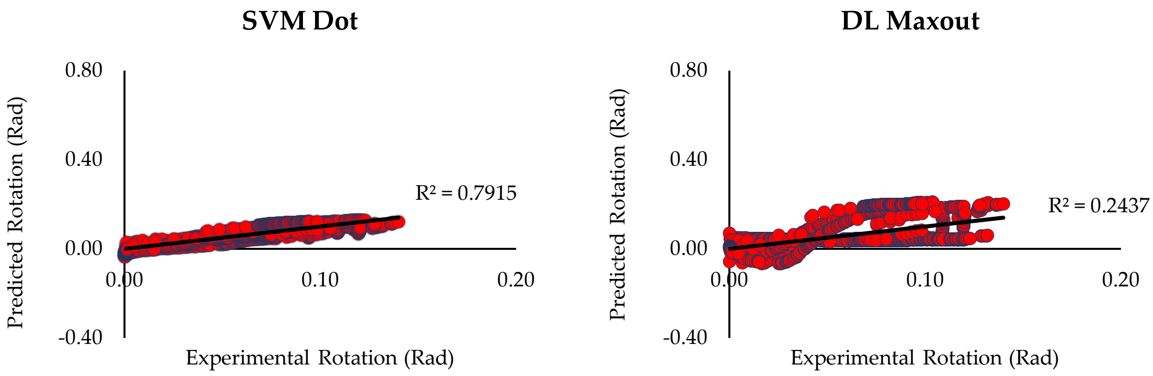
In the development of Support Vector Machine (SVM) and Deep Learning (DL) models for predictive analysis, the parameters for each model were carefully configured as specified in Tables 1 and 2. The SVM Dot model, in particular, demonstrated substantial enhancements in its capacity for rotation projection, as illustrated in Figure 5(a). This model accurately forecasted rotation within the range of the experimental data, signaling its effectiveness in capturing the rotational behavior of the given inputs. Optimizing the model's parameters also resulted in a marked improvement in its performance, specifically reflected by the positive correlation between the predicted and experimental rotation values, as measured by the Root Mean-Square Error (RMSE). This improvement further confirms that the SVM Dot model is reliable within the constraints of the input range. The SVM Dot model's performance was evaluated using the R^2 value, which was recorded at 0.2327. Although this R^2 value might seem modest, it is critical to recognize that the model still managed to perform well in practical applications. The low R^2 value did not hinder the SVM Dot model from reducing errors effectively, even with some negative values in the experimental data. This ability to minimize negative rotation predictions is indicative of the SVM Dot model's robustness, particularly in handling data irregularities and fluctuations. This quality reflects the model's capability in processing the training data with three input variables, leading to a robust understanding and handling of variation within the data. Therefore, the SVM Dot algorithm shows high practical applicability for predicting boltless steel connections' rotation characteristics, even if its R^2 metric alone may suggest otherwise.

Table 1 *SVM parameters in RapidMiner*

SVM Parameters	M-θ Model Value
Kernel type	Dot
C	1.0
Convergence epsilon	0.0132
L positive	1.0
L negative	1.0

Table 2 *DL parameters in RapidMiner*

DL Parameters	M-θ Model Value
Activation	Maxout
Hidden Layer Sizes	2
Numeration	50:50
Epochs	10



(a) **(b)**

Fig. 5 *Simulated ML models in RapidMiner (a) SVM Dot; (b) DL Maxout*

In contrast, the DL Maxout model, as shown in Figure 5(b), presented a different performance profile. This model yielded a significantly higher R^2 value of 0.7151, which implies a strong positive correlation between the predicted and actual rotation values. However, this apparent strength was somewhat mitigated by the model's tendency to overestimate rotation values. Despite optimization through RMSE adjustments, the DL Maxout model exhibited considerable discrepancies between its predictions and the actual rotation data. This inconsistency can be problematic, as it suggests the model lacks an adequate fit to the experimental data, reducing its reliability for precise predictive tasks. This limitation indicates a potential need for refinement in the model's training process, particularly in terms of achieving a closer match with the experimental data. In evaluating the feasibility of these predictive models for determining the rotation characteristics of boltless steel connections, it is clear that the SVM Dot model outperforms the DL Maxout model. Although the SVM Dot model has a relatively lower R^2 value, it achieved the best optimization results with RMSE, establishing it as a highly efficient tool for practical prediction within this domain. Conversely, the DL Maxout model was found to be inconsistent and was therefore deemed unsuitable for practical application due to its lack of stability in output predictions. The nature of DL Maxout as a stochastic machine learning algorithm, which inherently introduces randomness and uncertainty, contributed to this inconsistency. Moreover, the model's reliance on a limited dataset from a larger population increased its sensitivity to data fluctuations, further detracting from its precision.

Given these findings, improving the DL Maxout model would require targeted strategies to enhance data consistency and model performance. For instance, expanding the size of the training dataset could reduce variance in the output by providing the model with a more representative data sample, thereby enabling it to generalize more effectively to unobserved conditions. Additionally, tuning the hyper-parameters of the algorithm could optimize its learning capacity, reducing the influence of stochastic variations and improving its alignment with real-world data. This step is crucial, as it could help mitigate the model's current tendency to overestimate, leading to a more accurate and reliable prediction mechanism. In conclusion, while the DL Maxout model holds promise with its high R^2 value, the SVM Dot model proves to be the more viable choice in this specific context due to its stability and accuracy. The SVM Dot model's lower R^2 does not detract from its practical utility, as its optimized RMSE reflects a strong predictive performance. The DL Maxout model's stochastic nature and reliance on limited data hinder its application; hence, further work should focus on dataset expansion and hyper-parameter adjustments to address these weaknesses.

4.1 Implications and Benefits of ML Applications

The integration of machine learning (ML) in structural engineering, particularly for the analysis and optimization of boltless connections, brings forth substantial advantages across multiple domains, including enhanced efficiency, cost optimization, and safety improvements;

1. Enhanced Efficiency: ML enables a streamlined approach to engineering analysis by automating complex data processing tasks, thus reducing the dependency on manual intervention. By accelerating the speed of data analysis and enhancing the accuracy of predictive modeling, ML allows engineers to make well-informed decisions more promptly. This efficiency is critical for design iterations and performance assessments, where prompt adjustments can mitigate potential design flaws early in the process. Furthermore, ML algorithms continuously learn and adapt from newly collected data, meaning they improve over time, refining their predictive capabilities and enhancing the precision of engineering outcomes.
2. Cost Optimization: In manufacturing and material management processes, ML contributes significantly to cost efficiency by accurately forecasting resource needs, thus minimizing material wastage and reducing operational expenses. Machine learning models can predict the optimal quantities of materials required for various stages of construction, such as steel and concrete in structural frameworks, reducing overuse or underuse, which are common sources of cost overruns. Additionally, ML-based projections of electrical power demands and resource allocation facilitate the efficient distribution of resources, further streamlining budgets. By automating these predictions, ML aids in establishing a more sustainable construction process with predictable, controllable costs.
3. Safety Improvements: One of the most critical advantages of ML integration is its ability to improve structural safety, particularly in seismic-prone regions. ML models can analyze large datasets concerning structural responses to seismic loads, thereby providing highly reliable predictions on how boltless connections will perform under stress. Such predictive power allows engineers to adjust design parameters proactively, ensuring that safety requirements are met without the need for costly redesigns. This capability is especially valuable for high-density storage systems, where precise engineering is necessary to maintain stability and structural integrity. With ML, engineers can implement data-driven modifications that align with safety codes and regulations, offering enhanced resilience for infrastructure in earthquake-vulnerable areas.

In summary, the application of ML in structural engineering supports a highly efficient, cost-effective, and safe design process, optimizing boltless connection systems for better performance and reliability. By embracing ML technologies, the structural engineering field can make significant strides in achieving sustainable, resilient, and economically viable engineering solutions.

5. Conclusion and Future Directions

This research explores the critical role of machine learning (ML) in advancing structural engineering, specifically in predicting the behavior of boltless connections. Through comprehensive analysis, it demonstrates that ML techniques particularly Support Vector Machines (SVM) offer significant potential in accurately forecasting connection responses, which is instrumental in optimizing material usage and enhancing structural safety. The findings suggest that SVM-based models can serve as reliable predictive tools in structural applications, paving the way for more efficient and resilient design practices.

Future research could extend this work by embedding dynamic environmental factors into ML models, thereby increasing their robustness under varying operational conditions. Additionally, expanding the dataset to incorporate a broader range of structural configurations would provide greater predictive accuracy and applicability. Further testing of these models across diverse structural contexts could also refine their generalizability. Moreover, exploring hybrid ML models or integrating ML techniques with advanced simulation methods may yield deeper insights, enabling a more nuanced understanding of structural responses. Such an approach could bridge the gap between predictive modeling and practical engineering requirements, creating models that not only anticipate structural behavior more precisely but also align closely with real-world engineering demands. This integration of ML with complex simulations holds the potential to revolutionize predictive modeling in structural engineering, enhancing both its accuracy and its relevance to industry applications.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Author RG, Author KN;* ***data collection:*** *Author RG;* ***analysis and interpretation of results:*** *Author RG, Author MFAL, Author MEM;* ***draft manuscript preparation:*** *Author RG, Author MAH, Author RN. All authors reviewed the results and approved the final version of the manuscript.*

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