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ML-CCD: machine learning model to predict concrete cover delamination failure mode in reinforced concrete beams strengthened with FRP sheets

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ABSTRACT

ML-CCD is an open-source Python software based on a Machine-Learning model that was utilized to predict the premature failure of reinforced concrete (RC) beams strengthened with Fiber Reinforced Polymers (FRP). The model was trained using a database consisting of 70 experimentally tested beams that failed prematurely due to Concrete Cover Delamination (CCD). The significant beams parameters that influence the CCD failure were used in training the ML-CCD. This software predicts the ultimate strain in the FRP sheets at failure, thus finding its ultimate tensile strength and the effective strengthening ratio for design purposes.

Code metadata

Current code version	V1.0.0
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2024-124
Permanent link to reproducible capsule	
Legal code license	MIT License
Code versioning system used	Git
Software code languages, tools and services used	Python
Compilation requirements, operating environments and dependencies	Python v3.11
If available, link to developer documentation/manual	https://www.youtube.com/watch?v=rb_vmrLaQ50
Support email for questions	salahatf@ksu.edu

1. Introduction

Structural strengthening is very important to restore existing structures and rehabilitate any structural damage due to extreme loading events such as earthquakes. Fiber Reinforced Polymers (FRP) is a very common and reliable technology that proved efficiency in strengthening Reinforced Concrete (RC) elements against flexural stresses [1–7]. The ultimate capacity of FRP strengthened flexural elements, such as RC beams, is represented by two possible failure modes: concrete crushing of the extreme compression fibers Fig. 1(a) or FRP rupture located at the extreme tension fibers Fig. 1(b). When certain reinforcement characteristics, such as high FRP reinforcement, exist, high stresses become attracted to the FRP zone. If these stresses overcome the bond between the FRP and the RC beam being strengthened, FRP sheet debonding failure mode controls the ultimate strength, Fig. 1(c). When the stresses exceed the bond between the concrete strata itself, Concrete Cover Delamination (CDD) is the controlling failure mode, Fig. 1(d). The last two modes are called premature failure modes [8]. The American Concrete Institute (ACI) published guidelines for the design and construction of externally bonded FRP systems [9] in which a design limit state was specified for the sheet debonding limit state. However, the CCD is not yet addressed as a design limit state due to the complexity of obtaining a practical and accurate predicting model for this failure mode. This paper presents the development of software that utilizes Machine-Learning (ML) to predict the CCD failure mode. The software is called ML-CCD.

2. ML-CCD workflow

The process of predicting the CCD premature failure mode using a ML-based model, specifically Random Forest (RF) regression, involves

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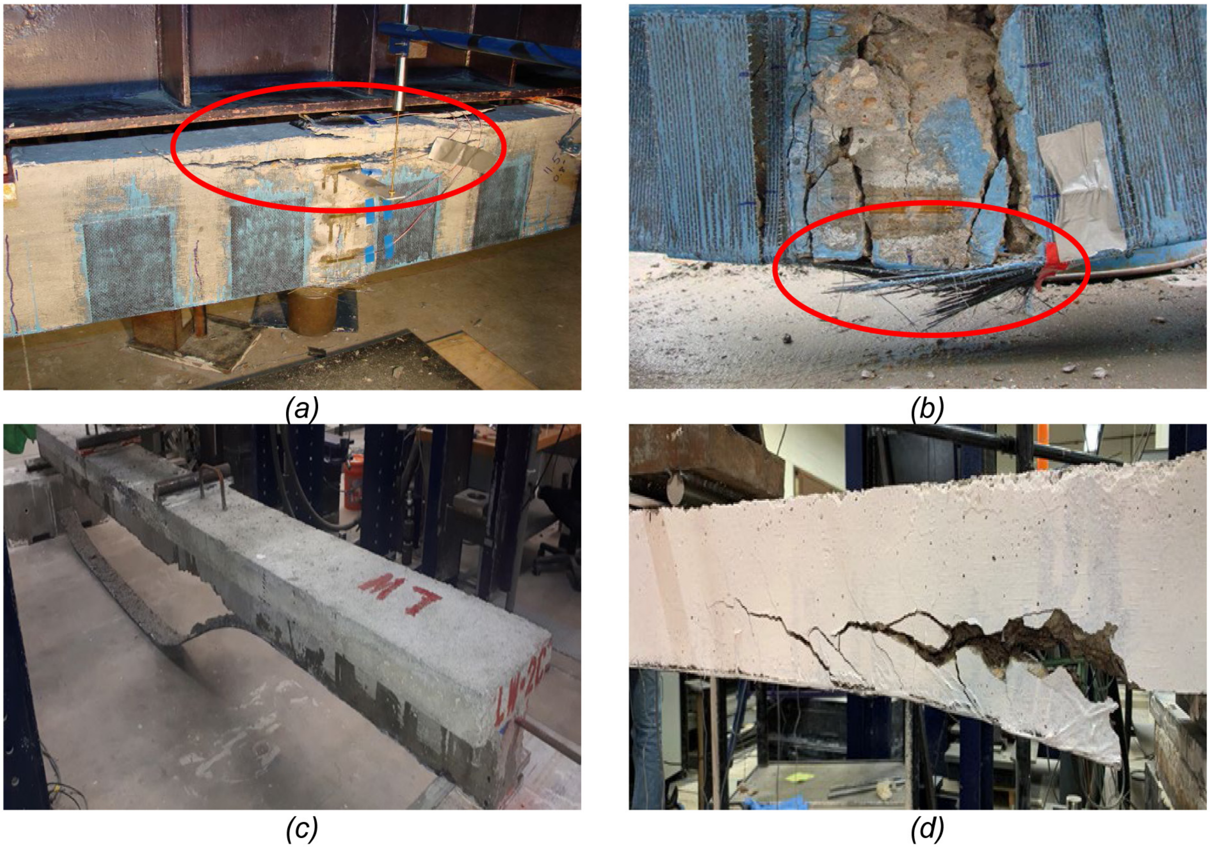


Fig. 1. Failure modes of FRP strengthened RC beams.

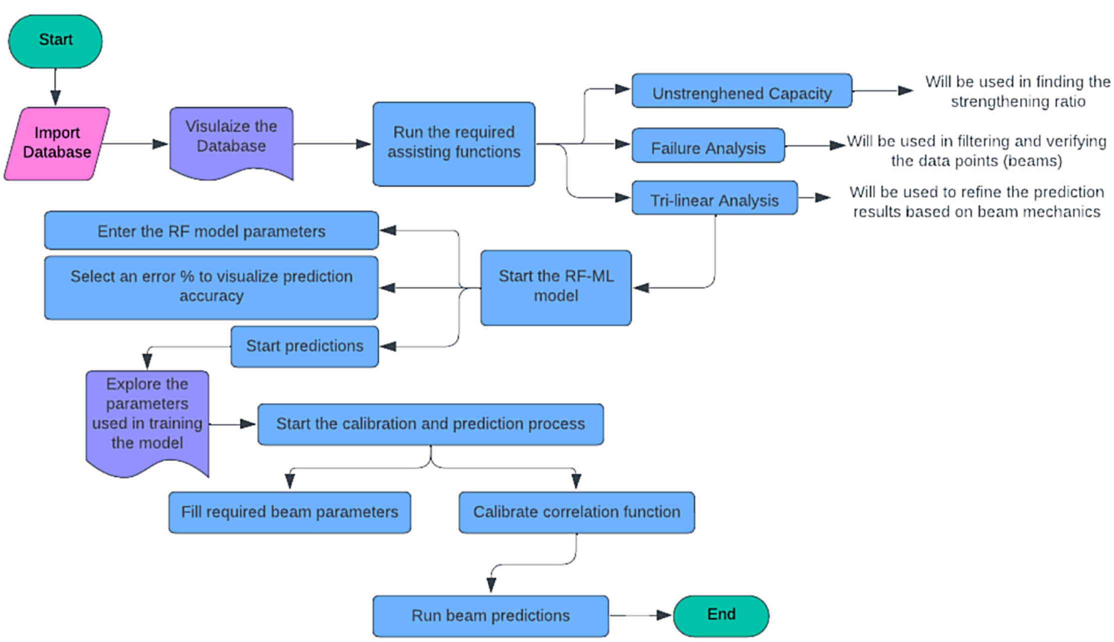


Fig. 2. ML-CCD process flowchart.

a series of interconnected steps. Fig. 2 shows the flowchart of the prediction process. It starts with data collection, where a database containing various features like beam dimensions and FRP properties is gathered and passed to verifications functions. The database will form the dataset for training the RF model. Within the RF model, the dataset then undergoes data preprocessing to handle issues such as missing values and outliers while ensuring feature scaling and normalization. Finally, RF performs feature selection in which it determines the most relevant attributes that influence CCD. In this software, the authors helped preprocess the collected dataset to ensure the best feature selection based on mechanics-based model as will be discussed in the **Impact Overview** section. The database was split into training (80%)

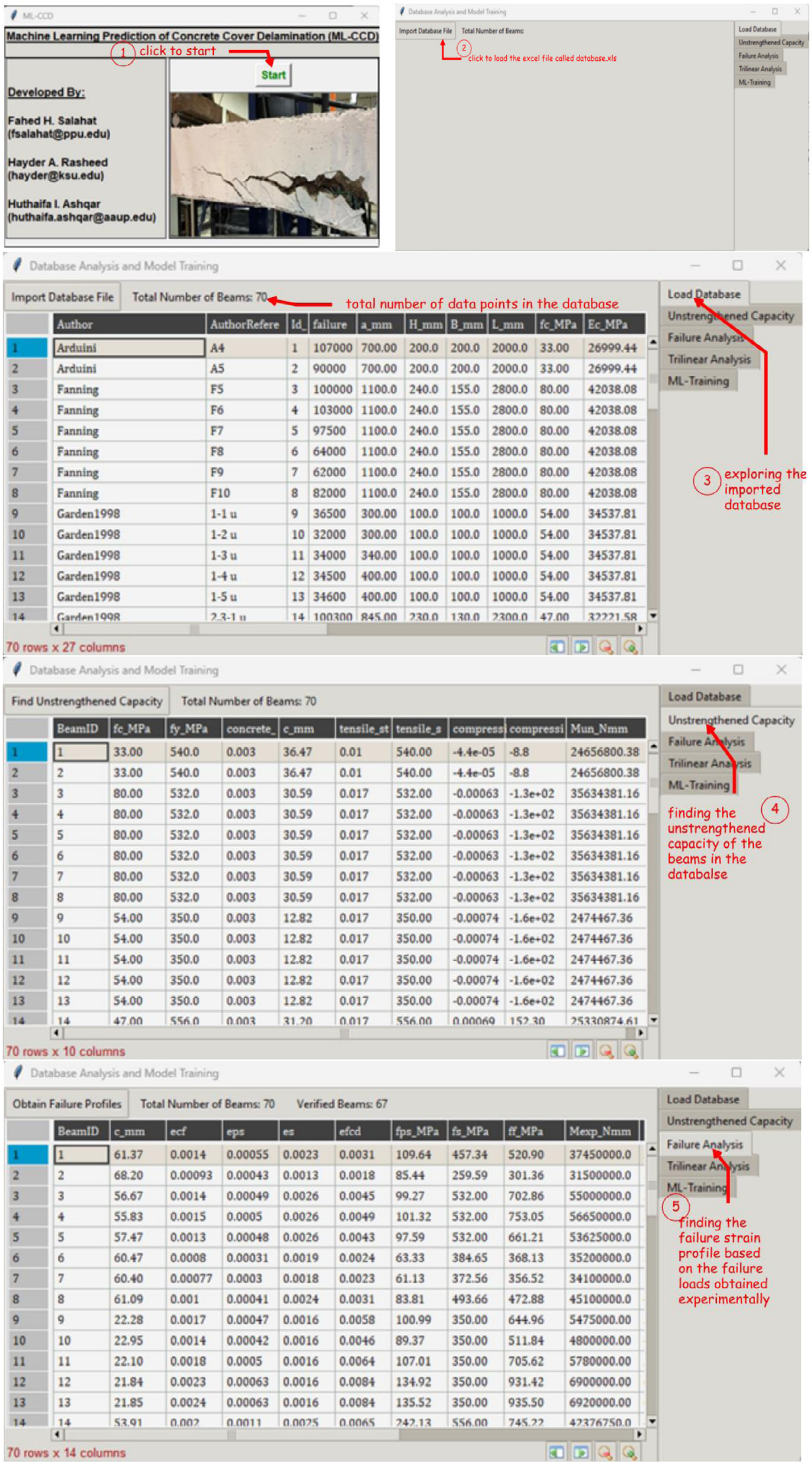


Fig. 3. Steps of using the software as it appears in the user interface.

and testing (20%). Model evaluation is facilitated by allowing the user to visualize the error after the prediction is completed. Once the model performance is satisfactory, it can be deployed for use in predicting the critical strengthening ratio considering all possible failure modes shown in Fig. 1. Continuous monitoring and maintenance are crucial to ensure the model's accuracy and relevance as new data becomes available, allowing it to provide valuable insights into the likelihood of CCD in CFRP-strengthened RC beams.

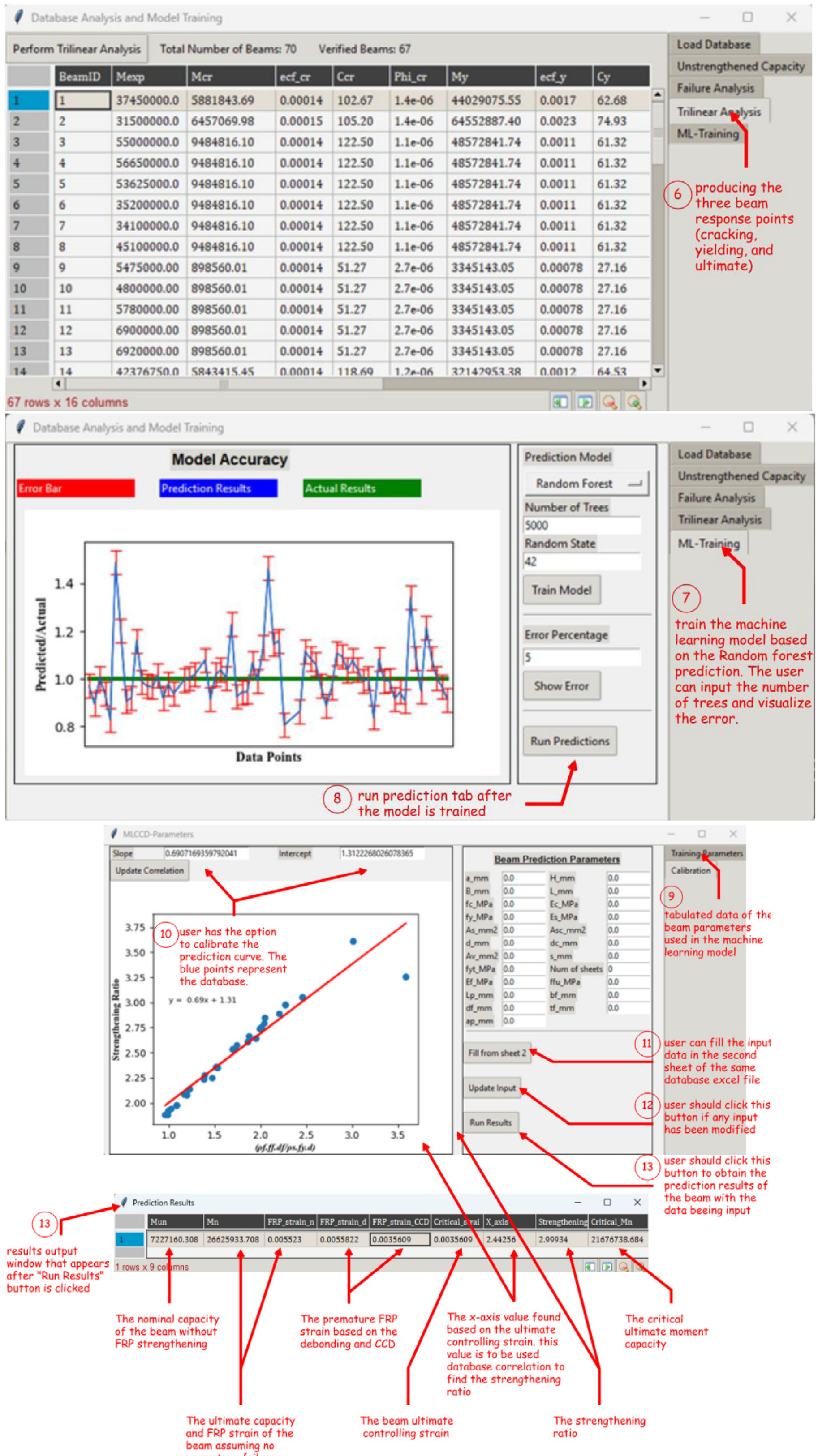
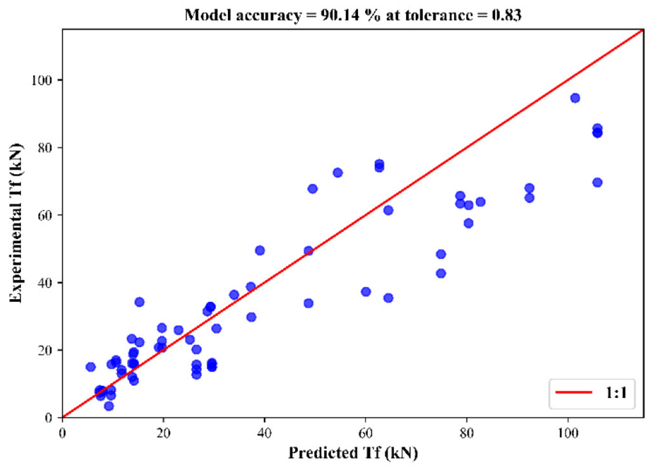


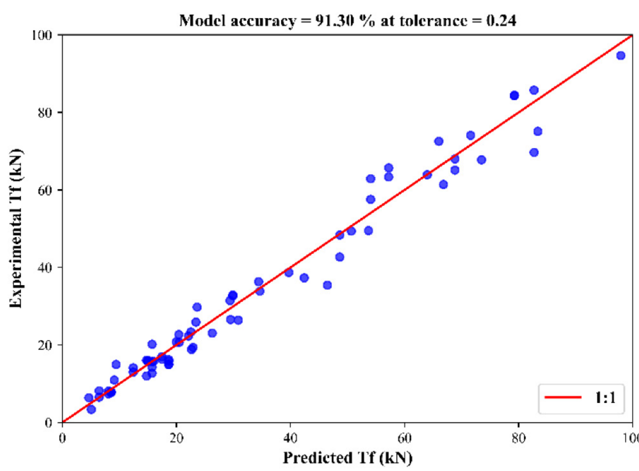
Fig. 3. (*continued*).

3. ML-CCD description and use

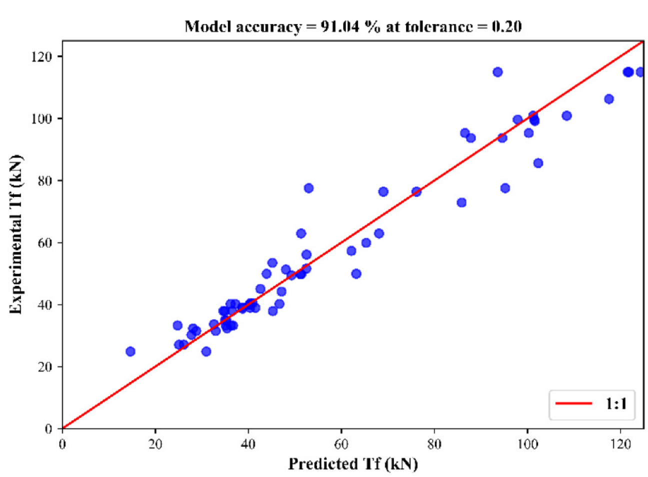
In the Code Metadate section at the beginning of this paper, the user is directed to download or clone the ML-CCD code. The software needs to read the excel file that exists in the master code directory "database.xls". This file contains the database used to train the model and contains two sheets. The first sheet is the database that contains 70 beams tested experimentally and were found to fail in CCD, these



(a)



(b)



(c)

Fig. 4. Accuracy of ML-CCD (a) Mechanics-based model – unknown critical surface (b) Mechanics-based model — known critical surface (c) ML-CCD — unknown critical surface.

are the beams that will be passed to the verification functions and will be used to develop and train the RF model. The second sheet is made available as an additional input location the software can read from when making new predictions. The titles of the columns in both sheets should not alternate since they are the key for proper file reading and processing. The graphical user interface of this software is simple and easy to follow and is shown in Fig. 3.

4. Impact overview

The authors of this work developed a mechanics-based model that provides accurate predictions of the CCD failure mode [10]. However, the developed model has one limitation: the accuracy of the prediction is dependent on determining the location of critical surface of failure in the concrete strata. Due to the complexity of the failure mechanism, the critical surface of failure is still an unknown property that is not yet accurately determined. ML-CCD overcomes this limitation through utilizing machine-learning and training the model to predict the CCD failure mode without the need to determine the critical surface of failure. Also, ML-CCD took advantage of having the critical parameters influencing the CCD identified from the mechanics-based model and employed in the RF feature selection. Fig. 4 shows how ML-CCD helped achieve prediction accuracy without compromising the error tolerance. In Fig. 4(a), the prediction is made based on the mechanics-based model that was developed by the authors [10] disregarding the critical surface of failure. The figure indicates that in order to achieve 90% accuracy or above, the error tolerance was about 83%. In Fig. 4(b), the authors used the experimental information to decide the critical surface of failure and implemented that in the mechanics-based model. The required accuracy was achieved at 24% error. Finally, using ML-CCD, and without any regards to the critical surface of failure, the required accuracy was achieved at even lower error margin of 20%.

This development will have a major impact on structural designers who implement FRP strengthening strategies to produce safe strengthening designs. ML-CCD not only offers a novel approach to CCD failure prediction but also opens avenues for exploring new research questions. Moreover, ML-CCD can provide more accurate estimations of ultimate flexural capacity and effective strengthening ratio, thus aiding in the optimization of RC beam designs and avoid unpredicted failure mechanisms. The software's user-friendly interface and accurate predictions have the potential to transform daily practices for engineers and designers, controlling and monitoring the strengthening design process of RC beams.

5. Future development

While ML-CCD represents a significant advancement, it also comes with limitations, such as reliance on experimental data for training and potential biases in predictions. Future improvements could involve incorporating more diverse datasets to further enhance prediction accuracy and applicability across a broader range of beam characteristics. Another development feature is to expand the ability of ML-CCD to predict premature failure under cyclic loading pattern. This will have a major impact on FRP strengthening for seismic applications. Finally, as more features are incorporated in ML-CCD, the user interface (UI) might need further professional development to include error handling and provide the user with more options and functionalities.

CRediT authorship contribution statement

Fahed H. Salahat: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Graphical User Interface (GUI) development. **Hayder A. Rasheed:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Huthaifa I. Ashqar:** Writing – original draft, Validation, Software, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] H.N. Garden, L.C. Hollaway, A.M. Thorne, A preliminary evaluation of carbon fibre reinforced polymer plates for strengthening reinforced concrete members, Proc. Inst. Civ. Eng. - Struct. Build. 122 (2) (1997) 127–142, http://dx.doi.org/10.1680/istbu.1997.29302.

[2] H. Rahimi, A. Hutchinson, Concrete beams strengthened with externally bonded FRP plates, J. Compos. Constr. 5 (1) (2001) 44–56, http://dx.doi.org/10.1061/(ASCE)1090-0268(2001)5:1(44.

[3] M. Abdallah, F. Al Mahmoud, A. Khelil, J. Mercier, B. Almassri, Assessment of the flexural behavior of continuous RC beams strengthened with NSM-FRP bars, experimental and analytical study, Compos. Struct. 242 (2020) 112127, http://dx.doi.org/10.1016/j.compstruct.2020.112127.

[4] K.W. Al Shboul, M.M. Raheem, H.A. Rasheed, Debonding characterization for all-lightweight RC T-beams strengthened in flexure with FRP, J. Build. Eng. 44 (2021) 103377, http://dx.doi.org/10.1016/j.jobe.2021.103377.

[5] S.M.S. Salman Alshamrani, Hayder A. Rasheed, Fahed H. Salahat, Modeling cyclic response of CFRP strengthened fiber anchored RC frame members to failure, in: ACI Symposium Publication, Vol. 360, 2024, [Online]. Available: https://www.concrete.org/publications/internationalconcreteabstractsportal/m/details/id/51740641.

[6] S. Alshamrani, H.A. Rasheed, F.H. Salahat, A. Borwankar, N. Divilbiss, Seismic flexural behavior of CFRP strengthened reinforced concrete beams secured with fiber anchors, Eng. Struct. 305 (2024) 117728, http://dx.doi.org/10.1016/j.engstruct.2024.117728.

[7] K.W. Al Shboul, F.H. Salahat, H.A. Rasheed, Effects of U-wrap anchored doubly FRP strengthened reinforced concrete beams on ductility and serviceability improvements, Eng. Struct. 314 (2024) 118349, http://dx.doi.org/10.1016/j.engstruct.2024.118349.

[8] H.A. Rasheed, Strengthening Design of Reinforced Concrete with FRP, first ed., CRC Press, 2014.

[9] ACI PRC-440.2-17: Guide for the design and construction of externally bonded FRP systems for strengthening concrete structures, 2023, [Online]. Available: https://www.concrete.org/store/productdetail.aspx?ItemID=440217&Format=DOWNLOAD&Language=English&Units=US_AND_METRIC. (Accessed 28 November 2023).

[10] F.H. Salahat, H.A. Rasheed, H.I. Ashqar, Explaining concrete cover delamination failure mechanisms in CFRP strengthened RC beams to propose mechanics-based design approach, Structures 63 (2024) 106295, http://dx.doi.org/10.1016/j.istruc.2024.106295.