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Disability Classification Using Deep Learning on Functional Assessment Data

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ABSTRACT Disability has been defined through various conceptual models, with the medical model categorizing individuals with impairments as disabled regardless of their daily life limitations. The World Health Organization estimates that 1.3 billion people experience significant disabilities, a number projected to exceed two billion by 2050 due to aging populations and increasing non-communicable diseases. Traditional disability evaluation processes often focus on symptoms or impairments, leading to challenges in accurately assessing work disability, which is linked to public health issues such as poverty and limited access to healthcare. This study explores the applications of Deep learning techniques in conjunction with a functional assessment tool to classify disability types. We aim to develop a Deep learning model that automatically classifies disability types based on functional assessment results.

The results were obtained using a one-dimensional convolutional neural network (1D CNN) with an accuracy of 95.04%. This study demonstrates the potential of AI to enhance disability classification, improve accuracy, and reduce human error in medical assessments.

INDEX TERMS Artificial intelligence, Deep Learning, Machine Learning, Disability Classification.

I. INTRODUCTION

Disability has historically been defined through various models, leading to distinct measures for identifying individuals with disabilities. The medical model views disability as a consequence of disease or injury, categorizing anyone with an impairment as disabled, regardless of daily life limitations (WHO, 1980) [1].

The rapid growth of databases has spurred interest in tools for automatically extracting knowledge from data, particularly in machine learning, which recognizes complex patterns to inform decision-making. According to the World Health Organization's 2022 report [2], approximately 1.3 billion people experience significant disabilities, projected to exceed two billion by 2050 due to aging populations and rising non-communicable diseases [3]. Individuals with disabilities often face poorer health outcomes and limited economic opportunities.

Disability evaluation processes, such as the US Social Security Administration's assessments, focus on symptoms or impairments, but the relationship between these and work performance can be unclear [4]. This presents challenges in accurately assessing work disability, which is linked to public health issues like poverty and limited social participation [5].

Numerous questionnaires have been developed to assess disability, including The Roland–Morris disability questionnaire (RMQ) [6, 7], Pain Disability Index (PDI) [8, 9], European Quality of Life 5 Dimensions 5-Level (EQ5D) [10], Hospital Anxiety and Depression Scale (HADS) [11], Avoidance endurance questionnaire (AEQ) [12], and Subgroups for Targeted Treatment Back Screening Tool (START) [13, 14].

This paper explores the use of deep learning model in conjunction with a functional assessment tool used in Egypt to identify individuals with disabilities or those unable to work. The assessment involves physicians evaluating patients through a set of 32 questions about their daily life tasks. However, accurately determining the type of disability can be time-consuming and prone to misclassification.

The process of conducting a medical and functional evaluation requires the physician to review the case medically and then answer 32 diverse questions covering all aspects, so that we can determine whether the citizen can work or is unable to work and needs support from the state. Another challenge is determining the type of disability that consumes the physician's time. Sometimes, the type of disability chosen is wrong and has nothing to do with the evaluation, so we will use machine learning to classify disabilities.

Our Objective: We aim to develop an enhanced machine learning model that automatically classifies disability types based on the results of functional assessment tools. This model is designed to support clinical decision-making by accurately identifying disability categories, thereby reducing the burden on physicians, minimizing human error, improving classification accuracy, and shortening the time required for each case evaluation.

II. Literature Review

The section discusses various approaches to measuring disability and the integration of machine learning in this field.

I. Measuring Disability

Disability measurement has traditionally relied on standardized surveys and administrative data, particularly in the context of government programs such as those administered by the U.S. Department of Housing and Urban Development (HUD) [1]. Tools like the American Community Survey and the American Housing Survey incorporate six core disability-related questions to assess limitations in functional, social, and daily activities. While these methods provide a comprehensive overview of disability status across populations, they primarily focus on static assessments and do not leverage emerging technologies such as machine learning. Researchers must carefully align their chosen metrics with relevant theoretical models and programmatic goals. However, there remains limited integration of adaptive or intelligent systems in these traditional approaches.

II. Machine Learning for Linking PROMs to ICF Categories

Recent studies have explored the use of machine learning to automatically map Patient-Reported Outcome Measures (PROMs) to the International Classification of Functioning, Disability, and Health (ICF) categories defined by the World Health Organization [15]. One such study, focused on chronic low back pain (CLBP), implemented a Random Forest model that achieved promising AUC values between 0.73 and 0.81 across multiple ICF categories. This approach demonstrated the potential of ML to automate the classification of patient-reported data, improve clinical decision-making, and support more structured integration with international classification systems. Nonetheless, challenges remain in ensuring model validity across diverse populations and healthcare settings and mitigating potential biases in training data.

III. Disability Prediction in Multiple Sclerosis Using Machine Learning

Machine learning has also been applied in the context of neurodegenerative diseases, particularly for diagnosing and predicting disability progression in Multiple Sclerosis (MS). Studies utilizing Optical Coherence Tomography (OCT) in combination with clinical features have shown that models like Random Forests and Long Short-Term Memory (LSTM) networks can predict MS outcomes with high accuracy, achieving AUC values as high as 0.877 [16]. This integration of advanced imaging and temporal modeling techniques reflects the growing role of ML in complex longitudinal health predictions. However, model interpretability and the need for large, high-quality datasets remain limiting factors for broader clinical adoption.

IV. Comparing ICF Ratings with Traditional Health Instruments

Secondary analyses have compared ICF qualifier ratings with conventional health assessment tools such as the Short-Form 36 (SF-36) and the WHO Disability Assessment Schedule 2.0 (WHODAS 2.0) [17]. These studies found that aggregated ICF ratings offer a broader and more nuanced picture of patient functioning. This suggests an opportunity for machine learning to further enhance existing health instruments by extracting deeper insights and improving predictive capacity in disability classification.

V. ML Techniques in Post-Stroke Rehabilitation Outcome Prediction

A recent scoping review explored the application of machine learning techniques in predicting functional outcomes for post-stroke rehabilitation patients [18]. The review highlighted several effective algorithms, including XGBoost, Random Forest, Artificial Neural Networks (ANN), and Support Vector Machines (SVM). These models demonstrated potential in forecasting patient recovery trajectories and personalizing rehabilitation strategies. However, a noted limitation was the scarcity of real-world case studies and the heterogeneity of methods, which may impact the reliability and comparability of findings.

VI. Deep Learning for Predicting Disability in Multiple Sclerosis

Recent advancements in deep learning have significantly enhanced the prediction of disability progression in Multiple Sclerosis (MS) patients [26]. A study employed deep neural networks to analyze complex patterns in patient data, enabling the classification of lesion types and the prediction of Expanded Disability Status Scale (EDSS) scores. The model demonstrated high accuracy, underscoring the potential of deep learning in providing fully automatic solutions for disability assessment in MS patients. This approach not only improves predictive performance but also offers a scalable method for clinical decision support in managing MS.

III. Methodology and Dataset

1) Dataset and Attributes

Data were collected from one governorate using the Egypt functional assessment tool. The data set consists of 177640 records divided into 9 types of disability. Table 1 shows the number of records for each type of disability.

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Id	Title	Number of Records
1	Move disability	24624
2	Mental disability	8567
3	Chronic diseases	14631
4	Hearing disability	3323
5	Visual disability	9854
6	NO disability	114811
7	Autistic spectrum	51
8	Learning difficulties	81
9	Psychiatric illness	1968

Each record contains 32 characteristics that represent questions that cover all aspects so that physicians can determine whether the citizen can or cannot work and needs state support. Table 2 shows descriptions of all the features.

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Id	Title	Description
1	Body Mass Num	Body mass index, calculate BMI by using weight in kilograms (kg) divided by the square of height in meters (m2)
2	Eye Acuity Num	The degree of visual acuity with both eyes together
3	Eye Vision Field Num	The degree of visual field
4	Walk	Ability to walk a distance of about 50 meters without assistance
5	Climb Stairs	The ability to climb stairs without assistance
6	Standing Sitting	Ability to sit and stand without assistance
7	Arm Raise	The ability to raise the affected arm to chest level
8	Lifting Weight	Can he lift a weight of half a kilogram/liter with his weaker arm?
9	Chewing	Can he chew and swallow?
10	Catch	Can he pick up or turn the pages of a book with the affected limb?
11	Control Output	Can he control defecation and urination?
12	Can Feed	Can he feed himself?
13	Pass out	Does he lose consciousness more than once a month?
14	Bathing	Can he shower alone?
15	Preparing Food	Can he prepare a meal for himself?
16	Currency Deal	Can he deal with currencies?
17	Crossroad	Can he cross the road alone?
18	Shopping	Can he shop alone?
19	Walk Independent	Can he walk around independently (day and night)?
20	Need Supervision	Does the applicant need supervision more than 50% of the time?
21	Unruly Behavior	Does the applicant engage in bouts of uncontrollable, unconscious or aggressive behavior?
22	Speak	Is the patient able to communicate verbally in a manner appropriate to his age?
23	Understand	Does the applicant understand and carry out simple instructions?
24	Daily Risk	Is the applicant able to recognize daily hazards such as stove flames, the smell of gas, electrical wires, etc.?
25	Social Situation	Is the applicant able to recognize social situations that may expose him to danger, such as (harassment and dealing with strangers)?
26	Make Decision	Can he make decisions independently?
27	Hearing	Degree of hearing loss according to the decibel (decibel)
28	Speech Recognition	Is he able to distinguish speech?
29	Eye Disease	Is there an eye disease that directly affects the ability to see?
30	Kidney Failure	Is there a failure in kidney function that requires periodic dialysis?
31	Cancer	Does he suffer from a cancerous tumor that requires surgical, radiation, or chemical intervention, marrow failure, or blood tumors?
32	Incurable Diseases	Does he suffer from any of the following diseases (AIDS - tuberculosis – leprosy - blood diseases)?

2) Data Preprocessing

Data preprocessing is an essential step in machine learning that prepares raw data to improve model performance and accuracy. This process tackles data quality issues such as noise, missing values, and

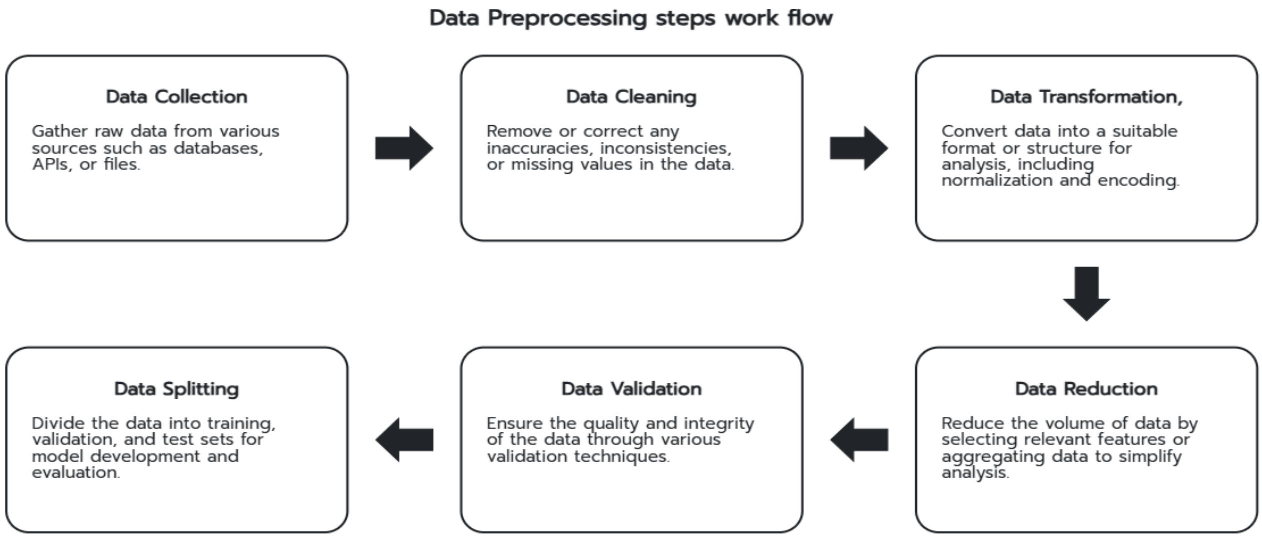


Figure 1 Data preprocessing steps workflow

inconsistencies, ensuring the data is suitable for analysis. High-quality data is crucial for achieving accurate model outcomes. Techniques like normalization, feature encoding, and missing value handling are employed to ensure models are trained in clean and relevant data. A workflow diagram (Figure 1) illustrates the various steps involved in data preprocessing [19].

3) Data Cleaning:

This foundational step involves identifying and correcting errors in the dataset, such as handling missing values through imputation or removal, correcting outliers, and standardizing formats[19][20][21].

4) Data Transformation:

Data transformation is a critical step in preparing data for analysis, which includes normalization and scaling to ensure that features contribute equally to model training.

- **Normalization and Scaling:** Adjusting the scale of features to ensure they contribute equally to model training [22].

- **Feature Encoding:** Converting categorical variables into numerical formats for better compatibility with algorithms [19].

Data Normalization using Min-Max Scaling transforms features into a specified range, typically between 0 and 1 [22].

5) Data Partitioning:

Splitting the dataset into training, validation, and test sets is crucial for evaluating model performance effectively. This helps prevent overfitting by ensuring that models are tested on unseen data [23].

6) Convolutional Neural Network

A 2D convolutional neural network (CNN) is a type of neural network designed explicitly for image-processing tasks. It is composed of multiple layers of artificial neurons that process and analyze images using convolutional filters. The primary function of a CNN is to extract features from an input image and use these features to classify the image or make a prediction. A 2D CNN is called a "2D" network because it processes images in two dimensions, with both width and height. One of the key advantages of a 2D CNN is its ability to process images at different scales and orientations. Using multiple convolutional layers with different sized filters, a CNN can learn to recognize features at different levels of abstraction, such as edges, shapes, and objects. A 2D convolutional neural network is a powerful tool for image processing tasks, such as object recognition and image classification.

A 1D convolutional neural network (CNN) is a type of deep learning model designed to process one-dimensional data sequences, such as time series or text. It is a variant of the more general 2D CNN, which is designed to process two-dimensional data arrays such as images. One of the critical features of a 1D CNN is its ability to learn local patterns or features in the one-dimensional input data using a set of learnable convolutional filters sliding over the data. For one-dimensional data, the 1D CNN has several significant advantages. First, the computational complexity in 1D CNN is significantly lower than in 2D CNN. Second, 1D hidden layers use a shallow architecture format (usually around 10k parameters to be tuned). Third, with typical architecture, 1D CNN can be calculated using a standard computer. In contrast, for 2D CNN, the use of GPU is mandatory. Recent studies proved that with limited labeled data and high variation 1D data, the 1D CNN showed superior performance [24, 25].

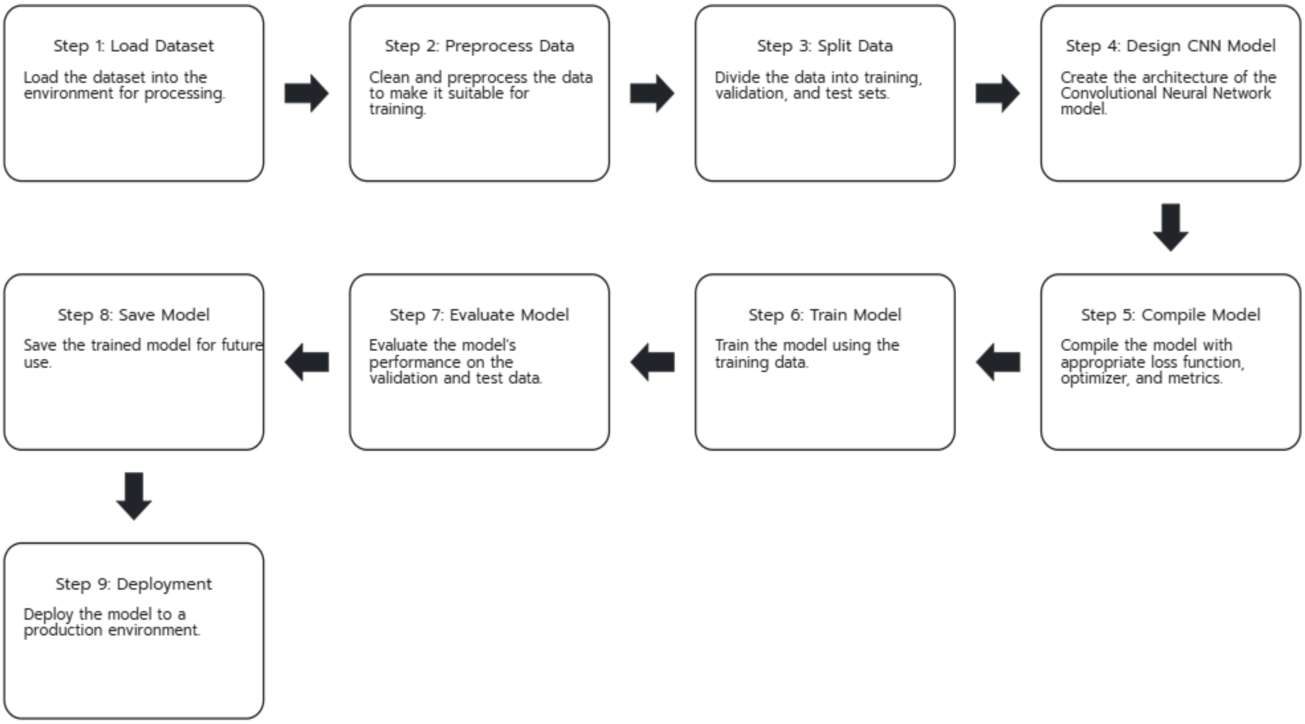


Figure 2 The Flow chart Steps for CNN-based Classification Model

In this study, the 1D CNN was used for structured data in a tabular format. However, those were not time series data, meaning no time information or dependencies were available. The typical use of 2D CNN is for image-based data, due to how CNN architecture works; furthermore, in this study, the motivational reasons behind the 1D CNN are, first, the same as for an image, which is a collection of pixel values with a limit in values, the tabular data can be kept within a limit using a normalization technique. Second, the position of pixels is critical in 2D CNN. Similarly, positioning features in input, which is tabular formatted data, is critical. Hence, finding the correct position for the features in the tabular list is challenging, which can be figured out using CNN architecture. However, like 2D CNN, in 1D CNN, the architecture is in charge of whether a specific feature strongly correlates to the class variable or has a strong relationship with other features. As shown in Figure 2, the Flow chart steps for the CNN-based Classification Model Are Presented.

Figure 3 shows the CNN Model Design. This CNN model is designed to classify data with 32 features into 9 classes. Each layer extracts and processes features, culminating in the SoftMax layer to provide class probability.

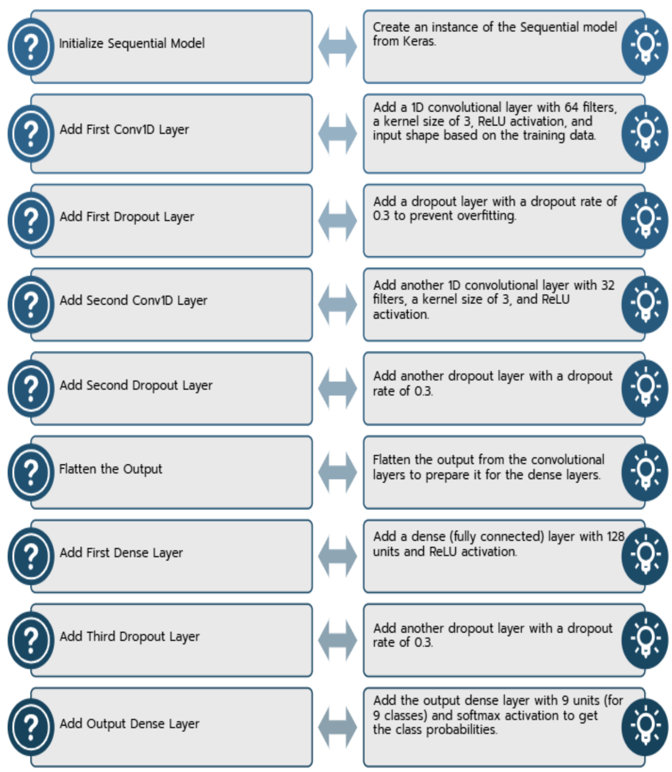


Figure 3: Shows the CNN Model Design used to classify Disability Dataset.

IV. Results

Deep learning can assist healthcare professionals in enhancing their ability to identify disability cases by utilizing functional assessment tools, ultimately determining the correct type of disability. Specifically, classification algorithms can analyze questionnaire data to improve classification efficiency, saving time, increasing accuracy, and reducing human error. In this study, based on the evaluation measures, the suggested 1D CNN model for classifying disability types performed well. We used the complete data of 177640 records to predict the disability type of each patient based on the answers to the questionnaire. The model accuracy of 95.04% indicates that it achieved an overall good prediction rate. The model achieved an F1 Score: 0.95, Precision: 0.95, Recall: 0.95. Table 3 shows the 1D CNN model Results.

Table 3 shows the 1D CNN model Results.

Model	Accuracy	F1	Precision	Recall
1D CNN	95.04%	0.95	95	95

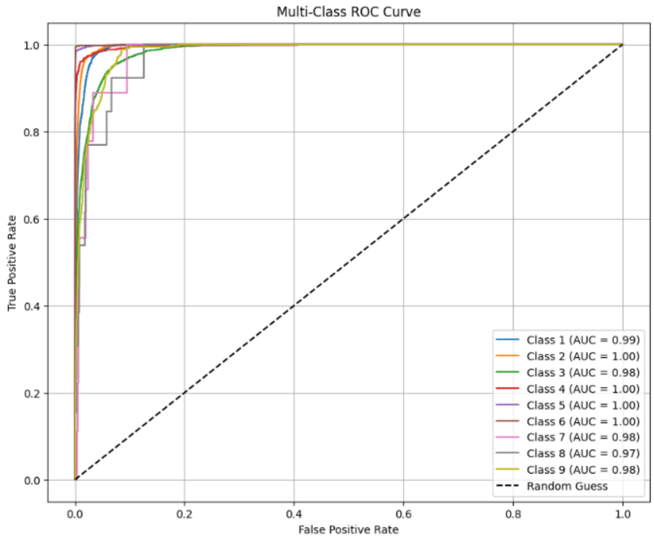
Number of records: 177640.

Figure 4 Shows the 1D CNN confusion matrix. The correct classification is shown as a percentage in blue for each type of disability.

	1	2	3	4	5	6	7	8	9
1	4531	17	322	3	3	10	0	0	2
2	4	1570	81	17	6	3	0	0	34
3	612	74	2134	10	10	24	0	0	20
4	1	68	18	586	7	2	0	0	3
5	13	5	20	0	1882	19	0	0	1
6	26	2	40	2	15	22958	0	0	1
7	0	8	0	1	0	0	0	0	0
8	0	8	1	1	1	0	0	0	2
9	9	175	51	6	1	4	0	0	104

Figure 4 shows the 1D CNN confusion matrix.

Using the ROC curve and by interpreting the curve's shape and calculating the AUC, you gain insights into the model's ability to distinguish between positive and negative cases. The ROC curve plots TPR on the y-axis and FPR on the x-axis. The ROC curve is a useful tool for evaluating a model's performance in distinguishing between positive and negative cases. By interpreting the shape of the curve and calculating the Area Under the Curve (AUC), you can gain valuable insights into the model's effectiveness. Figures 5 Show the ROC Curve analysis to the 1D CNN model.



Figures 5 Show the ROC Curve analysis of 1D CNN model.

V. Conclusion

This study highlights the effectiveness of a deep learning, 1D convolutional neural network (CNN), in predicting disability types based on questionnaire data. CNN demonstrated high accuracy and robust performance metrics, indicating its potential utility in clinical settings for enhancing the identification of disabilities. The 1D convolutional neural network (CNN) achieves an accuracy rate of 95. 04%.

These findings suggest that deep learning can significantly improve the classification of disability cases, thereby aiding healthcare professionals in making informed decisions. The successful application of these algorithms underscores the importance of leveraging advanced analytical techniques to enhance diagnostic accuracy and optimize patient outcomes. Future research could explore additional algorithms and larger datasets to further refine these predictive models, ultimately contributing to more effective disability assessment and management strategies.

VI. Declarations

- ***Ethics approval and consent to participate***

This study does not involve human participants, animals, or personal information, and therefore did not require ethical approval or consent to participate.

- ***Consent for publication***

I, the author, give my consent for the publication of this manuscript.

• ***Availability of data and materials***
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

• ***Competing interests***
There are no conflicts of interest or competing interests related to this research

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