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Predicting Work-Related Musculoskeletal Disorders in Indian Construction Workers Using Machine Learning and Deep Learning Classifiers

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Abstract

Background: Construction workers often experience work-related musculoskeletal disorders (MSDs) at a high rate. The poor performance of workers due to its presence is a serious concern to all the stakeholders and it is necessary to diagnose before it develops. The study aimed to ascertain the performance of machine learning (ML) classifiers and multi-layer perceptron (MLP) neural networks in predicting MSDs.
Materials and Methods: The cross-sectional study utilized the data on potential MSD risk factors collected from 1040 construction workers on infrastructure projects across different states in India. The data was gathered through direct interactions with the construction workers and also, through the health records maintained by the safety department of the project sites. Stratified random sampling was the approach used for sampling. The prediction of the development of MSDs is based on nine features. In this study, Naive Bayes (NB), K-Nearest Neighbors (KNN), and XGBoost classifiers were applied to predict the presence of MSDs, and the results were compared with the MLP neural network based on the metrics.
Results: In predicting the presence of MSDs, XGBoost's classifier, with 91% accuracy, was superior to NB, KNN, and MLP neural networks having 87%, 72%, and 85% accuracy, respectively. A powerful prediction tool has been developed to diagnose MSDs and effectively interpret the outcomes confidently.
Conclusions: The performance metrics of the XGBoost classifier resulted in the best compared with the other classifiers. The prediction tool is useful to diagnose the prevalence of MSDs in the early stages.

Keywords: Musculoskeletal Disorders, Machine Learning, Deep Learning

Introduction

MSDs are caused by the musculoskeletal system's stress and strain resulting from various occupational activities. Workers face a heightened risk of developing MSDs when they are required to maintain awkward postures during their tasks. This is a pressing issue that calls for immediate attention and action to protect the well-being of workers. Construction operations are contributing to the development of MSDs among workers, and it is a major occupational health and safety (OHS) issue worldwide. Construction workers are vulnerable to MSDs based on their work activity. The symptoms of the existence of MSDs in one or more body parts are common among construction workers worldwide. The subject ergonomics, which deals with human performance in the work environment, faces a challenge from the various construction activities resulting in MSDs. Ergonomics issues comprise MSDs, back pain, and health disorders. MSDs cause muscle, tendon, ligament, joint, nerve, and blood vessel injuries [1]. The past studies on MSDs were conducted in the manufacturing sector, and the research about the construction sector was available from the USA, Canada, and European countries [2]. Despite the presence of risks associated with MSDs in construction activity, there is a dearth of research in the construction sector. MSDs impact the quality of life of construction workers through absenteeism and inability to perform work, thereby influencing a worker's well-being. Construction work necessitates monotonous activities, awkward postures, and the application of high force levels, which increases the risk of acute and cumulative MSDs. In addition to strenuous physical work, the other factors that influence the risk of MSDs are handling heavy materials, extreme temperatures, humidity, repetitive movements, and vibration transmitted by the equipment and tools. Most MSDs are chronic disorders and progress from mild to severe over time, affecting the quality of life among the workers.

Adhering and following the best practices have been established in minimizing the MSDs. A few practices are job rotation among workers performing repetitive tasks, implementing engineering controls wherever practicable, ergonomic design of hand and power tools, wearing personal protective equipment to minimize exposure to vibration, assessing the noise at the workplace, and conducting the risk assessment for the job tasks [3]. In the past, statistical methods and questionnaire surveys were adopted to analyze the occurrence of MSDs and their influence on workers' health. MSDs at construction work concern the workers due to their impact on physical activity. Awareness of MSDs in various construction trades is expected to be useful in implementing preventive measures. The construction industry is well-known for its work-related risks and hazards and the resulting negative health effects. MSDs are a leading cause of lost productivity, decline in efficiency, and permanent disablement among construction workers [4]. To avoid the pain, suffering, and absenteeism due to the prevalence of MSDs among construction workers, it is vital to diagnose the disorders and plan and implement the appropriate measures to eliminate their effects [5]. Preventive steps should be appropriate to fulfill the requirements of workers such as individual attributes, work demands, and mental condition.

The results of the previous studies indicate that the bricklayers suffer from lower back pain, concrete mixer operators have an increased risk of back pain, waist pain, and shoulder pain, and fixed body postures, prolonged working hours, and stress levels were contributing to the prevalence of MSDs among the construction workers [6-9]. The results of the studies indicate that construction workers are suffering from pain in the different parts of the body due to the development of MSDs, irrespective of their trade. In addition to physical activity, the other factors influencing the development of MSDs include gender, age, body mass index (BMI), previous job history, duration of work, education level, job task, ambient temperature, and equipment-related factors.

Researchers have applied different tools to analyze the occurrence of MSDs among construction workers. The tools include the application of descriptive statistics, chi-square analysis, and the relative Importance Index method to determine how personal and work-related factors are linked to MSDs [10,11]. From the literature, it is observed that the majority of the studies in the past have applied statistical tools and questionnaires to assess the prevalence of MSDs. This study aims to identify the best model from ML and deep learning (DL) classifiers to predict MSDs among construction workers and develop an MSD prediction tool.

Materials and Methods

The cross–sectional study collected data from 1040 construction workers at Indian project sites between January and November 2022. The approach of using ML classifiers to predict the occurrence of MSDs among construction workers is detailed in the following paragraphs.

The study underwent rigorous stages, and the framework is depicted in Fig. 1. This section presents a framework for adopting ML classifiers to predict MSDs. The various stages involved in the framework are explained briefly.

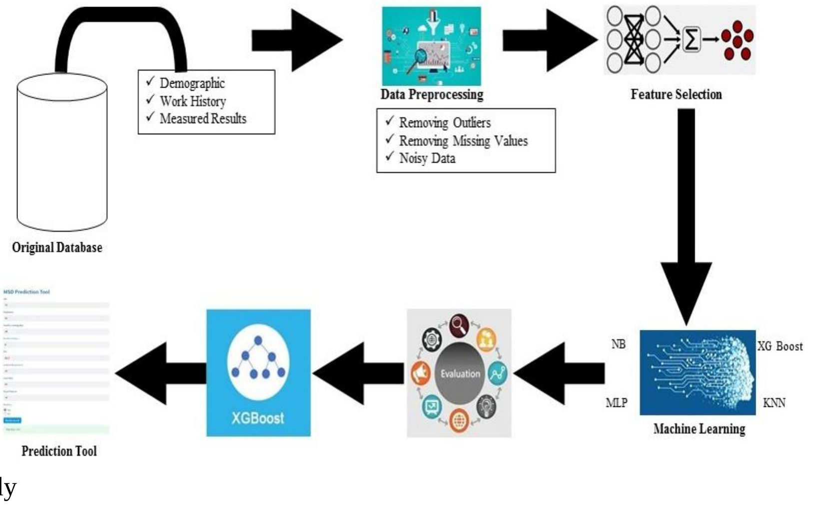

Fig.1. Framework of the study

- ✓ Feature or variable selection: Independent variables are identified carefully.
- ✓ Data collection: Data set was collected from the construction workers.
- ✓ Before analysis, the dataset was preprocessed to identify and address outliers and null values, ensuring the integrity of our findings.
- ✓ Training and testing: The ML classifier framework was developed, and the training and testing steps were performed.

Finally: applying an ML classifier to predict the presence of MSDs. The study used XGBoost, KNN, and NB classifiers and compared the performance metrics with the MLP neural network structure.

The prediction of the MSDs dataset consists of nine independent variables. The variables are finalized based on literature and brainstorming sessions with occupational health experts and safety professionals. The independent variables are age, experience(years), Monthly working days, no of working hours per day, body mass index (BMI) [12-14], ambient temperature (0 c) [15], heart rate [16], diastolic blood pressure [17], and the habit of smoking [18], and the outcome is the presence of MSDs. While posture undoubtedly stands as the leading risk factor for MSDs, it's crucial to recognize that specific personal and job-related factors also heavily influence their development. According to the literature, human factors such as age, gender, and smoking habits are also linked to MSDs [19]. To categorize the data, the outcome is split into two factors: 0(MSDs not present) and 1 (MSDs present). Using a trained classifier, important variables are identified with an Extra Tree Classifier and recursive feature elimination (RFE) using a Gradient Boosting Classifier.

The most important stage in this research is data collection to justify the objectives within the scope of the study. The data collection is limited to male construction workers working on infrastructure projects across different states in India. The projects include the construction of elevated metro corridors, mega road projects, bridges, and flyover works. The features considered for the analysis are finalized considering the outdoor construction activity. The data was collected utilizing a stratified random sampling approach with construction workers and through the health records maintained by the respective safety departments of the project sites. In the data collection process, certain measuring instruments include; a pulse oximeter for heart rate, a digital thermometer for ambient temperature, a blood pressure monitor, and a digital weighing machine for body weight. An online calculator is used to calculate the BMI after measuring the height and weight of the workers. The data for the other features is collected directly from workers: age, experience, monthly working days, number of working hours per day, and the habit of smoking. All the features are continuous except categorical smoking (yes/no).

In this study, three advanced ML algorithms, namely XGBoost, KNN, Naive Bayes, and MLP neural network, were utilized to forecast the development of MSDs among construction workers. The optimization of hyperparameters in the models was carried out using the grid search method. This method has proven to be highly effective in refining variables during the training phase and enhancing the efficiency of the machine learning classifiers [20].

Extreme gradient boosting (XGBoost) Classifier: This ML algorithm falls under the ensemble learning category, more specifically, the gradient boosting framework. It uses decision trees as basic learners and applies regularization techniques to improve the model's generalization. This algorithm excels in computational efficiency, feature importance analysis, and handling missing values. Due to these properties, XGBoost is widely used for various tasks such as regression, classification, and ranking. Owing to its high scalability, this classifier requires less time and memory than other ML methods [21]. The XGBoost classifier performs better than other ML algorithms, excelling in accuracy, training speed, and adherence to the normality assumption of input variables. Moreover, it necessitates minimal variable tuning while providing lucid explication.

K-Nearest Neighbor (KNN) Algorithm: The fundamental principle behind this algorithm is that data points that share similarities are likely to have corresponding labels or values.

The KNN algorithm stores the entire training dataset as a reference during the training phase. In making predictions, the algorithm employs the Euclidean distance to compute the distance between the input data point and all the training examples. This enables the algorithm to determine the K nearest neighbors by assessing their distances from the input data point. In the context of classification problems, the algorithm then proceeds to predict the most prevalent class label among the K neighbors. The classifier is useful to work on a large dataset owing to the speed of execution, extreme power and ease of application [22].

Naive Bayes (NB) Algorithm: The Bayes theorem-based NB Classifier is a classification method. The NB Classifier is known to outperform other classification methods. The characteristics of NB are a very strong (naive) assumption of independence from each condition or event, simple design, and application with large data sets. The NB classifier uses a series of probabilistic calculations to determine the appropriate classification for a dataset. KNN is simple to interpret. Evaluation is based on the training dataset and responds to selected features. Compared to all other classifiers, NB is relatively fast to generate predictions and easy to train using a small dataset [23].

Multi-layer Perceptron's (MLP) Network: The system comprises multiple layers of artificial nodes that facilitate unidirectional forward connections of inputs and outputs. MLPs consist of input signals, hidden layers with nodes, and an output layer. The hidden layer needs an activation function to work. More functions improve the network's performance by modeling complex relationships between inputs and outputs, leading to accurate predictions. The MLP network's multiple layers of neurons provide improved input-appropriate output mapping proficiency [24].

Performance Metrics: The performance and reliability of ML classifiers are assessed using various parameters. These include accuracy (reflecting the total number of correctly classified points), recall (measuring the comprehensiveness of the outcomes), precision (assessing the usefulness of the outcomes), specificity (representing the portion of true negatives correctly classified), and f-measure (indicating the probability that a positive prediction is accurate). The receiver operating characteristic (ROC) curve is a probability curve for evaluating binary classification problems. It plots the true positive rate against the false positive rate at different thresholds, effectively separating signal from noise. The area under the curve (AUC) is a crucial metric for evaluating a classifier's ability to differentiate between classes and provides an insightful summary of the ROC curve. The AUC value indicates a classifier's capacity to distinguish between positive and negative classes, with a higher AUC value signifying better classifier performance. The values of these performance metrics are determined using "equations 1 to 4."

Formula 1.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100$$

$$Recall = \frac{TP}{(TP + FN)} * 100$$

$$Precision = \frac{TP}{(TP + FP)} * 100$$

$$f - measure = \frac{2 * Precision * Recall}{(Precision + Recall)} * 100$$

The terminology True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) is used to assess the performance of ML models. True Positive (TP) occurs when the model correctly predicts the positive class, while False Positive (FP) arises when the model incorrectly predicts the positive class. False Negative (FN) represents incorrect predictions of the negative class, and True Negative (TN) denotes correct predictions of the negative class. The experiments involving ML classifiers and MLP models were conducted using the Google Colab platform for training the learning models.

Results

The MSDs dataset comprises 1040 samples (MSDs present = 623, MSDs not present = 417). After data preprocessing and deleting the outliers, missing, and null values, the dataset was reduced to 1010 samples (MSDs present = 607, MSDs not present = 403). The data was analyzed to identify variables influencing MSD prevalence. Feature Importance was used to score the nine independent features. Higher scores indicate a more positive effect on the predictive model. Variables were selected using this method with the help of classifiers. All nine independent variables were chosen for further analysis based on the results. The dataset of the dependent variables is balanced, and the question of imbalance doesn’t arise.

The data was analyzed by using three ML classifiers and MLP neural network by considering 1010 data points, 70% of the data is used for training, and the rest 30% for testing. In this study, a six-layer MLP neural network using Python programming was developed to predict MSD diagnosis. The network processes 1010 samples with 2 output units and utilizes 'hyperbolic tangent' activation in the hidden layers and a 'relu' activation in the output layer [25]. Based on the performance metrics outlined in Table 1, the XGBoost classifier has demonstrated superior predictive capabilities in identifying MSDs among construction workers. This conclusion is supported by the model's impressive accuracy of 91.0%, precision of 90%, recall of 91.0%, f-measure score of 90%, and an AUC score of 87%. The findings are further substantiated by the corresponding confusion matrix (Fig. 2) and ROC curve (Fig. 3), firmly establishing the XGBoost classifier as the most effective model for predicting MSDs.

Table 1. Performance metrics of classifiers

ML classifier	Accuracy (%)	Precision (%)	Recall (%)	F- measure (%)	AUC (%)
XGBoost	91	90	91	90	87
NB	87	88	87	87	83
KNN	72	71	71	71	70
MLP	85	84	84	84	80

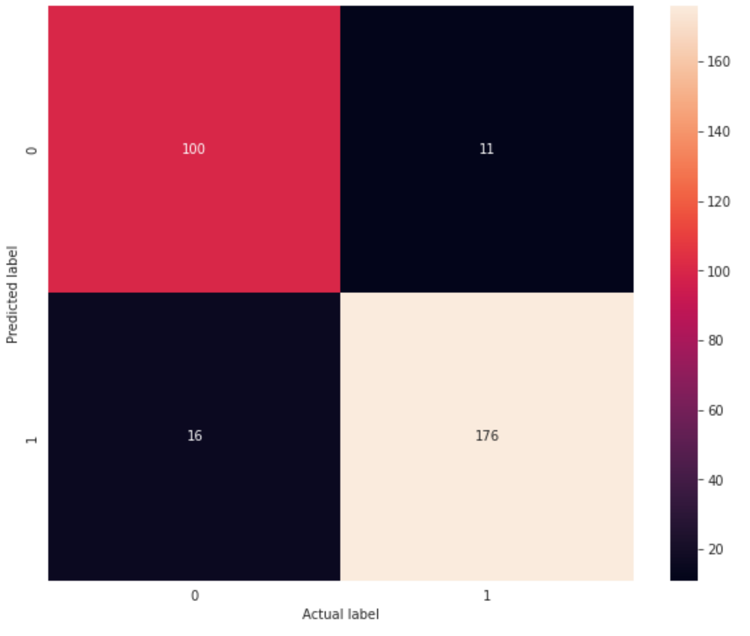

Fig. 2. Confusion matrix of XGBoost classifier

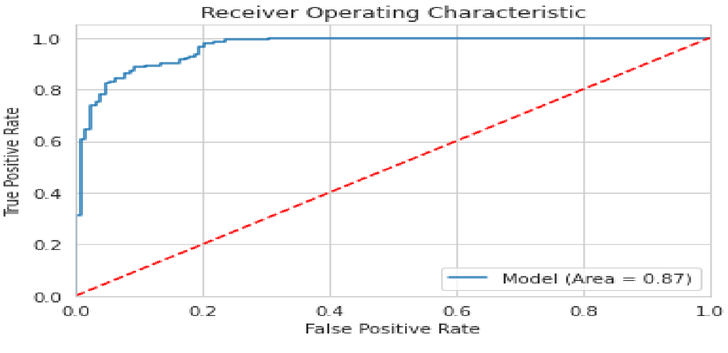

Fig. 3. ROC curve of XGBoost classifier

In developing an ML classifier, the interpretation of results is crucial. Utilizing the Streamlit framework, a prediction model was developed and employed the XGBoost classifier within the Python integrated development environment. The resulting MSD prediction tool effectively diagnoses "MSD - No" for results near 0 and "MSD - Yes" for results nearing 1. Testing confirmed the tool's consistency and accuracy aligned with the dataset.

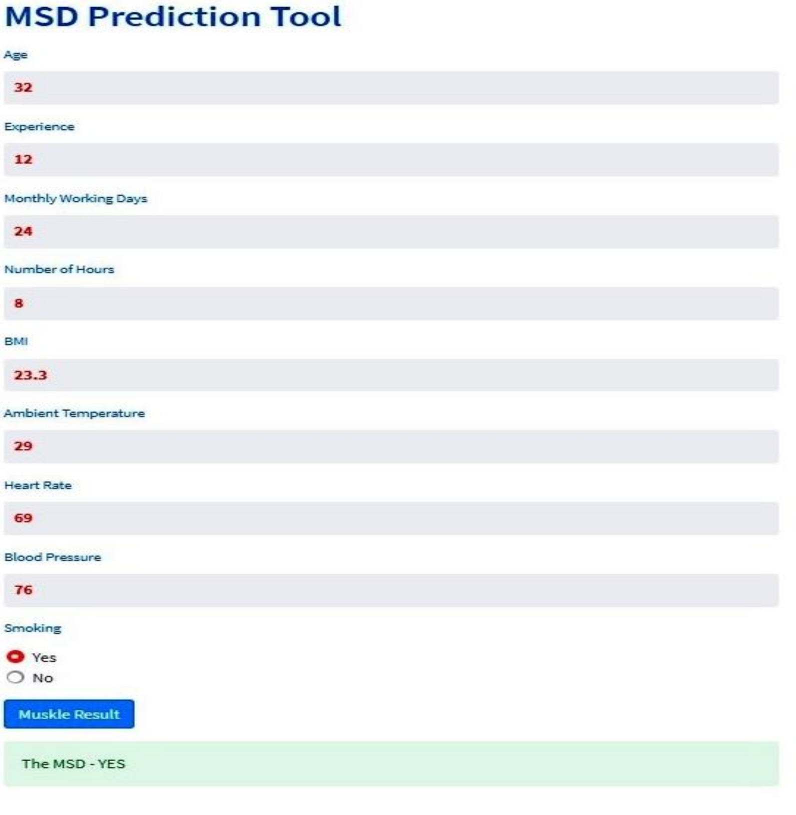

Fig. 4. MSD diagnosis tool

Discussion

In the present study, three ML and DL classification algorithms namely NB, KNN, XGBoost, and MLP neural network, were trained using the variables that affect the presence of MSDs. The application of ML and DL algorithms in the analysis of MSDs is gaining momentum in addition to traditional statistical approaches [26]. Bayesian network-based ML algorithm resulted in the best performance while analyzing the impact of working conditions on the risk of WRMSDs [27]. KNN classifier is proved with an accuracy of 86.79% while developing a model to identify factors associated with the prevalence of WRMSDs in the general workforce [28]. To classify physical loads carried by the construction workers resulting in MSDs, a bidirectional long short-term memory algorithm is used with an accuracy of 98.6% and f1 score of 99% [29]. In the past, ML and DL algorithms have been extensively adopted to predict the development of MSDs among construction workers. Decision tree and random forest classifiers resulted in 100% accuracy while predicting the risk factors related to MSDs of bus drivers in India [30]. XGBoost classifier is proven to be the best in predicting mechanical and stress-related muscle activity [31]. The accuracy score of ML and DL learning algorithms is considerably on the higher side due to which the researchers in the domain of OHS are using these techniques to develop the best model to predict the results.

Studies have concluded that physical exercise will decrease the development of MSDs [32]. Apart from implementing ergonomic interventions, management and individual factors are crucial in minimizing the incidence of MSDs among workers. The study intended to highlight ML applications in predicting the development of MSDs construction workers working in infrastructure projects. The algorithms used in the present study were mostly applied in recent studies about OHS. The study results show that the XGBoost classifier predicts correctly and diagnoses the probability of developing the symptoms MSDs or not, and based on the performance metrics, the scores are significantly increased compared with NB, KNN classifiers, and MLP neural networks. According to performance metrics, the accuracy score shows a 4%,19%, and 6% improvement for the XGBoost classifier compared with NB, KNN classifier, and MLP neural network, respectively.

Similarly, the precision, recall, and f1scores of the XGBoost classifier outperformed the three algorithms. The XGBoost classifier is a superior and enhanced version of the gradient-boosting algorithm. Notably, it excels in performing parallel processing, handling missing values, and making decisions on maximum depth by splitting the levels. It's imperative to optimize hyper-parameters in this algorithm, as failure may lead to overfitting [33]. The ability of the MLP neural network considerably high compared with the ML classifiers, support vector machine, and KNN in predicting the probability of an individual is suffering from blood pressure (accuracy of 68%) and diabetes (accuracy of 77.6%) [34], whereas the accuracy of XGBoost classifier in the current analysis is 91%

The analysis results enlighten safety professionals and occupational health specialists to monitor the development of MSDs among construction workers and implement ergonomic interventions to reduce the pain and suffering of the workers. The XGBoost algorithm outperformed other classifiers. Based on the results of the models' performance metrics, the MSD prediction tool was designed to assist safety professionals in predicting the need for initiating measures to overcome the prevalence of MSDs. The designed tool was tested by randomly inputting the data from the dataset, and the results were satisfactory. The area under the curve of ROC curve of the best predicted XGBoost classifier is 87%, and it is well supported by the results of the same classifier (85.3%) in its ability to diagnose intubation risk in COVID-19 hospitalized patients [20]. XGBoost classifier was established as the best algorithm for predicting the results for the data of the occupational and general health domains.

The ML classifiers in the present study showed satisfactory results in predicting the development of MSDs, but certain limitations need to be addressed. First, the dataset pertains to the outdoor construction workers involved in the execution of infrastructure projects. Therefore, the application of the diagnosis tool can't be generalized. Second, the used dataset did not include information from other infrastructure projects like ports, irrigation, defense, and power plants. The findings of the current study need further research for validation. Using the consolidated dataset, including the real estate sector, is useful to generalize the diagnosis of MSDs. Other features/variables, in addition to those used in the present study, are useful in predicting the development of MSDs.

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More prospective research is necessary to validate the findings of the present study. Using the consolidated dataset, including the real estate sector, is useful to generalize the diagnosis of MSDs. The study can be extended further by considering the vibration, load carrying, repetitive movements, force, work tools, and body posture.

Conclusion

Recently, researchers applied ML and DL algorithms to predict, classify, and diagnose diseases. The present study applied four classification algorithms to predict the development of MSDs among outdoor construction workers with an accuracy of 91%. The dataset is split into training and test parts and applied dataset variations (70% training, 30% testing). The performance metrics of the XGBoost classifier resulted in the best compared with the other classifiers. The results indicate clearly that the XGBoost algorithm diagnoses the MSDs more accurately. Timely diagnosis is useful for implementing the planned measures and minimizing the risks associated with MSDs.

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Conflict of interest

None declared.

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Ethical Considerations

The participants were informed about the objectives of the study, and written consent was obtained. Also, the managers and officials in the Safety Department were informed of these objectives and methods. They've been assured that all information will be kept confidential.

Authors' Contributions

Raja Prasad: Conceptualization, Methodology, Writing-Original draft, Review & editing. Rambabu Mukkamala: Analysis and interpretation of data. Amit Hedau: Review & editing. All the authors participated in the initial writing of the article or its revision, and all accept the responsibility for the accuracy and correctness of the contents of the present article with the final approval of this article.

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