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Predictive Modeling of Work-Related Musculoskeletal Disorders among Shuttle Car Operators Using Artificial Neural Network

Ali Murtoja Shaikh* and Bibhuti Bhusan Mandal

Department of Mining Engineering, Indian Institute of Technology Kharagpur, Kharagpur - 721302, West Bengal, India; murtoja6696@gmail.com

Abstract

Background: *Work-related Musculoskeletal Disorders (WRMSDs) are highly prevalent among equipment operators in the mining industry, particularly in underground coal mining. The multifaceted nature of risk factors contributing to WRMSDs necessitates a robust and accurate predictive model to assess the likelihood of these disorders among operators.* ***Methodology:*** *This study presents a novel Artificial Neural Network (ANN)-based predictive model developed to estimate the prevalence of WRMSDs among seated vehicle operators. Key input variables include demographic and ergonomic factors such as age, Body Mass Index (BMI), years of experience, posture scores (REBA), frequency-weighted Root Mean Square (RMS) acceleration, and Vibration Dose Values (VDV). Data on WRMSDs prevalence and severity were collected using the standard Nordic Musculoskeletal Questionnaire (NMQ).* ***Results:*** *The analysis demonstrated a strong positive correlation between the severity of WRMSDs and the identified risk factors. The optimal ANN configuration included hidden layers with sizes [5, 10, 15], learning rates [0.01, 0.1, 0.2], and class weights [1, 1], [0.5, 1.5], and [1, 2]. The model's performance was validated using 12 unseen datasets, achieving excellent predictive accuracy (0.975 ± 0.014), precision (0.805 ± 0.083), recall (1.000 ± 0.000), F1 score (0.890 ± 0.053), and AUC-ROC (0.996 ± 0.005) (mean ± standard deviation).* ***Conclusion:*** *This ANN-based model offers a powerful tool for predicting WRMSDs across different body regions of seated vehicle operators. Its ability to incorporate diverse input factors will support the implementation of targeted occupational health and safety interventions, particularly for shuttle car operators and other mining professionals at high risk of WRMSDs.*

Major Findings: *The study developed an ANN-based model to predict WRMSDs prevalence among seated vehicle operators in underground mining, incorporating demographic and ergonomic factors. The model achieved high predictive accuracy, with a strong correlation between WRMSDs severity and identified risk factors.*

Keywords: *Artificial Neural Network, Occupational Health, Predictive Model, Shuttle Car, Work-Related Musculoskeletal Disorders*

1.0 Introduction

Through sustained investment and the application of modern technologies, India's coal production has risen significantly. In the fiscal year 2023-24, all-India coal production reached 997.25 million tonnes, compared to 893.19 million tonnes in 2022-23, reflecting a positive growth of 11.65%[1]. This increase is attributed to advancements in surface mining methods and the adoption of high-production technologies in underground mining. The high production technology in underground mines includes Longwall and Continuous Miner technology. This Continuous Miner system combined works with machines like a cutting machine called Continuous

**Author for correspondence*

Miner (CM), two or three shuttle cars for carrying the cut coal from the cutting face to the discharge point, a feeder breaker for breaking the lump size coal and a bolter machine for supporting the unsupported area (shown in plan Figure 1). The shuttle car operators drive their vehicle (Figure 2) 50-60 trips per day during their 8-hour shift with an average cycle time of 6 to 8 minutes depending upon the lead distance. This technique of continuous miner, bolter and shuttle car combination has gained popularity in Indian coalmines with an estimated 40 big projects successfully deploying them. However, these shuttle car operators face considerable health risks during their 8-hour shift operations. Existing literature shows that Whole-Body Vibration (WBV) exposure of shuttle cars and other underground machinery operators often exceeds the Health Guidance Caution Zone (HGCZ) limits as per ISO 2631-1:1997 standards[2,3]. Research also indicates a positive correlation between chronic WBV exposure and an elevated risk of Musculoskeletal Disorders (MSDs), including low back pain, muscle fatigue, and discomfort[4]. The prevalence of Work-Related Musculoskeletal Disorders (WRMSDs) problems among shuttle car operators is largely unexplored, both in India and globally.

Musculoskeletal Disorders (MSDs) are injuries or disorders of the muscles, nerves, tendons, joints, cartilage, or spinal discs caused or exacerbated by workplace activities[5]. A systematic review by Shaikh *et al.,* identified significant causative and risk factors for WRMSDs prevalence, including exposure to whole-body vibration as the leading factor followed by poor posture, repetitive movements, lifting tasks, applied force/load, along with personal factors such as age, BMI, experience, and gender[6]. The studies have found that the body parts most affected by musculoskeletal disorders include the neck, shoulder, upper back, lower back, knees, pelvis, and abdomen[7,8]. The detailed review article by Shaikh *et al.,* clearly states that there are multiple causative and risk factors responsible for developing WRMSDs cases[6]. So, a complex relationship exists between WRMSDs occurrences and various influencing factors.

Although few studies have been conducted utilizing Artificial Neural Networks (ANN), these have predominantly focused on predicting vibration transmission either through a vehicle's body to the seat surface or from the seat surface to the seated operators[9-13]. However, no such research has specifically addressed the issues of the occurrence of Musculoskeletal Disorders (MSDs) due to vibration exposures. Therefore, there is a critical need for the development of a comprehensive model that accurately predicts Work-Related Musculoskeletal Disorders (WRMSDs). Such a model must be universally applicable across diverse populations of seated drivers and account for various factors, including age, BMI, experience, driving postures, and vibration exposure (intensity and duration).

Therefore, modeling approaches that incorporate nonlinear dependencies on various factors are necessary to enhance the general applicability of the model and to forecast a good prediction of WRMSDs occurrences. Artificial Neural Networks (ANNs) have become a cornerstone in machine learning, providing robust solutions for various predictive tasks. Their ability to model complex, non-linear relationships within the data makes them ideal for applications of any prediction or forecasting. ANNs have shown promise in modelling complex systems like human body responses to vibration exposure[14].

This paper focuses on the application of ANNs for binary classification tasks, to predict WRMSDs occurrences at different body regions among seated shuttle operators with the given input of age, BMI, experience, postures (REBA scores), frequency-weighted RMS acceleration (a_w) and Vibration Dose Values (VDV). By employing a neural network, trained on an oversampled dataset, we aim to achieve high accuracy and robustness in our predictions.

2.0 Material and Method

2.1 Data Collection

To formulate the Artificial Neural Network (ANN) prediction model, we needed examples to learn the relationship between inputs and outputs. Based on the previous studies we have chosen six input parameters of age, BMI, experience, posture, frequency-weighted RMS acceleration (a_w) and Vibration Dose Values (VDV) (shown in Figure 5 ANN architecture) which significantly influence the occurrences of WRMSDs[6,15,16]. Field data was collected from 56 underground shuttle car operators working in five different underground mines in eastern

India, under varying vibration and seating conditions. Information such as age, height, weight, and experience were also gathered from each participant.

Whole-body vibration measurements were taken at the seat surface under the ischial tuberosities according to ISO 2631-1/1997 standards, using a Norsonic Nor136 Vibration meter and a Nor1288 tri-axial accelerometer (Figure 3). Data acquisition occurred over one operational cycle varying from six to eight minutes duration per individual. Raw data, without any frequency weighting, was extracted from the Nor136 vibration meter's data acquisition system. This raw data was then used to generate outputs at six strategic body parts (pelvis, lumbar spine, abdomen, thoracic spine, shoulder, and neck) for each operator. Consequently, each whole-body vibration reading at the seat surface resulted in six output vibration values for each individual. These data were then converted into frequency-weighted RMS acceleration values and Vibration Dose Values (VDV) according to ISO 2631-1/1997 vibration standards for use as input parameters of the prediction model[17].

Video recordings of seated operators were conducted from within the operator's cabin, covering a complete operational cycle. These recordings allowed for a detailed analysis of vehicle operators' postures throughout each phase of the cycle, providing insights into their positioning and movements. From this analysis, two predominant postures were identified as recurring patterns during the cyclic operations (Figure 4). To quantify these postures, a time-weighted Rapid Entire Body Assessment (REBA) score was calculated based on a detailed time cycle study of one complete operational cycle. Consequently, 56 REBA scores were derived, corresponding to the 56 operators involved in the study. This resulted in a total of 336 vibration datasets (6 input parameters × 56 operators = 336). Each dataset comprised critical parameters including age, Body Mass Index (BMI), experience, Posture (REBA score), frequency-weighted RMS acceleration (a_w), and Vibration Dose Value (VDV). For the development and training of the Artificial Neural Network (ANN) predictive model, 324 of these datasets were allocated for model training, while 12 randomly selected datasets were reserved for final model testing.

Operators' subjective responses, including the prevalence of Work-Related Musculoskeletal Disorders (WRMSDs), were collected using the Standard Nordic Musculoskeletal Questionnaire (NMQ)[18]. The severity of WRMSDs was rated on a four-point scale (0 to 3), as recommended by Jensen *et al.*,[19] in their study. For ANN model output, only binary responses indicating the presence or absence of WRMSDs (yes/no) were considered. This resulted in 336 output data points (6 body regions × 56 operators), with those corresponding 12 datasets reserved for final testing, consistent with the input dataset allocation. Before training the ANN model, a correlation analysis was performed using SPSS software to assess the alignment between subjective WRMSDs prevalence data and the input variables (age, BMI, experience, REBA score, frequency-weighted RMS acceleration, and VDV). This ensured that the input parameters meaningfully contributed to predicting WRMSD exposure. The ANN model (architecture depicted in Figure 5) was then trained using the input variables and the binary output (WRMSDs exposure: yes/no). To ensure uniform contribution of all features to the model training, feature normalization was applied. Given the presence of class imbalance in the data, a basic oversampling technique was employed to balance the dataset, ensuring an adequate representation of the minority class and enhancing the model's predictive accuracy.

2.2 Inclusion Criteria of the Participants

The inclusion criteria for the ANN input data and WRMSDs prevalence response data for 56 adult subjects were as follows:

- Only underground shuttle car operators were included.
- Only full-time or full-shift operators were considered.
- Participants were above 18 years old (statutory restriction in Indian mines).
- Participants had more than one year of experience (first-year service is a training period where operators perform multiple tasks).
- Only male operators participated in the study, as no female operators were available due to the statutory restriction of women deployed in underground mines.
- Participants were free from any injuries or accidents in the past year.

The subjects' details, including age, weight, height, BMI, experience, and posture (REBA score), are summarized in Table 1.

2.2.1 Ethical Clearances

Prior to vibration measurements, experimental procedures and safety guidelines were explained to each subject, who then provided consent as per the protocol approved by the Ethics Committee of the Indian Institute of Technology, Kharagpur (Approval number: IIT/SRIC/DEAN/2024/Revised, dated 08.01.2024).

2.3 Model Architecture

The ANN model was implemented using MATLAB's 'patternnet' function, designed for pattern recognition tasks. The architecture consisted of three layers:

- An input layer with six neurons corresponding to the input features of age, BMI, experience, REBA score, RMS acceleration and VDV.
- A single hidden layer with a variable number of neurons (5, 10, 15), determined through hyper-parameter tuning.
- An output layer with one neuron for binary classification.

2.4 Hyper-Parameter Tuning

A comprehensive grid search was conducted to identify the optimal configuration of the Artificial Neural Network (ANN) model. The following hyper-parameters were tuned:

- Hidden layer size: [5, 10, 15]
- Learning rate: [0.01, 0.1, 0.2]
- Class weights: [1 1], [0.5 1.5], [1 2]

Five-fold cross-validation was employed to assess the performance of each configuration. The F1 score was used as the primary evaluation metric for selecting the best-performing model. This approach ensured a balance between precision and recall, providing a robust measure of the model's classification effectiveness.

2.5 Performance

In the context of an Artificial Neural Network (ANN) prediction model, the following terms (accuracy, precision, recall, F1 score, Area Under the Receiver Operating Characteristic curve (AUC-ROC)) are used to evaluate the performance of the model[20].

Accuracy: Accuracy measures the proportion of true results (both true positives and true negatives) among the total number of cases examined. It is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Precision: Precision, also known as positive predictive value, measures the proportion of true positive predictions among all positive predictions made by the model. It is calculated as:

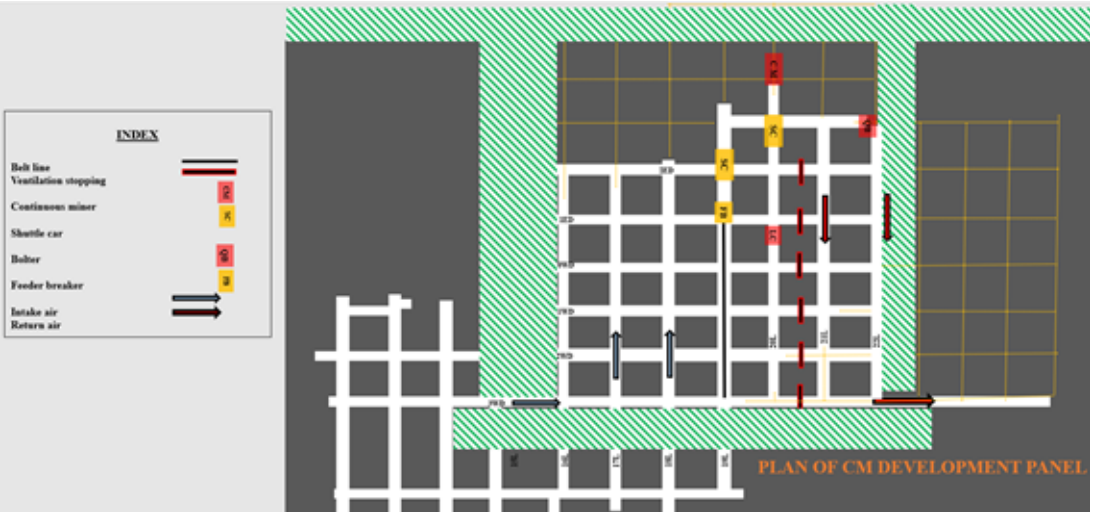


Figure 1. A plan of continuous miner, shuttle car, bolter combination development panel.

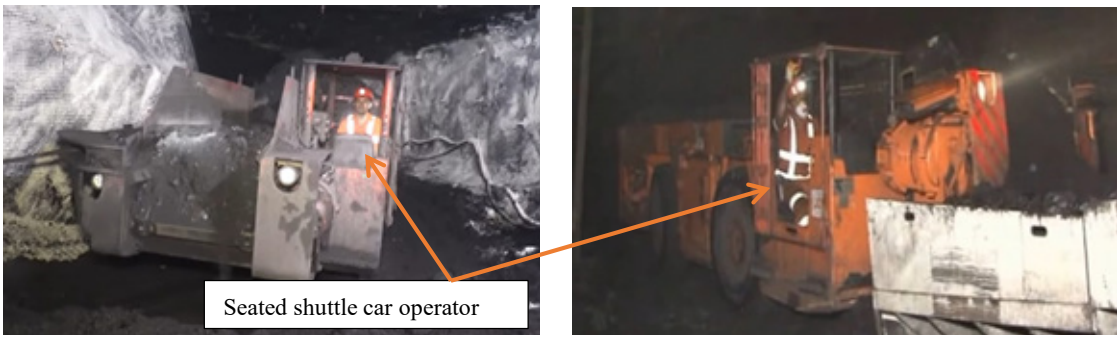


Figure 2. Seated shuttle car operator in operation.

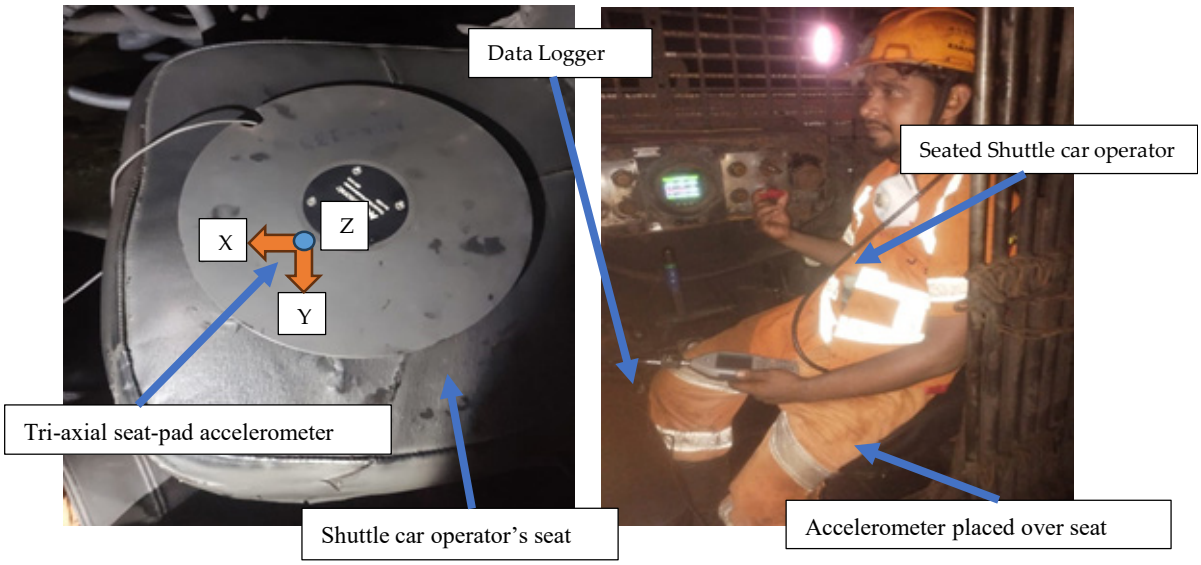


Figure 3. Measuring whole body vibration over seat surface of seated shuttle car operators.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of actual positives that are correctly identified by the model. It is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1 Score: The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both the false positives and false negatives. It is calculated as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC-ROC: The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a critical metric for evaluating a model's ability to discriminate between classes. The ROC curve itself is a graphical representation that plots the true positive rate (recall) against the false positive rate across various threshold settings. The AUC quantifies the overall performance by representing the probability that a randomly selected positive instance is ranked higher than a randomly selected negative



Figure 4. Two major postures of shuttle car operators during operation.

instance, providing a single scalar value to assess the model's effectiveness[20].

2.6 Training and Evaluation

The final model, with the best hyper-parameters, was trained on the entire oversampled dataset. The performance of the model was evaluated using a separate test set, and key metrics such as accuracy, precision, recall, F1 score, and AUC-ROC to provide a comprehensive assessment of its predictive capabilities.

3.0 Results

The average (Mean ± Standard Deviation) of age, BMI and experience of the participants were found to be 35.11 ± 6.80 years, 25.14 ± 2.61 kg/m^2, and 9.83 ± 2.82 years respectively (Table 1).

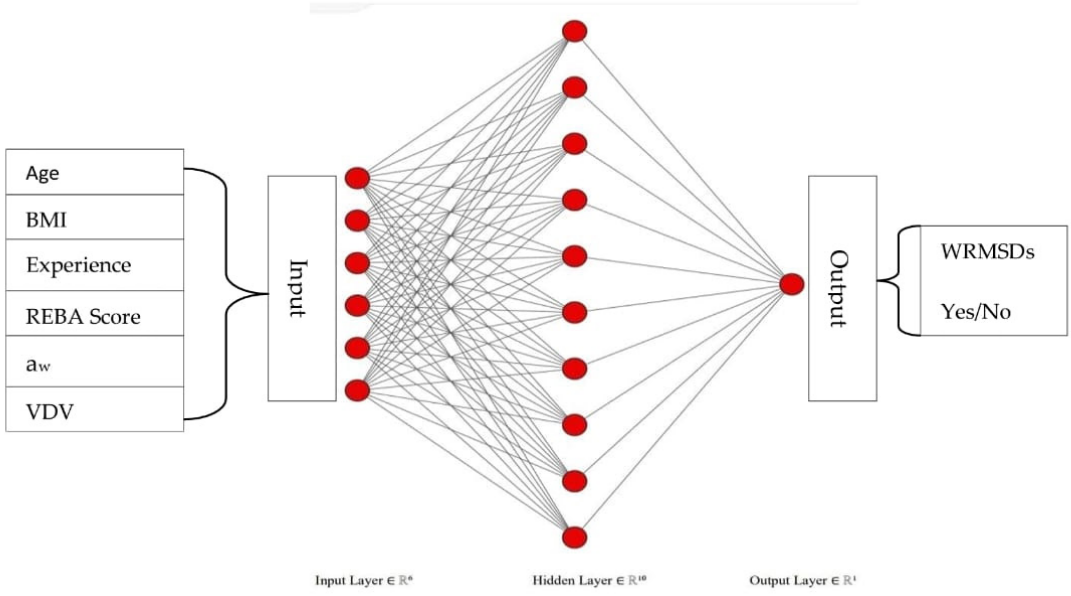


Figure 5. Architecture of the ANN prediction model.

Table 1. The input parameters and their minimum, maximum, mean values for the participants

Parameters	Minimum value	Maximum value	Mean ± Standard Deviation
Age (years)	25	51	35.11. ± 6.80
Weight (Kg)	59	88	60.46 ± 6.59
Height (m)	1.58	1.74	1.67 ± 0.03
BMI (kg/m^2)	20.76	33.53	25.14 ± 2.61
Experience(yrs.)	5.0	18	9.83 ± 2.82
REBA score	4.0	5.6	4.98 ± 0.59

Table 2. Correlation between parameters and MSDs severity ratings

Parameters	Pearson correlation	Significance level
Age	0.654***	< 0.001
BMI	0.138	Not significant
Experience	0.464**	0.008
REBA Score	0.515**	0.003
a_w	0.689***	< 0.001
VDV	0.818***	< 0.001

Table 3. Performance metrics for each unseen dataset tested

Datasets	Accuracy	Precision	Recall	F1 Score	AUC-ROC
1	0.988	0.886	1	0.939	1
2	0.984	0.861	1	0.925	1
3	0.978	0.816	1	0.899	0.998
4	0.984	0.861	1	0.925	0.999
5	0.957	0.689	1	0.816	0.994
6	0.966	0.738	1	0.849	0.992
7	0.975	0.794	1	0.886	0.999
8	0.985	0.861	1	0.925	0.999
9	0.978	0.816	1	0.898	0.998
10	0.981	0.837	1	0.911	0.988
11	0.941	0.620	1	0.765	0.983
12	0.988	0.886	1	0.939	0.999

A significant positive correlation was identified between WRMSDs severity rating scores provided by the participants and individual factors such as age, experience, posture (measured by REBA scores), frequency-weighted RMS acceleration, and Vibration Dose Value (VDV). However, BMI did not show any significant correlation, as illustrated in Table 2. These findings highlight the importance of considering input parameters such as age, experience, posture, and vibration exposure when predicting the WRMSDs occurrences among shuttle car operators.

In the ANN prediction model, the grid search identified a model with a hidden layer size: [5, 10, 15], learning rate: [0.01, 0.1, 0.2], class weights: [1 1], [0.5 1.5], [1 2] as the optimal configuration. This configuration demonstrated robust performance across all metrics on the test set. To evaluate the generalization capability of our ANN prediction model, we tested its performance on 12 new, unseen datasets. These datasets were selected to represent a diverse range of scenarios and were processed using the same normalization parameters as the training data. The performance metrics for each dataset are summarized in Table 3, and the aggregated results are presented in Table 4.

Table 4. Mean and standard deviation of performance metrics

Metrics	Mean	Standard Deviation
Accuracy	0.975	0.014
Precision	0.805	0.083
Recall	1	0
F1 Score	0.890	0.053
AUC-ROC	0.996	0.005

The performance metrics shown in Table 3 and their aggregated values (mean ± standard deviation) in Table 4 demonstrate that the ANN prediction model maintains high accuracy (0.975 ± 0.014), precision (0.805 ± 0.083), recall (1.000 ± 0.000), F1 score (0.890 ± 0.053), and AUC-ROC (0.996 ± 0.005). The relatively low standard deviation in these metrics indicates consistent performance across different unseen datasets, suggesting that the model generalizes well to new data.

These results demonstrate the model's ability to handle imbalanced datasets effectively, yielding accurate and reliable predictions for the incidence of Work-Related Musculoskeletal Disorders (WRMSDs) among operators. The high recall and AUC-ROC values are particularly noteworthy, highlighting the model's strong capability in identifying true positive cases and distinguishing between classes, respectively.

4.0 Discussion

The correlation test, conducted using SPSS software, aimed to verify the alignment between subjective responses of WRMSDs occurrences and input parameters. The results were consistent with previous research, revealing a significant positive correlation between WRMSDs severity ratings and individual factors such as age, BMI, experience, posture (REBA score), frequency-weighted RMS acceleration, and VDV. These findings are well supported by some previous studies[6,15,16].

The results of this study highlight the effectiveness of using an oversampled dataset and comprehensive hyperparameter tuning in developing a robust ANN model for binary classification. The high F1 score and AUC-ROC values demonstrate that the model not only excels at distinguishing between the two classes but also maintains a crucial balance between precision and recall. The use of class weights was instrumental in addressing the class imbalance issue, ensuring that the minority class was adequately represented during training. This approach helped the model to learn the characteristics of the minority class more effectively, thereby reducing bias and improving overall predictive performance.

The performance metrics, averaged over 12 unseen new datasets, demonstrate that the ANN prediction model consistently maintains high accuracy, precision, recall, F1 score, and AUC-ROC. Specifically, the model achieved an average accuracy of 0.975, precision of 0.805, recall of 1.000, F1 score of 0.890, and AUC-ROC of 0.996. The relatively low standard deviation across these metrics indicates that the model performs consistently well across different datasets, suggesting a high degree of generalizability. The robustness of the model is further

supported by its high recall value, indicating its strong ability to correctly identify all actual positive cases. This is particularly critical in scenarios where missing a positive case can lead to severe consequences. Similarly, the high AUC-ROC value underscores the model's excellent capability in distinguishing between the classes across various threshold settings. The results underscore the importance of using advanced techniques like oversampling and hyper-parameter tuning in developing machine learning models, especially in the context of imbalanced datasets.

Needless to say, there is scope for validating the model on larger and more diverse datasets to further confirm its generalizability.

5.0 Conclusion

This study demonstrates the potential of predicting Work-Related Musculoskeletal Disorders (WRMSDs) among seated shuttle car operators using Artificial Neural Networks (ANNs) for binary classification tasks, particularly in scenarios involving class imbalance. By employing a systematic approach to data pre-processing, model architecture design, and hyper-parameter tuning, we achieved a model that delivers high accuracy and robustness in predicting WRMSDs among operators. Our results show that the ANN prediction model maintains high performance across various metrics, including accuracy, precision, recall, F1 score, and AUC-ROC, indicating its reliability and generalization capability. The use of techniques such as cross-validation, class imbalance handling, and comprehensive hyper-parameter tuning significantly contributed to the model's consistent performance on unseen data. The methodologies and findings presented in this paper contribute to the field of WRMSDs prediction using neural networks in predictive analytics.

This model may be used as an important tool to predict Musculoskeletal Disorders (MSDs) at different body regions of the seated operators based on a set of input parameters, thereby enhancing occupational health and safety measures for shuttle car operators and similar roles at risk of WRMSDs. This study lays a solid foundation for future research and practical applications.

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