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Comparative Ergonomic Posture Analysis of CNC Milling Machine Workers through Digital Human Modeling and Artificial Neural Networks

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Abstract

Objectives: To analyze the critical postures of the CNC milling machine operators by RULA (Rapid Upper Limb Assessment) scores and develop an ANN (Artificial Neural Network) prediction model. **Methods:** The methodology includes a postural analysis of 40 male CNC milling machine operators across Bangladesh, employing both manual (using manual RULA assessment worksheet) and digital (using CATIA V5R21 software) RULA methods complemented by an ANN prediction model. Finally, Digital RULA scores through DHM (Digital Human Modeling) and ANN predicted RULA scores would be compared. **Findings:** Digital RULA analysis reveals that lifting, carrying, and positioning are the most crucial ergonomic postures, and the most prominent high-risk category limbs are wrist and arm. The overall initial RULA score for lifting, carrying, and positioning are 7, 6, and 7, respectively, and reduced to 3, 3 and 4 respectively for ergonomically designed posture. The ANN model, structured with input, hidden, and output layers of 7, 10, and 1 nodes, significantly refines ergonomic risk prediction by aligning predicted scores closely with actual outcomes during the first stage, emphasized for training. It demonstrates a perfect correlation (R=1) in training, testing, validation, and overall performance for using manual RULA scores. The model's accuracy is further evidenced by minimal prediction offsets across all datasets for digital RULA score in the second stage, with correlation coefficients of 0.87003 (training), 0.93676 (validation), 0.89113 (testing), and (0.88395) for overall. This study contributes significant advancements in ergonomic risk assessment, highlighting the adoption of improved postures to reduce musculoskeletal disorders. **Novelty:** Employing both manual and DHM methods for RULA score calculation combined with ANN model, which can predict postural risk as floating number and fit a wider range of parameters.

Keywords: ANN; CNC; Digital Human Modeling (DHM); Ergonomics; RULA

1 Introduction

The 20th century saw rapid technological changes and the transition from manual to computer-assisted manufacturing systems, leading to different ergonomic risks. During Computer Numerical Control (CNC) machine operation, most operators lift, carry, and position workpieces onto the CNC bed for machining. These movements potentially lead to awkward postures like bending, twisting, lifting heavy loads, repetitive movements, static work, and forceful movements and cause work-related musculoskeletal disorders (WMSDs)[1]. WMSDs cause pain and muscle fatigue in various regions, contributing to worker disability and absenteeism in different occupational groups. It mainly affects the neck, shoulders, elbows, forearms, wrists, and hands. For every 10% increase in limitations caused by WMSDs, workplace productivity decreased by 4% to 5%[2].

In previous studies, many researchers have emphasized the significance of working posture in human performance for different working conditions, i.e., manufacturing tasks[3], sawmill workers[4], and space craft's drivers[5]. However, most of these studies discuss postures under conventional machining and heavy working conditions. The transition to automation, including automatic lathes and milling machines, presents a shift in ergonomic challenges. Although the exposure to direct hazards is decreasing, Boulila A[6] reported that automation in milling machines requires continuous monitoring, which can induce cognitive stress and visual strain. However, no previous study has investigated the postures of manual material handling in CNC milling machines. Moreover, previous records of CNC workers indicate that repetitions, accuracy-oriented positioning, and duration impact total effort more than movements, and forces[7]. From the literature analysis, most papers related to CNC machines discuss CNC machine interfaces, postural discomfort, display positioning, and CNC panel controllers. However, only a few studies have contributed to identifying postural risk assessments in precise positing, lifting, and carrying difficult-to-hold workpieces. On the other side, virtual reality and DHM is very effective to evaluate the human posture in the product development industry[8]. Application of DHM can assess the existing posture in the assembly process and recommend the improved posture alongside the improvement of the assembly process efficiency[9]. When integrated into CATIA's DHM software, the RULA tools, have marked a significant leap in digital ergonomics, enabling detailed simulations of workplace tasks and postures for precise ergonomic analysis. A study by Nikhilkumar et al.[10] in the small-scale fastener industry demonstrated RULA's utility in reducing the risk of musculoskeletal disorders (MSDs) through targeted ergonomic interventions. However, they mostly used only simulation-based methods for posture analysis, and there is no comparison with any mathematical risk prediction method. Whereas, in postural analysis, Hosseini NM and Arjmand N[11] successfully developed an ANN model to predict the postures of the entire body in dynamic lifting works by measuring the model's error, and Zhao J and Obonyo E[12] used deep neural networks to assess the postural risk in the construction sector. Yet, no previous research has been found on the prediction of CNC milling machine posture with ANN blended with DHM modeling.

Overall, there is a research gap in quantifying the postural risk factor of South Asian CNC milling machine workers using DHM. Moreover, a lacuna exists in hybrid posture analysis and prediction methods, such as employing both manual and DHM methods for RULA score calculation and using the ANN model to predict and compare with simulated RULA scores. This study is motivated by using the anthropometric data of South Asian demographics. It aims to contribute to the literature by conducting a risk assessment of the postures of CNC milling machine workers using both manual and digital RULA methods. Moreover, an ANN model is developed for overall RULA score prediction with evaluation of the model's performance, and finally, improved postures are suggested to reduce the overall RULA score.

2 Methodology

This research aims to investigate the critical postures and quantify their associated risk through the RULA score. The RULA score is calculated both manually and digitally. The manual RULA score is calculated through a manual RULA assessment worksheet, and the digital RULA score is obtained utilizing CATIA V5R21 software. Moreover, the ANN model is developed to make a floating point prediction of the digital RULA score.

2.1 Sample Size and Selecting Criteria

This cross-sectional study analyzed 40 male CNC machine workers working in Bangladesh's CNC horizontal milling machine from three locations. Data were collected via meetings with the employees, and the documented work was done using the employee assessment worksheet, which was equipped with various visual aids such as pictures and videos emphasizing lifting, carrying, and positioning workpiece postures. Participants must work 8 hours per day, be between 23 and 59 years old, and have experience of 1-10 years. The height range of around 167.4-182.88 cm was relevant for this study.

2.2 Manual RULA analysis

The Rapid Upper Limb Assessment (RULA) is a postural analysis method developed in the late 1990s by Lynn McAtamney and Nigel Corlett to evaluate the risk of musculoskeletal disorders associated with upper-limb tasks in the workplace[(13)]. RULA focuses on the neck, trunk, and upper limbs and is ideal for sedentary workers. The grand score for RULA is 7, reflecting the working posture associated with musculoskeletal loading. A score of 1 or 2 indicates acceptable working posture, while a score of 3 or 4 suggests further investigation and changes are needed.

2.3 CATIA V5R21 RULA Analysis

Virtual ergonomics and DHM are very effective tools for the rapid assessment of the MSD's and CATIA has many merits over other DHM software[(14)]. CATIA will use Digital Human Modeling (DHM) functionality to generate 2D and 3D human profiles that can be applied to their ergonomics assessment in a virtual environment. RULA is used for grading, while colors from green to red indicate the risk level, spanning from negligible to high risk[(15)]. Green stands for the score of the normal body posture (scores 1-2), while yellow (scores 3-4) indicates further research. Orange (scores 5-6) means immediate investigation and taking corrective action, and red (score 7) indicates prompt action demanded.

2.4 Artificial Neural Network (ANN) Prediction Model

ANNs are a potent tool in risk management practice, accident severity analysis, and data proofreading[(16)]. Among these, the multiple-layer perceptron, with its input, hidden, and output layers, is a testament to the power and potential of research in risk management. Training, an iterative process of backpropagation to adjust the weights and shift the bias at the end of the model, is aimed at enhancing precision[(17)].

Features mapping and desired output principles in MATLAB, like 'trail' and 'trainers' for backpropagation, are used to train the ANN model. Multifaceted, adequately extensive, and suitable enough data sets are pivotal to prevent the model from overfitting and enhance its generalizability. The accuracy of a network architecture dramatically affects its performance, its hidden layer being the critical one[(18)]. Models were compared based on the Mean Square Error (MSE) criterion using:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widetilde{Y}_i\right)^2$$

where network output yi (the desired output) and several datasets n were used. The non-linear activation function:

$$tan\ sig\,(n) = \frac{2}{1+exp(-2n)} - 1$$

Equivalent to tanh (N), which is computationally faster than Matlab's tanh, was used. In neural networks, Tansig(n) was selected as an appropriate compromise between speed and precision of the transfer function. Bayesian regularization learning function is based on the Jacobian matrix, which presupposes performance as the average or sum of squared MSE, for which calculation of the MSE performance requires function-trained networks.

To prevent overfitting, the neural network was separated into a training set (75% of data) and a test set (25%) classified randomly in each set. The ANN model was made possible using MATLAB 2022b software.

3 Results and Discussion

3.1 CATIA Simulation Analysis for the RULA Score

Digital RULA score is computed with simulation in CATIA V5R21 software and compared with the output of the ANN prediction model. For CATIA simulation, the position and angle of the major limbs (Figure 1 (a), Figure 2 (a) and Figure 3 (a)) are input into the CATIA user interface, and it generates the 3D manikin (DHM) of the worker, indicating the highest-risk limbs as red.

3.1.1 The Body Posture Analysis for Lifting in CATIA Software

Figure 1 (a) represents the highest risk working posture while lifting a workpiece from the ground on the CNC bed into the CNC milling machining operation. The actual pictures are transformed into simulated form using CATIA V5R21 during the RULA analysis (Figure 1 (b)). The chosen photo shows the workers' level of discomfort. In this position, the RULA score is 7 (Figure 1 (c)), which indicates a high-risk working posture.

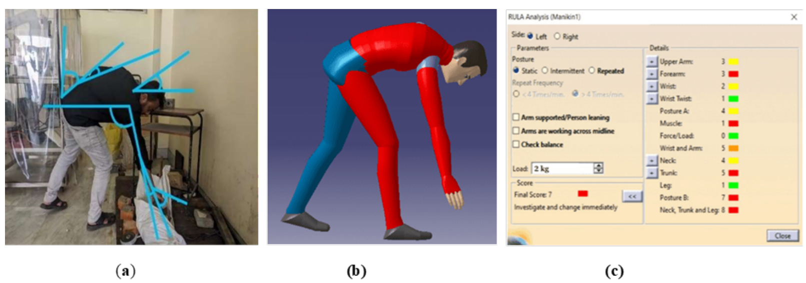


Fig 1. Lifting the workpiece from the ground on the CNC machine bed (a) current working posture, (b) Digital Human Modeling in CATIA, and (c) RULA scores of workpiece lifting

3.1.2 The Body Posture Analysis for Carrying in CATIA Software

Carrying activity is one of CNC milling workers' most risky working postures. (Figure 2 (a)) shows the real capture. In the digital model (Figure 2 (b)), the RULA score is 6 (Figure 2 (c)). That result indicates that it is outside acceptable ranges and requires immediate intervention.

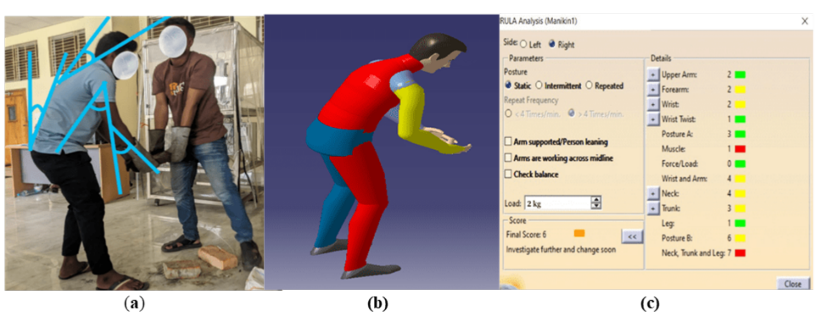


Fig 2. Carrying the workpiece to reach towards the CNC machine bed (a) current working posture, (b) Digital Human Modeling in CATIA, and (c) RULA scores of workpiece carrying

3.1.3 The Body Posture Analysis for Positioning in CATIA Software

Figure 3 (a) and (b) show the positioning activity on the CNC milling machine bed before the start of the machining operation. The actual working position pictures (Figure 3 (a)) are converted into manikin (Figure 3 (b)) through the CATIA software to perform the RULA analysis, and the highest awkward posture score, 7, is obtained (Figure 3 (c)).

Fig 3. Positioning the workpiece on the CNC machine bed (a) current working posture, (b) Digital Human Modeling in CATIA, and (c) RULA scores of workpiece positioning

3.2 Artificial Neural Network Model

An ANN model is developed to predict the overall RULA score, and the developed ANN model is evaluated in two stages. In the first stage, the model is focused on training, and the data set used for this purpose is obtained manually from the manual RULA assessment worksheet as it provides an accurate RULA score. The second stage emphasizes the testing and validation of the model, and the digital RULA score obtained from DHM was used as a data set as this method is used for RULA score calculation commonly.

3.2.1 First Stage

The manual RULA calculation table is used to train the prediction model. Seven factors such as Upper Arm, Lower Arm, Wrist Score, Wrist Twist, Neck Posture, Trunk Posture, Legs, and individual RULA score, were the inputs, while overall RULA score was the target variable. This was done by applying permutation and combination approaches to obtain 2520 datasets from tables A, B, and C of Ergonomic Plus's manual RULA score calculation worksheet[19], which were used as the training dataset. Before model training, the neural network was defined, and specifications for the plot layer and bias size were established. The network consists of an input layer with seven nodes, a hidden layer with ten nodes, and an output layer with one node.

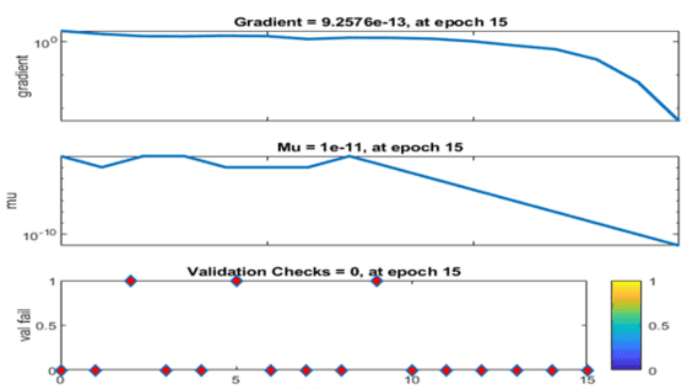


Fig 4. Training State Algorithm (a) Gradient (b) Mu (c) Validation Check

Figure 4 (a) shows the gradient of 9.2576e-13 at epoch 15, which accentuates the consistent updates curve, bringing an understanding of the optimization trajectory. Figure 4 (b) presents the prediction at epoch 15 and the corresponding loss (μ) of

1e-11; the model exactly produces the predicted output and close errors to actual figures. Figure 4 (c) shows that the validation accuracy marked as 0 at epoch 15 signifies the extraordinary convergence with the validation targets, thus confirming the quality used in real-world applications.

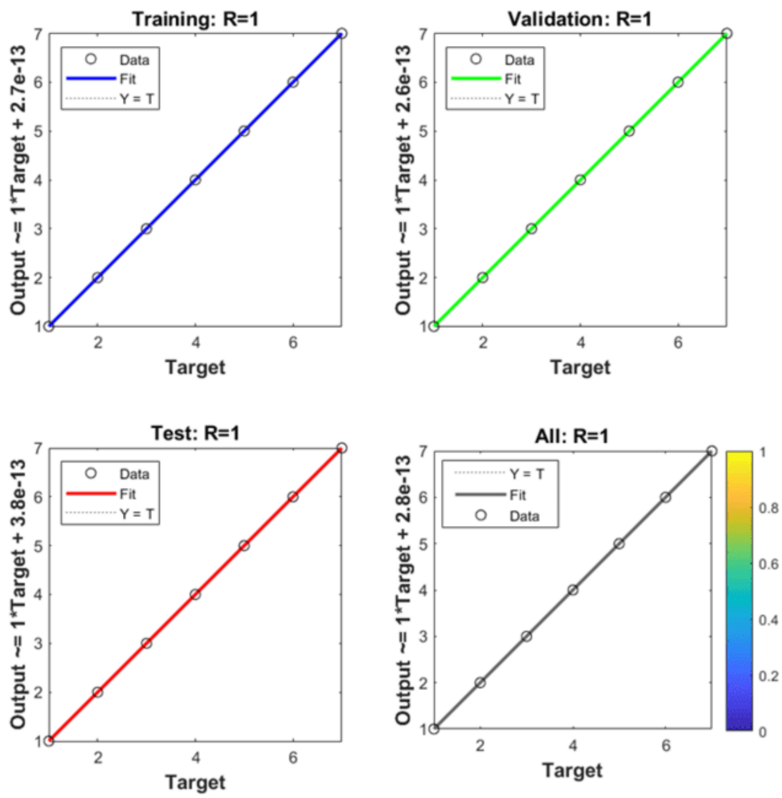


Fig 5. Graphical representation of Training Algorithm Model Regression

In the MATLAB regression analysis using ANN, four key graphs (Figure 5) depict training, testing, validation, and overall performance (All R). Notably, all graphs show a correlation coefficient (R) of 1, indicating a perfect linear relationship. Its underlying reason may be the shape of training data, which utilized the manual RULA calculation Tables A, B, and C to calculate the RULA score as a primary method. This method was developed by Ergonomic Plus[(19)]. The y-axis in each graph represents the model's output, approximated as 1 times the target value plus a minute offset. Specifically, for the training set, the offset is 2.7e-13; for validation, it is 2.6e-13; for testing, it is 3.8e-13; and for the overall dataset, it is 2.8e-13. These findings underscore the exceptional accuracy and precision of the regression model, with near-perfect alignment between predicted and actual values across all datasets. In ANN regression, a value of R=1 signifies high accuracy, a perfect sign for sensitive tasks such as risk factor analysis.

3.2.2 Second Stage

During the analysis of risk for CNC milling workers, a digital human model of the overall RULA score dataset comprising 120 entries is utilized. Employing a developed ANN model to predict values considers 40 CNC workers, three working postures, and seven different factors of body posture. These 120 data sets evaluate the model and serve as validation input values.

In prediction, data from Figure 6 (a), a noteworthy graph illustrates an essential aspect with a gradient of 1.3259e-09 at epoch 2. This graph provides insights into the early stages of the prediction model's learning process. The observed gradient value suggests a moderate rate of change in model parameters, signifying a measured adjustment during the initial training epochs. The significant observation is reflected in Figure 6 (b), depicting a mean squared loss (mu) of 1.3259e-09 at epoch 2, accompanied by the presence of "y" values within the range of 10-10. This finding suggests a finely tuned model performance in the early prediction stages, with the low mean squared loss indicating minimal prediction errors. Including "y" values within this range further under-scores the accuracy and precision of the model's predictions during this epoch, laying a solid foundation

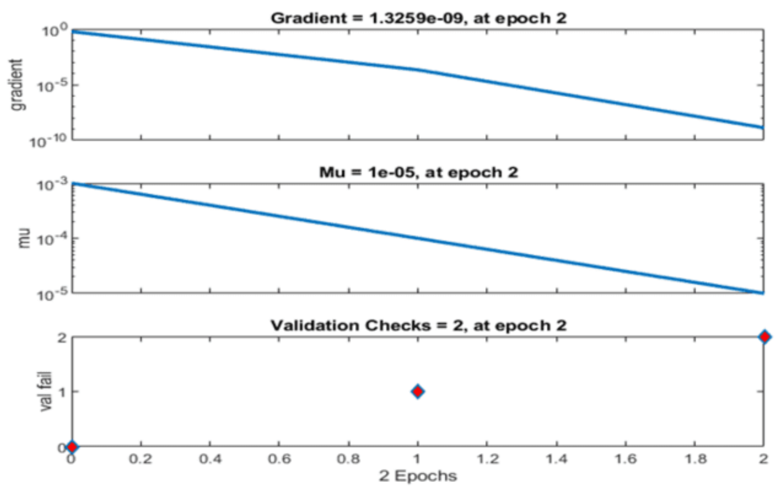


Fig 6. Visual representation of Prediction State Algorithm (a) Gradient (b) Mu (c) Validation Check

for reliable predictions as the model evolves. At Figure 6 (c), Epoch 2 displays validation checks on the y-axis (ranging from 0 to 1) and the x-axis denotes the 2nd epoch. Notably, the graph indicates the occurrence of 2 validation checks. Also, the graph's distinctive points are marked: one dot at 0, another at 1, and a third at 2, each represented by a dotted mark. These points likely signify instances where the model's predictions aligned perfectly with the expected outcomes (0, 1, and 2 validation checks). This graphical representation provides a concise overview of the model's validation accuracy at the epochs.

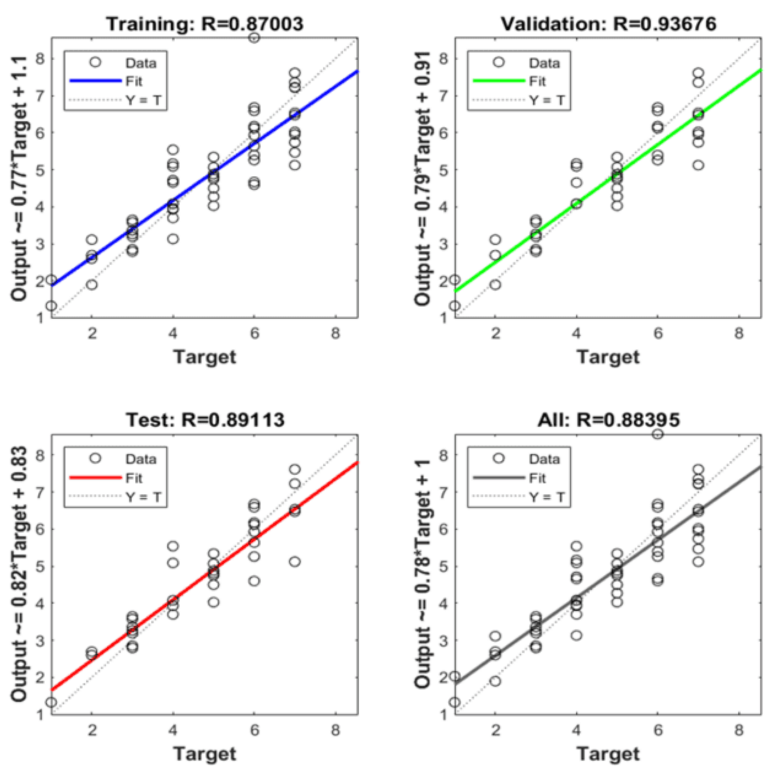


Fig 7. Graphical representation of Prediction Model Regression

Four important graphs describe the model results in training, testing, validation, and general cases (All R) (Figure 7). It is important to note that the correlation coefficient (R) for training is 0.87003, indicating a robust linear relationship whereby the model's output closely approximates 0.77 times the target plus a constant of 1.1. Also, the validation set shows a more significant correlation (R = 0.93676), and the model output is estimated to be approximately 0.79 times the target plus a constant of 0.91. For the test set, R is 0.89113, indicating good predicting ability, with the model output approximated as 0.82 times the target plus a constant of 0.83. The overall data set correlates with 0.88395, and the model output was estimated as 0.78 times the target with a constant value of one. These results highlight the ability of this model to describe relationships in different datasets, thus supporting its suitability for use in prediction tasks. The reason for not getting the perfect correlation in the testing dataset may be the small sample size, as we have performed a risk factor analysis among 40 CNC operators. The training data (first stage) varied from level 1 to 7 on the RULA score, but our predictions (second stage) mainly resulted in scores between 4 and 7. Moreover, the training data set (first stage) was obtained from the manual RULA worksheet, whereas the prediction data set (second stage) was calculated from the CATIA simulation, which shows some nuances in the final RULA score compared to the manual RULA score.

Table 1. Comparison between CATIA V5R21 Software-based RULA Score and ANN model-based RULA Score using MATLAB

Operation Type: Carrying / Lifting / Positioning								
SI	**DHM**	**ANN**	**SI**	**DHM**	**ANN**	**SI**	**DHM**	**ANN**
1	7	5.7718	41	4	4.4553	81	7	6.7750
2	7	5.7718	42	4	3.6034	82	6	6.5752
3	6	6.8512	43	3	3.5637	83	6	4.4758
4	6	6.3253	44	3	3.5637	84	7	4.8953
5	7	5.0600	45	5	4.2041	85	6	4.8208
6	6	5.0127	46	4	3.4390	86	6	7.3752
7	6	6.3253	47	3	3.5894	87	4	4.4553
8	6	6.8512	48	3	2.5894	88	4	3.6034
9	5	6.5727	49	3	3.5637	89	3	3.5637
10	6	4.4445	50	3	5.1231	90	3	3.5637
11	7	5.0352	51	5	4.3626	91	5	4.2489
12	7	5.7718	52	4	4.4553	92	4	3.4390
13	7	5.7718	53	4	3.6034	93	3	2.5894
14	6	6.8512	54	3	3.5637	94	3	2.5894
15	6	6.3253	55	3	3.56373	95	3	3.5637
16	7	4.9981	56	5	4.3569	96	3	5.1231
17	6	5.0127	57	4	3.4390	97	5	2.4663
18	6	6.3253	58	3	2.5894	98	4	4.4555
19	6	6.8512	59	3	2.5894	99	4	3.6034
20	5	6.5727	60	3	6.5412	100	3	3.5637
21	6	5.4445	61	3	3.7336	101	3	3.5637
22	7	4.0352	62	5	3.4099	102	5	4.3256
23	7	5.7718	63	4	3.4974	103	4	3.4390
24	7	5.7718	64	4	5.7393	104	3	3.5894
25	6	6.8512	65	3	6.9249	105	3	2.5894
26	6	7.3253	66	3	5.6430	106	3	7.3253
27	7	5.0600	67	5	4.3644	107	3	5.0600
28	6	5.0127	68	4	3.8810	108	5	5.0127
29	6	6.3253	69	3	6.9328	109	4	7.3253
30	6	6.8512	70	3	6.9328	110	4	4.4553
31	5	6.5727	71	3	6.5412	111	4	3.6034
32	6	5.4445	72	3	4.8419	112	3	3.5637
33	7	4.0352	73	5	5.1952	113	3	3.5637
34	7	5.7718	74	4	2.7646	114	3	4.3214
35	7	5.7718	75	4	5.6430	115	4	3.4390
36	6	6.8512	76	3	4.3728	116	4	3.5894
37	6	7.3253	77	3	4.2809	117	4	4.5894
38	7	5.0600	78	5	4.9912	118	3	3.5637
39	6	5.0127	79	4	3.9621	119	4	5.1231

Continued on next page

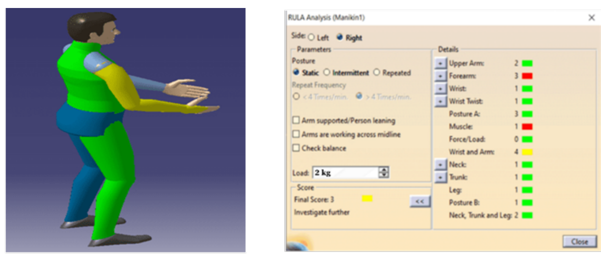
Table 1 continued

40	6	7.3253	80	7	6.7750	120	4	4.3626

The data presented in Table 1 represents the combined data of three positions (carrying, lifting, and positioning) and a comparison between the software-based CATIA V5R21 RULA scores and MATLAB-based RULA scores employing ANN. CATIA simulation provides integer RULA scores varying from 1 to 7, whereas MATLAB RULA score obtained by applying ANN, shows fractional scores such as 1.589407 or 6.851238. These fractional values may be interpreted as evidence of preciseness. This difference shows the correctness of ANN calculations over CATIA analysis according to the given results.

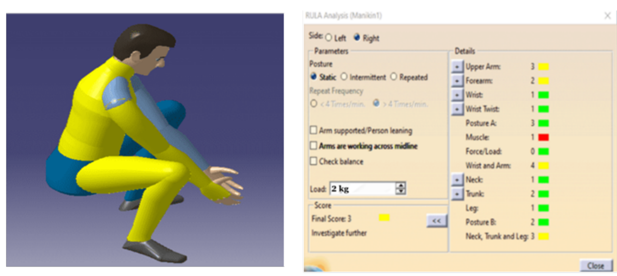
3.3 Suggested Improvement

All the risky postures, such as carrying, lifting, and positioning, are observed as most unwanted and inconvenient for CNC milling workers, affecting daily overall performance. The observed RULA score of these postures in the existing practice are in high risk category (Figures 1, 2 and 3), which indicates a need for a better solution. Manual material handling principles are adopted to obtain a better posture and CATIA V5R21 simulation software has evaluated it based on the reduced RULA score.



(a) (b)

Fig 8. Suggested improved posture in carrying (a) Digital Human Modeling in CATIA and (b) RULA scores

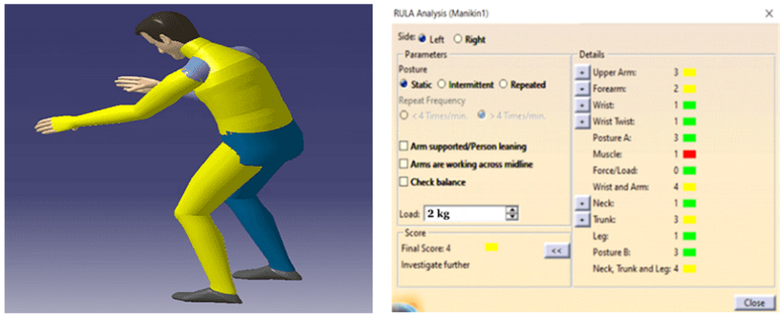


(a) (b)

Fig 9. Suggested improved posture in lifting (a) Digital Human Modeling in CATIA and (b) RULA scores

Figure 8 suggests the CNC milling workers' improved posture in carrying tasks with the CATIA DHM RULA score set as 3. Using the same simulation method, the workpiece's lifting (Figure 9) and positioning (Figure 10) could lead to an acceptable scores of 3 and 4 respectively. These improvements follow appropriate manual material handling standards aimed at the optimal positioning of the limbs.

The ergonomics Risks should be reduced by keeping a neutral spine at a continuous angle of 90 degrees and ensuring no twisting motion. The load should be kept close to the body, at waist level, and less than 31 kg for the entire body (Figure 8). To prevent lifting by the force of gravity from the ground, a squat or leg loading rather than leaning on the back is recommended for effective lifting. Moreover, the waist, spine and shoulder should be kept as straight as possible (Figure 9). Ensure the worktable elevation is adjustable, as it will aid in performing the tasks bodily forward and eliminate bending. Wrist posture should not be bent more than needed to avoid impact pressure on the nerves (Figure 10). Implementing these actions can significantly minimize MSDs as work activities align with natural human movements. This, in turn, enhances work safety and productivity.



(a) (b)

Fig 10. Suggested improved posture in positioning (a) Digital Human Modeling in CATIA and (b) RULA scores

This study finds the overall RULA score for the existing lifting posture as 7. Gajbhiye et al. obtained a similar score while analyzing the lifting activities of the Indian excavation workers[(20)].At the same time, the RULA score for carrying activities is found to be 6 here. Rahman et al. observed identical overall RULA scores for carrying logs in the sawmill workers[(4)]. Moreover, DHM RULA analysis indicates a score of 7 for positioning posture in this study. Hussain et al. observed analogous RULA scores in positioning posture for stone-cutting workers in India[(15)]. After improvement, the modified RULA score is 3, 3, and 4 for lifting, carrying, and positioning, respectively. While suggesting postural improvement for the sawmill workers, Rahman et al. observed similar improvements[(4)]. However, none of these authors investigated the posture of CNC milling workers for this particular type of material handling. This study is novel regarding the definition of material handling tasks and demographic perspectives.

On the other hand, in the first stage, emphasized for training, the ANN model demonstrates a perfect correlation (R=1) for using manual RULA scores. Gadekar MR and Ahammed MM developed an ANN model for modeling dye removal with an R-value close to 1, indicating the high reliability of the model[(21)]. In the second stage, emphasized for testing and prediction, the ANN model shows correlation coefficients of 0.87003 (training), 0.93676 (validation), 0.89113 (testing), and an overall (0.88395) due to the use of DHM RULA score from CATIA. Mahmoud et al. found a similar R-value from the developed ANN model while analyzing discomfort in the picking task[(22)]. However, they only used the ANN model for prediction, not comparing the predicted result with any simulated result. This study is novel in using hybrid methodology as it predicts the RULA score with ANN and compares it with their counterparts obtained from DHM.

Lastly, this research finds the postural risk as a fraction number with the ANN prediction model. Muhammad et al. predicted the pancreatic cancer risk in fraction numbers ranging from 0 to 1[(23)]. However, no one observed the RULA score as a fraction number. Fraction number observation is beneficial for preciseness as an overall RULA score of 2 indicates an acceptable working posture, whereas 3 indicates a risky working posture that requires improvement. Hence, precise prediction may help to identify whether the score is 2.1 (close to safe category) or 2.9 (close to risky category), as both are not in the same category of risk. Moreover, the ANN model can incorporate a wider range of input parameter and can be easily customized.

4 Conclusion

CNC milling, a modern manufacturing process, makes complex manufacturing easier and quicker, but at the same time, it engenders unique ergonomic challenges. The present study underscores the significant ergonomic risks that CNC milling machine operators' face in Bangladesh, highlighting the critical need for interventions in workplace practices to enhance safety and efficiency. Through a comprehensive analysis using manual and digital human modelling RULA techniques, along with an innovative ANN predictive model, this research provides a nuanced understanding of the ergonomic challenges in the manufacturing sector. The Digital RULA analysis carried out by CATIA V5R21 software showed that some high-risk postures significantly affect the arms and wrists of the CNC milling operators. 3D manikin generated in the DHM indicates that the overall RULA scores for lifting, carrying, and positioning are 7, 6, and 7 for the existing work practice, which necessitates immediate intervention. After the proposed posture, based on the manual material handling principles, the overall RULA score reduced to 3, 3, and 4, respectively. The developed ANN model was evaluated in two stages. Firstly, manual RULA scores are focused on training as these scores are more accurate and suitable for machine learning model training. Secondly, digital RULA scores are focused on testing and validation as these scores are commonly used due to their ease of calculation. The model exhibited a perfect correlation (R=1) in the training dataset (first stage) in training, testing, validation, and overall performance, where the actual value was very close to the predicted values. The model's accuracy was further demonstrated by minimal prediction offsets across all datasets (second stage), with correlation coefficients ranging from 0.870 to 0.937. The model output for this data set ranged from 0.77 to 0.82 times the target plus constants between 0.83 to 1.1.

This study contributes to ergonomic risk assessments in industrial settings, particularly within CNC milling machine operations. It emphasizes the importance of adopting improved postures to significantly minimize the risk of MSDs. This recommendation is grounded in a comprehensive analysis of ergonomic risks and introduces practical measures for workplace adaptation. The novelty accompanied by this study is the hybrid ergonomic assessment methodologies that employ both the DHM and ANN to calculate RULA scores. ANN provides postural risk scores as floating numbers, offering a more precise evaluation of ergonomic risks than the conventional CATIA software. Also, the flexibility of the ANN model allows for a broader range of input parameters, such as twist and wrist angles, facilitating a more tailored assessment of ergonomic risks and enabling specific interventions to enhance worker safety and comfort. This innovative approach provides improved methodologies for minimizing MSDs, improving the precision of risk evaluations, and offering a more adaptable tool for workplace safety analysis.

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