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ORIGINAL ARTICLE

Modelling Ergonomic Hazard Risks in Manual Handling: Insights from Ponorogo's Traditional Industry

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ABSTRACT

Introduction: As the center-cultured region in Indonesia, Ponorogo Regency is dominated by traditional manufacturing industries which support regional economic growth. Most production in this sector is labor-intensive and depends on manual handling processes, which may increase the risk of work-related musculoskeletal disorders (WMSDs). This study aims to develop a model to evaluate and predict ergonomic hazards using a neural network algorithm, focusing on the relationship between manual handling postures and musculoskeletal pain in 12 body regions. **Method:** A cross-sectional study involved data of 250 workers measured using used Nordic Musculoskeletal questionnaire and manual handling exposure checklist based on SNI 9011:2021. A neural network model was developed based on GLM's output to explore the complex interrelationships between manual handling postures (X variables) and musculoskeletal pain across 12 body regions (Y variables). **Result:** The outputs identified carrying object over 9 meters (X10), one-handed lifting (X3), and trunk twisting (X2), with X10 confirmed as the most predictor for multiple outcomes, affecting six regions. Neural network models demonstrated adequate learning capacity with stable architecture, proved by average CEE values ranging from 0.21 to 0.54. The models showed improved predictive accuracy across epochs. C**onclusion:** The finding shows that NN modelling may be expanded to include broader industries in Indonesia's traditional manufacturing sector as an integrated data-based information system application. However, further validation using external datasets is recommended to enhance generalizability.

Keywords: ergonomic hazards, manual handling, neural networks, ponorogo regency, the manufacturing sector

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INTRODUCTION

The traditional manufacturing sector in Ponorogo plays a significant role in supporting the regional economy by providing employment for a large portion of the population and as a source of basic necessities. As an important livelihood, this industry, a vital source of income for many households, relies largely on human labor and conventional production methods (Vinatra, 2023). In most of the less industrialized areas in Indonesia, such as Ponorogo Regency, manufacturing industries often rely on manual-traditional processes rather than adopting automated technology to help with work activity. According to the Indonesian Central Bureau of Statistics (BPS, 2022), approximately 62% of small and medium enterprises (SMEs) in the manufacturing sector still depend on manual labor, with automation adoption remaining below 10% in rural areas. As the potential social impact of job losses due to automation is a significant concern in a densely populated country like Indonesia, keeping on manual processes helps maintain employment for local communities (Harahap and Tambunan, 2022; Nugraha and Hendrati, 2023). Human labor, picked up by hands instead of machines, may be less

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efficient but will provide a sustainable economic model by ensuring that people are still employed and preventing social issues.

Moreover, many of these industries work with very slim margins and might not possess the financial means to implement automation. As a result, the traditional manufacturing sector in Ponorogo Regency is struggling with an aging workforce, with younger people lured into urban areas or into other industries with more job stability. This failure to regenerate the workforce puts extra strain on older workers, who are at greater risk of manual handling injuries due to increasing vulnerability to ergonomic hazards. This is confirmed by national labor survey BPS (2022) which revealed that 48% of traditional industry workers in rural areas, including Ponorogo, are aged 45 and above, highlighting the growing concerns over workforce sustainability and injury risks.

Extensive manual handling tasks often lead to musculoskeletal disorders (MSDs), especially among older workers, who dominate Indonesia's traditional manufacturing sector (WHO, 2022). This risk is primarily linked to several key factors, such as maintaining uncomfortable postures, lifting heavy loads, and performing repetitive movements (Chan *et al.*, 2020; Sauter *et al.*, 2021). An observational study conducted by Yuyun (2020) found more than 50% of workers in the traditional food industries are affected by musculoskeletal complaints at medium-high level. Another study from bakery industries reported a similar result, that the bakers (92%) were exposed to medium-high risk ergonomic hazards due to manual handling methods (Arifah and Basri, 2021).

Acknowledgment of these hazards has led to the establishment of standards designed to alleviate ergonomic hazards. To follow global trends in the implementation of occupational safety and health, the Indonesian government established the SNI 9011:2021 (Badan Standardisasi Nasional, 2021) which is a national standard to assess and evaluate ergonometric hazards in the workplace in 2021. Providing clear guidelines, this standard also ensures that Indonesian industries, including those in Ponorogo Regency, comply with global standards, which are crucial for firms that conduct cross-border business

At the same time, developments in automation technology are bringing about changes to the implementation of occupational safety and health (OSH). The management of workplace safety is transitioning from reactive to proactive and predictive approaches through the integration of advanced technologies like wearables, robotics, AI, and IoT technology (Sarkar and Maiti, 2020; Chan *et al.*, 2022). Moreover, these technologies also ensure compliance with laws and regulations, such as SNI 9011:2021 Indonesia, which regulate measuring and assessing ergonomic risks at work and other social security obligations.

Neural networks (NN) a subclass of machine learning algorithms, holds a great potential in the enhancement of occupational safety and health (Lambay *et al.*, 2021; Senjaya, Yahya and Lee, 2021). It has also become an efficient method of implementation as the algorithm encompasses large and complex datasets through a centralized integration system. Their ability to simulate the models of the interaction between various non-linear variables makes the algorithms capable of providing an evaluation of the ergonomic hazards in a working environment, including MSDs, which have been proven to be significantly interrelated and typically non-linearly related phenomena subject to skewing when used in traditional statistical analysis. Continuous learning capability helps the NN model to be optimized and continuously updated, ensuring that the same ergonomic risk assessment is effectively performed under ever-changing working conditions (Popescu *et al.*, 2009; Wang *et al.*, 2019; Baek *et al.*, 2021; Amelio *et al.*, 2023).

Moreover, manual measurement may not be able to capture important details such as posture angle, effort, or duration of work. Early signs of ergonomic risk can also be identified from data patterns before it progresses to disabling MSDs, thereby allowing preventive measures to mitigate the effects and damage that ensues. Additionally, the NN-based interpretations provide insights that can facilitate the decision-making process in OSH risk management by providing interpretable recommendations for how to adjust tasks, tools, or processes.

This study aims to determine the manual handling tasks associated with a particular WMSD and develop a robust model using neural network algorithms regarding the body region affected. In addition to improving occupational health standards in traditional industries, the study findings are expected to have a broader impact by improving worker safety and productivity.

METHODS

Research Design and Sampling Method

The data collection in this study employed a cross-sectional design. The minimum sample size as training data was determined based on a statistical considerations estimated using the Cochran formula for proportion-based sampling (Cochran, 1942):

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{e^2}$$

where:

Z=1.96 (for a 95% confidence level)

p=0.5 (assumed proportion for maximum variability)

e=0.065 (desired margin of error of 6,5%).

With infinite population correction adjustment (unestimated number of workers in the manufacturing sector), the minimum sample size was calculated as:

$$n_0 = \frac{1.96^2.\ 0.5\ (1-0.5)}{0.06^2}$$

$$= 227.31 \sim 228 \text{ respondents}$$

In this study, the sample size was set to 250 respondents to maintain data missing. To ensure randomization, respondents were selected using a stratified random sampling approach. They were selected to represent the scale of the industry consisting of: small (<50 workers), medium (50-100 workers), and large (>100 workers). Proportional allocation was applied to select respondents from each stratum.

The respondents' criteria were met with a minimum of five years of full-time work experience and no history of injury or chronic disease in the last decade. All participants provided their consent following a thorough explanation of the study's goals and methods.

Variables and Measurements

The main goal of this study is to generate data modelling based on the relationship between manual handling postures (Xn) as determinant, which consist of (11 activities, and musculoskeletal pain/MP in the 12 body regions (Yn) accumulatively measured as Overall Musculoskeletal pain/ OMP(Y). The conceptual framework of variables association is illustrated in Figure 1.

The primary instrument was based on the Indonesian National Standard (Badan Standardisasi Nasional, 2021), ensuring validity and reliability through standardized assessment criteria. Musculoskeletal pain was self-reported by respondents across 12 body regions, with severity graded from 0 (no pain) to 3 (very painful). In this study, we categorized any reported pain as "pain," resulting in a binary classification: "No" (Grade 0) and "Yes" (Grades 1–3). While self-reported measures introduce subjectivity, reliability was reinforced by providing clear definitions and illustrations to aid respondents in accurately identifying pain locations.

Following the SNI guidance, manual handling hazards consist of 11 determinants classified using various rating scales (0–3) based on exposure level, determined by the accumulation of severity and exposure duration. While the standard includes office tasks like keyboard typing, this study specifically focuses on manual handling activities with higher physical demands. Therefore, tasks primarily associated with sedentary work, such as typing, were not included in the analysis. However, similar postural stressors (e.g., prolonged static postures) were considered in cases where they overlapped with manual handling risk factors.

Data Collection and Ethical Clearance

Ergonomic assessments were carried out on-site by trained observers to guarantee precise data on tasks, work environments, and worker postures. In the meantime, employees finished the surveys about their subjective musculoskeletal pain and gave input on their working environment. Finally, the gathered information was added to a database.

According to ethical research standards and guidelines, this study was reviewed and approved by the Ethical Committee for Health Research (KEPK) at Universitas Muhammadiyah Ponorogo with the registration number 01142235021212420240911090.

Data Analysis

Data modelling in this study is built up by analyzing musculoskeletal pain based on its determinants represented by manual handling postures. There are two modelling steps with the different algorithms. Factors associated with independent variables are determined using multinomial logistic regression with a generalized linear model (GLM) at a significance level based on a 95% confidence interval (CI). The Multilayer Perceptron Neural Network modelling was generated by SPSS to determine the correlations between variables, specifically in predicting manual handling postures (Xn) and how they affect musculoskeletal discomfort (Yn). The network structure for each model is determined by X variable/s as input nodes, binary response (Yes, No) as output nodes and 1-2 hidden layers. In order to improve worker safety and health in conventional production settings, this analytical phase made it possible to identify important risk indicators and create predictive models.

RESULT

Descriptive Result

Data were obtained from 251 workers of traditional manufacturing industries in Ponorogo. Every work posture contributes to specific manual handling aspects presented by the percentage of exposure rates as described in Figure 2. Based on the descriptive result, lifting with one hand (X3) is the most common activity experienced by workers (78.14%), followed by lifting object below elbow height (X8: 68.64%) and twisting the trunk (X2: 54.04%). These results imply that workers often

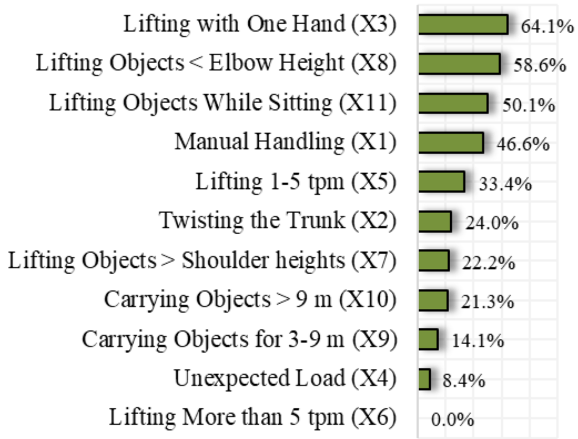

Figure 2. Ergonomic Hazards Based on Posture

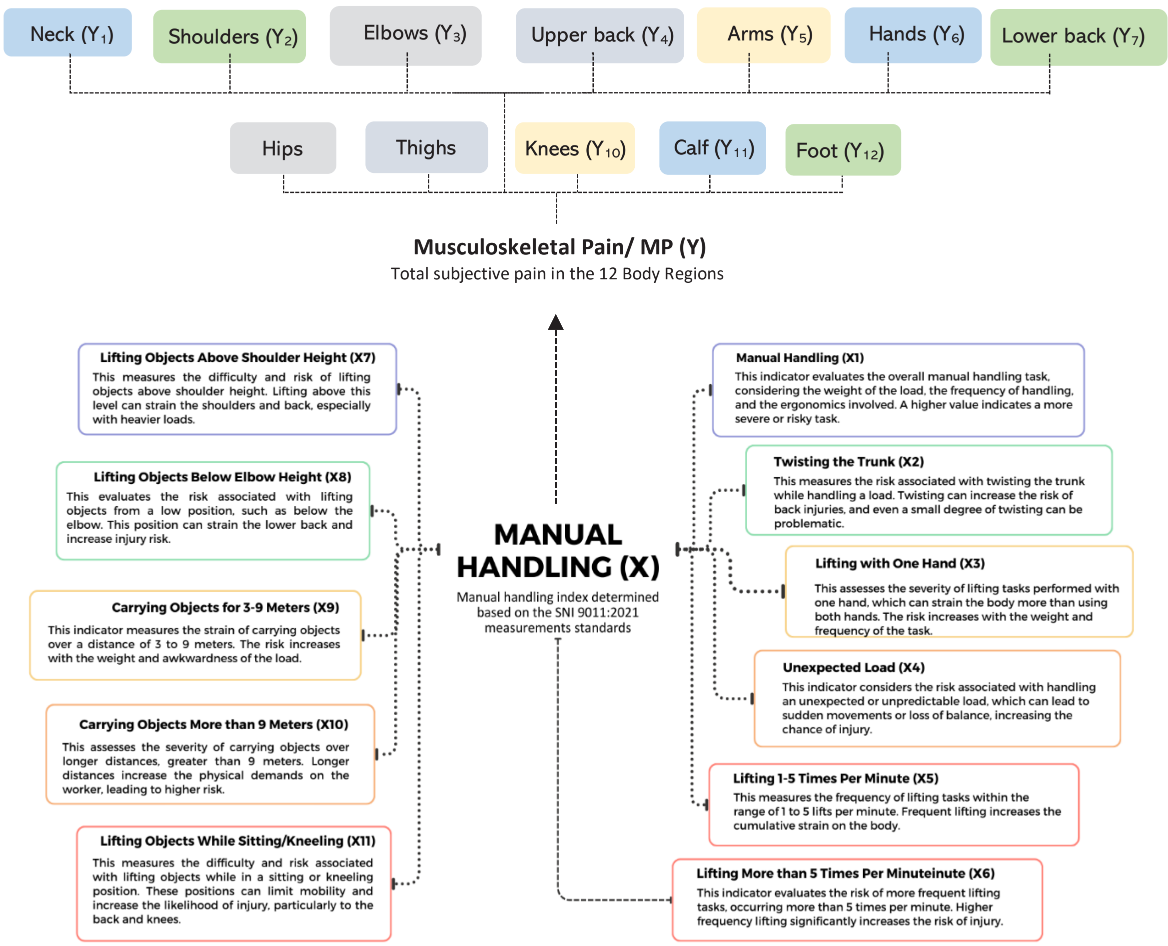

Figure 1. Conceptual Framework in the Data Modelling

perform awkward lifts and postures requiring a lot of trunk movement, therefore increasing their risk of musculoskeletal strain.

As seen in Figure 3, musculoskeletal pain was quantified in 12 distinct body areas. The SNI 9011:2021 measures musculoskeletal exposure by adding up the severity and frequency scores in the MSDs matrix. Lower back (39.7%), neck (29.4%), and shoulder (20.6%) are the body segments most susceptible to musculoskeletal disorders. Even so, there are no elbow complaints.

The upper and lower body regions susceptible to musculoskeletal and ergonomic dangers were separated in this study based on work position. The

Table 1. Estimated Parameters in the GLM Models

MP (Yn)	Parameters	Manual Handling Postures (Xn)										
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
Neck (Y_1)	B	0.01	0.03	-0.24	-0.84	-0.01	0.00	-0.25	0.12	0.00	1.07	0.16
	Exp(B)	1.01	1.34	0.79	0.43	0.99	1.00	0.78	1.13	1.00	2.91	1.18
	p-value	0.97	0.89	0.35	0.06	0.96	.	0.57	0.64	0.95	0.36	0.52
Shoulders (Y_2)	B	0.47	0.25	-0.02	-0.13	-0.01	0.00	0.44	-0.23	-0.06	1.84	0.16
	Exp(B)	1.60	1.28	0.98	0.88	0.99	1.00	1.55	0.79	0.95	6.32	1.17
	p-value	0.09	0.53	0.94	0.78	0.95	.	0.32	0.39	0.36	0.11	0.54
Elbows (Y_3)	B	-0.75	0.32	0.27	-0.59	0.05	0.00	0.77	-0.11	-0.04	2.21	0.19
	Exp(B)	0.47	1.37	1.31	0.56	1.05	1.00	2.16	0.90	0.96	2.07	1.21
	p-value	0.18	0.50	0.40	0.35	0.85	.	0.13	0.74	0.50	0.03*	0.55
Upper back (Y_4)	B	1.18	1.67	-0.27	0.61	0.16	0.00	1.31	0.25	0.05	4.87	-0.16
	Exp(B)	0.31	5.33	1.31	1.84	1.17	1.00	3.72	1.29	1.05	11.39	0.85
	p-value	0.01*	0.00**	0.37	0.30	0.62	.	0.03*	0.48	0.41	0.00**	0.69
Arms (Y_5)	B	0.28	0.72	-0.15	-1.02	0.13	0.00	0.89	0.42	-0.07	2.86	-0.16
	Exp(B)	1.32	2.04	0.86	0.36	1.13	1.00	2.43	1.53	0.51	10.40	0.85
	p-value	0.34	0.23	0.72	0.22	0.71	.	0.19	0.29	0.94	0.01*	0.71
Hands (Y_6)	B	-0.26	0.23	0.00	-0.29	-0.33	0.00	0.61	-0.33	0.21	1.96	-0.24
	Exp(B)	0.77	1.25	1.00	0.75	0.72	1.00	1.84	0.72	1.23	7.07	0.79
	p-value	0.55	0.63	0.99	0.62	0.30	.	0.23	0.33	0.35	0.05*	0.48
Lower back (Y_7)	B	-0.68	-0.28	-0.07	-0.56	0.03	0.00	0.96	-0.48	-0.07	2.59	-0.19
	Exp(B)	0.51	0.76	0.93	0.57	1.03	1.00	2.61	0.62	0.94	3.28	0.83
	p-value	0.27	0.59	0.84	0.43	0.93	.	0.08	0.20	0.51	0.01*	0.59
Hips (Y_8)	B	-0.63	0.31	0.60	-1.19	-0.20	0.00	0.77	-0.03	0.03	0.68	0.21
	Exp(B)	0.53	1.36	1.81	0.31	0.82	1.00	2.16	0.97	1.03	1.98	1.23
	p-value	0.17	0.49	0.05*	0.06	0.42	.	0.11	0.91	0.63	0.49	0.49
Thighs (Y_9)	B	0.14	-0.12	-0.18	-0.78	-0.30	0.00	0.42	0.05	0.04	0.03	0.25
	Exp(B)	1.15	0.89	0.84	0.46	0.74	1.00	1.52	1.05	1.04	1.03	1.28
	p-value	0.56	0.77	0.50	0.12	0.21	.	0.36	0.87	0.50	0.98	0.36
Knees (Y_{10})	B	-0.46	-0.26	0.16	0.34	0.09	0.00	1.13	-0.06	-0.07	2.03	0.29
	Exp(B)	0.63	0.77	1.17	1.41	1.10	1.00	3.10	0.94	0.93	7.63	1.34
	p-value	0.29	0.55	0.60	0.50	0.69	.	0.02*	0.84	0.15	0.04*	0.31
Calf (Y_{11})	B	-0.45	-0.31	-0.38	0.72	0.07	0.00	0.93	-0.19	-0.17	1.78	0.38
	Exp(B)	0.64	0.74	0.69	2.05	1.07	1.00	2.52	0.83	0.85	5.95	1.46
	p-value	0.41	0.54	0.28	0.21	0.79	.	0.09	0.57	0.09	0.09	0.24
Foot (Y_{12})	B	-0.32	-0.46	0.63	0.01	-0.08	0.00	0.25	0.43	0.11	1.67	-0.04
	Exp(B)	0.73	0.63	1.87	1.01	0.92	1.00	1.28	1.54	1.11	5.29	0.96
	p-value	0.28	0.29	0.03*	0.99	0.74	.	0.61	0.13	0.27	0.11	0.89

*) significant at p-value < 0.05;

**) significant at p-value < 0.01

findings in Figure 3 indicate that MSDs mostly affect the lower back, neck, and shoulders, with the lower back being the most vulnerable region. The estimated parameters of musculoskeletal pain (Y) based on the manual handling postures (X) model are presented in Table 1.

Generalized Linear Models of Musculoskeletal Pain (Y) based on Manual Handling (X)

Table 1 serves as a structured summary of the generalized linear model (GLM) outputs, detailing the parameter values across 13 models. The B coefficient indicates the direction of the relationship, while a positive coefficient (B>0) suggests that as the independent variable increases, the likelihood of experiencing pain increases. A negative coefficient (B < 0) suggests a decrease in the odds or likelihood of musculoskeletal pain. The Exp (B) performs an odds ratio, which shows the strength of the association. The Exp (B) > 1 indicates a higher likelihood of the outcome (pain), while Exp (B) < 1 indicates a lower likelihood. Meanwhile, the p-value shows whether the independent variable is significantly associated with the dependent variable. A p-value of less than 0.05 in this study is regarded as statistically significant and is marked by a dark-colored cell.

According to the region-specific models, 'carrying objects for more than 9 meters' (X10) is significantly associated with most musculoskeletal pain, including Y3 (p-value = 0.03), Y4 (p-value = 0.00), Y5 (p-value = 0.01), Y6 (p-value = 0.05), Y7 (p-value = 0.01), and Y10 (p-value = 0.04).

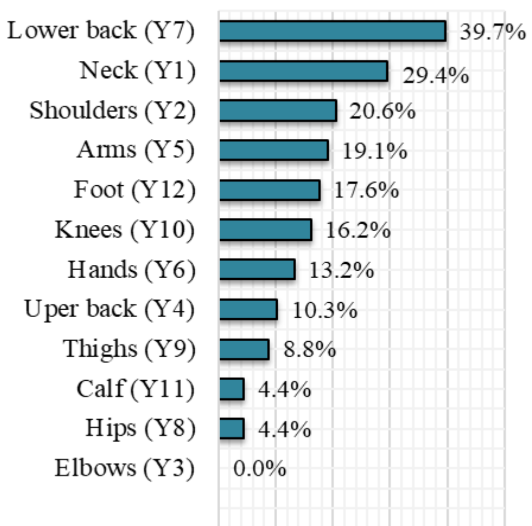

Figure 3. Musculoskeletal Pain Exposure Rates

Meanwhile, musculoskeletal pain in the upper back (Y4) is linked to the most common manual handling postures, specifically X1 ((p-value = 0.01), X2 (p-value = 0.02), X7 (p-value = 0.03), and X10 (p-value = 0.00). Among all of the significant estimated parameters, there is no single negative coefficient B, suggesting that worker risk of musculoskeletal pain was influenced by manual handling posture. Based on the odds ratio (Exp(B)) parameter, the effect of X10 on the increase in Y4 shows the strongest association (Exp(B) = 11.39), where a 1-point increase in X10 will raise the risk of Y4 by 10.39 (11.39–1) or 10 times higher. Particularly, X10 has the highest parameter estimation value across all Y variables it significantly affects, indicating that this variable represents the most influential manual handling posture contributing to multiple musculoskeletal pain.

Figure 4 provides a visual representation of the significant associations between various manual handling postures (X variables) and the occurrence of musculoskeletal pain in different body regions (Y variables). The figure illustrates the strength and direction of these relationships based on the estimated odds ratio, highlighting key predictors of musculoskeletal disorders among workers.

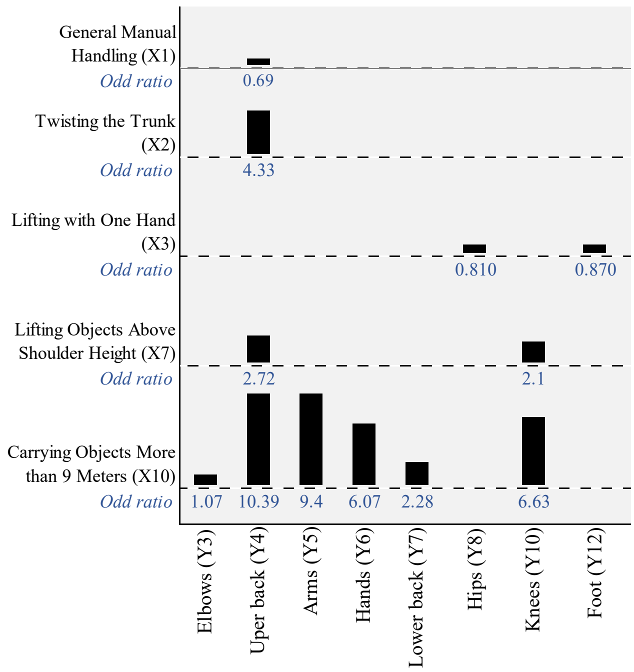

Figure 4. Ergonomic Hazard Risks Mapping Based on Region-Specific Pain Summary Model

Determinants' Important Analysis

An important analysis was performed to evaluate the degree of predictor's suitability (fitness) to predict response variables (Y). Table 2 presents the normalized importance values of different predictor variables (X) in predicting musculoskeletal pain in various body regions (Y).

The percentages indicate the relative contribution of each X variable in determining the likelihood of Y possibility. This analysis complements the generalized linear model (GLM) p-value analysis by quantifies the relative contribution of each predictor (X) in determining the response (Y) by rescaling their impact to a 0–100% range. This allows for ranking variables based on their influence.

Enhanced statistical result in GLM shows X_{10} has a normalized importance of 100% for Y_3, Y_5, Y_6, Y_7, and Y_{10}, confirming its dominant role in predicting MSDs across multiple regions. Lifting with one hand (X_3) is the strongest predictor for Y_8 and Y_{12} (100% importance), aligning with its significance in GLM.

Integrated GLM and normalized importance analysis from neural networks in this study ensures that only statistically significant and highly impactful predictors are used for modeling MS risks.

Neural Networks Model Architectures

The model architecture, depicted in Figure 5, employs a multi-layer feedforward neural network using 100 data trainings and 100 data testings, with up to three automated hidden layers, enabling the capture of nonlinear relationships between the predictor (X) variables and the eight musculoskeletal pain outcomes (Yn).

The synaptic weights represent the connection of each input variable (X) on the probability of a musculoskeletal disorder (Y), where the outcome is binary (0=no pain, 1=pain). These weights are visualized as lines in the network diagram: grey lines indicate positive weights (>0), while blue lines denote negative weights (<0). A positive synaptic weight (grey) indicates that an increase in the corresponding X variable is associated with an increased likelihood of musculoskeletal pain in the target Y region. Conversely, a negative synaptic weight (blue) suggests that higher values of that X variable are associated with a decreased likelihood of pain, indicating a potentially protective or mitigating effect. The magnitude of the weight reflects the strength of this relationship—larger absolute values (regardless of sign) indicate a stronger effect, either positive or negative.

Figure 5 presents eight neural network diagrams illustrating the predictive modeling of musculoskeletal pain in specific regions: Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, Y_{10}, and Y_{12}. Each diagram represents the model structure that appeared most frequently across five to six repeated modeling processes, indicating a degree of consistency in how the neural network maps input variables (X) to these outcomes.

The variations in synaptic weight values, as well as the number of hidden nodes generated automatically in each training process, serve as indicators of model stability. Despite minor fluctuations, the core structure and influential predictors remain relatively consistent across runs, supporting the robustness of the modeling approach. These recurring patterns highlight key predictors and consistent network behavior in estimating the likelihood of musculoskeletal pain, reinforcing the credibility of the variable importance results.

Table 2. Normalized Importance of Determinants (Xn) in Each Y Prediction Model

Xs	Predicted Variables' (Yn), Normalized Importance (%)							
	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	Y_{10}	Y_{12}
X_1	70.2	58.1	51	60.6	33.6	76.2	57.5	40.9
X_2	50.3	100	33.6	19.5	3	48.4	64.3	3.3
X_3	49.1	32.4	40.2	95.5	47	100	79.8	100
X_4	88.1	31.9	54	77.4	23.6	64.5	66.6	50.4
X_5	57.5	49.8	86.1	46.5	80.4	17.5	49.5	62.5
X_6	24.1	21.2	13.8	38.9	18.8	68.4	26.8	21
X_7	34.1	79.5	29.3	14.1	66.4	58.1	100	52.7
X_8	53	32.9	46.9	66.9	22.6	93.9	54.6	69.1
X_9	27.1	30.1	1.6	61.1	19.2	6.3	54.2	29.8
X_{10}	100	97.8	100	100	100	25.5	91.2	33.5
X_{11}	14.3	9.6	6.3	56.5	43.1	59.6	35.8	13.7

Model Performance Stability

Figure 6 confirms these findings by visualizing the Sum of Cross Entropy Error (CEE) across five modeling repetitions (epochs) for each model, highlighting the model's ability to converge toward more accurate predictions. A lower CEE indicates a model that makes more accurate and confident predictions. Based on Figure 6, the overall CEE across models ranges from 21.2 to 54.4. Since the modeling process used 100 data points for training and testing, these values can be rescaled to average

CEE by dividing by 100, resulting in a range of approximately 0.21 to 0.54.

Models predicting Y_5 and Y_{10} show the lowest CEE, indicating stronger performance. In contrast, the model predicting Y_{12} consistently shows higher CEE values compared to the others. This comparative visualization also provides insight into model stability under repeated training, offering an empirical basis to evaluate both generalization and reliability. As shown in Figure 6, most models maintain relatively low CEE values across epochs, with Epoch 5 consistently producing the lowest CEE, suggesting improved model accuracy with more training repetitions.

DISCUSSION

The descriptive analysis indicates that certain manual handling postures are particularly prevalent in Ponorogo's traditional manufacturing sector. Activities such as lifting with one hand (X_3), lifting objects from below elbow height (X_8), and twisting the trunk (X_2) are most commonly reported by the workers. These tasks demand considerable

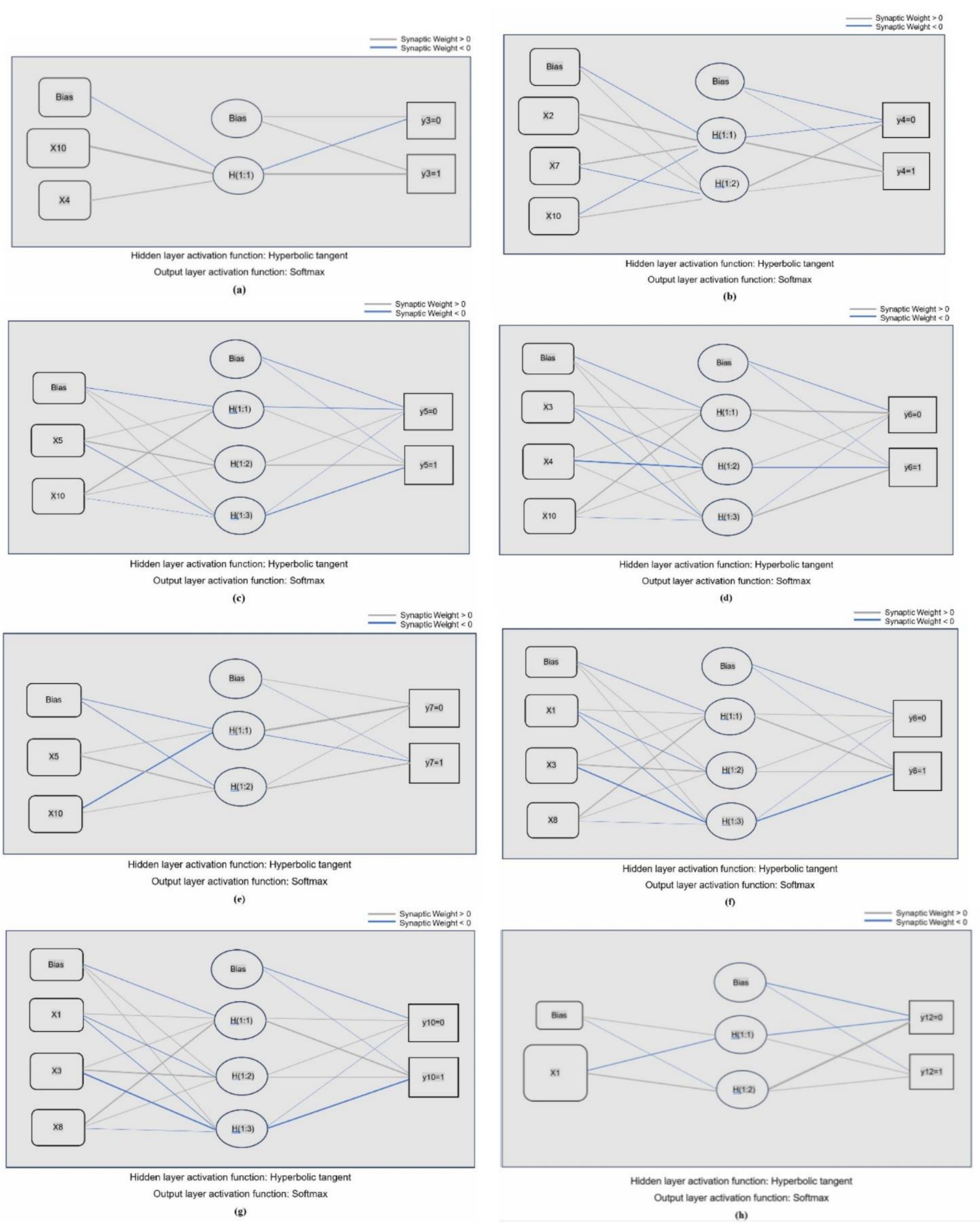

Figure 5. Neural Network Architectures of Eight MP Prediction Models: Y3 (a), Y4 (b), Y5 (c), Y6 (d), Y7 (e), Y8 (f), Y10 (g), Y12 (h)

physical exertion and often involve awkward or sustained postures, contributing to the high exposure to biomechanical strain. Twisting the trunk, for instance, is a known risk factor for lower back injuries due to the shear forces generated in the lumbar spine during such movements (Marras *et al.*, 1993). Similarly, lifting with one hand may result in muscular imbalance and increased load on specific body regions such as the shoulder and lower back, as corroborated by Punnett and Wegman (2004).

The distribution of musculoskeletal pain (MP) across body regions further substantiates these ergonomic concerns. The lower back, neck, and shoulders were the most frequently reported sites of pain, consistent with prior studies in similar occupational settings (Imagama *et al.*, 2020; Popescu and Lee, 2020; Kim, Park and Jeong, 2022). The absence of complaints in the elbow region may reflect task-specific biomechanics, where elbow involvement might be minimal or less strenuous compared to other regions.

The findings of this study give additional evidence for the widely held hypothesis that manual handling causes substantial health risks to employees, particularly MSDs, as noted by the World Health Organization (WHO, 2022). Automation is not commonly adopted by most industries in less developed areas like Ponorogo regency, so it puts high demand on human labor despite automation's shown efficiency and ability to increase worker safety.

This study confirms the widespread nature of ergonomic hazards in manual handling, particularly within traditional and labor-intensive industries. It underscores the necessity of ergonomic interventions targeting these common risk factors to prevent cumulative trauma disorders.

The GLM analysis also helps clarify the association of specific manual handling postures and musculoskeletal pain in the specific region. Carrying objects for more than 9 meters (X_{10}) presented as the most influential variable, significantly associated with six of the 12 Y outcomes. This finding aligns with evidence from Fox *et al.* which found the risks posed by prolonged load carriage on musculoskeletal health (Fox *et al.*, 2020). Long-distance carrying involves not only the burden of the object itself but also sustained muscle activation and joint loading, increasing the risk of fatigue and overuse injuries (Drew, Krammer and , Brown, 2020).

The strength of association, as reflected by the odds ratio (Exp(B)), underscores the magnitude of risk. For example, the association between X_{10} and upper back pain (Y_4) yielded an Exp(B) of 11.39, indicating that a unit increase in this posture variable multiplies the likelihood of upper back pain by more than tenfold. Such a substantial effect size is in line with the findings of Skals *et al.* (2021), who reported strong links between manual material handling and upper back/shoulder disorders.

The GLM results also revealed that musculoskeletal pain in the upper back (Y_4) is influenced by the highest number of manual handling postures. This suggests a biomechanical vulnerability of the upper back to varied handling tasks, possibly due to its role as a central stabilizer during lifting, carrying, and twisting motions (Govaerts *et al.*, 2021).

Interestingly, none of the statistically significant predictors showed negative coefficients, indicating that all the significant manual handling variables

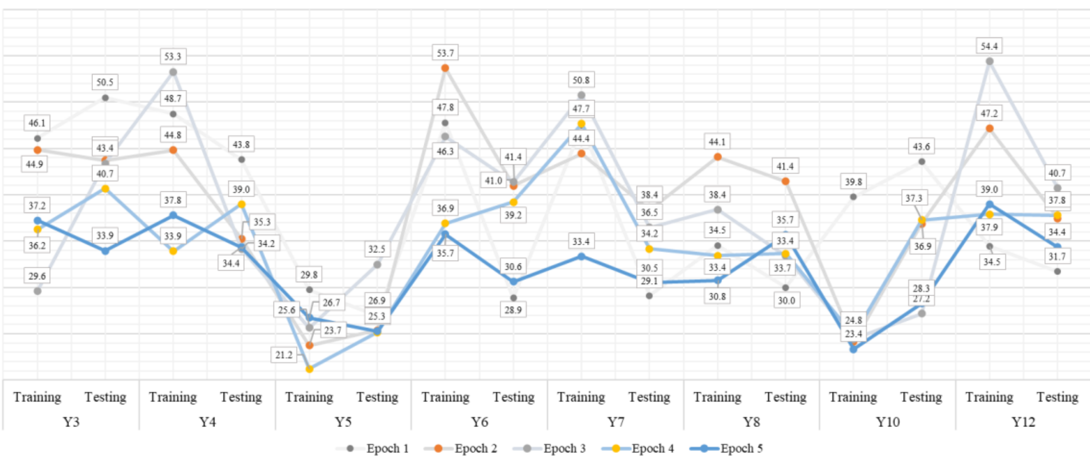

Figure 6. The CEE Comparison in Five Epochs for Eight Models

increase the risk of MP. This consistency in directionality reinforces the hypothesis that these manual handling tasks are detrimental to worker musculoskeletal health.

The NNs differ from conventional statistical models in that they can capture complex, non-linear associations between variables (Sahoo and Chakraverty, 2024); this deeper insight can reveal how specific manual activities contribute to different types of musculoskeletal discomfort. For instance, the model pointed toward targeted interventions within this work by identifying the transporting of moving objects over long distances (X_{10}) as a primary contributing factor to several MSDs.

The normalized importance values align well with the GLM findings, with X_{10} demonstrating the highest impact in multiple MP outcomes. Specifically, X_{10} had 100% normalized importance for Y_3, Y_5, Y_6, Y_7, and Y_{10}, underscoring its pervasive role in predicting pain across different anatomical regions.

This dual-approach of GLM and ANN ensures a more holistic understanding of predictor variables. While GLM provides statistical significance and effect sizes, ANN complements this by offering a scaled importance value that facilitates variable ranking. The convergence of both methods on X10 as the most predictor reinforces the reliability of the model (Mohammadinia *et al.*, 2019; Arabameri *et al.*, 2020; Monaco *et al.*, 2021; Saha *et al.*, 2022).

Other significant variables from the importance analysis include X_3 (lifting with one hand), which was the strongest predictor for Y_8 and Y_{12}, and X_2 (twisting the trunk), which consistently appeared in the top ranks for several MSP regions. These findings further confirm the multifactorial nature of ergonomic hazards, where different tasks contribute uniquely to stress on various body regions. These observations are consistent with findings from Umar *et al.* (2021), who noted that twisting and asymmetrical lifting significantly increase the risk of MSDs .

Emerging technologies are such as ML and AI: Disrupting OSH. In this study, neural network-based modelling illustrates a way in which these methods could provide an effective means by which to evaluate ergonomic hazards. In addition to NNs, machine learning has led to new developments in AI, including deep learning, reinforcement learning, and hybrid models, which are predicted to become even more prevalent in future OSH systems. These algorithms may also predict risks in real time, automate risk assessments, and provide appropriate-on-demand solutions based on dynamically changing work environments when they are integrated with workplace monitoring systems (Sarkar and Maiti, 2020).

The neural network models used in this study were designed to capture complex nonlinear relationships that may not be adequately modeled by GLM. The architecture included multi-layer feedforward networks with up to three hidden layers, automatically generated during the modeling process. This architecture enabled the capture of intricate interactions between manual handling postures and the probability of experiencing MP, reflecting the complex nature of real-world ergonomic exposures (Lambay *et al.*, 2021).

Figure 5 visualizes the synaptic weights between input variables (X) and output MP regions (Y). The predominance of grey lines in the diagrams suggests that most manual handling activities are associated with increased risk, which resonates with prior research using machine learning in ergonomics (Sarkar and Maiti, 2020). However, due to the limited frequency and magnitude of these negative weights, their protective role remains speculative and warrants further investigation.

Another noteworthy aspect is the consistency of model structures across five to six repetitions. This modeling stability underscores the robustness of the neural network approach in identifying core risk factors, despite variability in data sampling during each training iteration. Based on Figure 6, average CEE across models ranges from 0.21 to 0.54. This suggests that while all models remain within an acceptable performance range, models approaching a CEE near 0.60 may be at risk of underfitting or performing worse than a random guess. For reference, a random guess in a balanced binary classification would yield a CEE of approximately 0.693 (Heaton, 2018).

This comparative visualization also ensures model stability under repeated training, offering an empirical basis to evaluate both generalization and reliability. As shown in Figure 6, most models maintain relatively low CEE values across epochs, with Epoch 5 consistently producing the lowest CEE, suggesting improved model accuracy with more training repetitions.

Additionally, by integrating the Indonesian National Standard (SNI 9011:2021) into this study, a framework of ergonomic risk assessment and mitigation can be beneficial in various fields. Industry in Indonesia still uses manual labor as a common method, as such this model has been able to assist business on battel and compliance to the national and international legislations of OSH and at the same time ensures worker welfare and productivity.

Adoption of the ergonomic hazards assessment in the Indonesian National Standard (SNI 9011:2021) as a framework for evaluating and reducing ergonomic risk may be applied in other areas. The instrument can support enterprises in complying with national and international OSH regulations, thereby improving both the welfare of employees and work productivity since manual labor is still common in Indonesia (Ningtyas, Febrilian and Isharyadi, 2023; Wulandari, Rachmat and Handoko, 2023). Programs in integrated management of OSH should be included in system development for better optimization of risk evaluation. The training could then be personalized based on tasks found to be high risk., such as lifting and moving objects while traversing long distances. This must give workers practical ideas to apply in the workplace to reduce strain and enhance workplace safety culture (Fam, Azadeh and Azadeh, 2023).

Despite its strengths, this study has several limitations. First, the area focused on Ponorogo's traditional industry may limit generalizability to broader populations or other industrial sectors. The sample size, although sufficient for the scope of this research, could be expanded in further research to represent more varied occupational and ergonomic environments.

Another limitation related to the external validity of the neural network (NN) models. Although the models demonstrated good internal performance and stability across multiple repetitions in this study, their predictive capacity on external datasets remains untested. Neural networks are naturally data-driven and sensitive to the characteristics of the training dataset, which means that their performance to different populations may be limited unless validated externally. Future studies should seek to test these models on independent datasets from various occupational conditions to ensure their generalization capability. Moreover, applying other machine learning algorithms such as support vector machines (SVM) or decision trees may offer comparative insights (Chan *et al.*, 2022).

CONCLUSION

In conclusion, this study shows that using a neural network model is effective in predicting ergonomic risk in the traditional industrial sector in Ponorogo. Among the assessed manual handling activities, carrying objects more than nine meters (X10) presented as the most influential variable, contributing to musculoskeletal pain in multiple body regions. These variables were consistently ranked as important across both statistical and neural network models, proving its critical role in ergonomic risk modeling.

While GLM helped identify statistically significant relationships, NNM added value by uncovering nonlinear patterns and providing variable importance rankings that support risk prioritization. These findings provide a strong foundation for developing ergonomic interventions, especially in manual labor-intensive environments.

Moreover, future studies should focus on collecting larger and more diverse datasets, and exploring hybrid modeling techniques to strengthen prediction accuracy and generalizability. Such approaches can help traditional industries improve occupational safety, align with international standards, and achieve sustainable growth through enhanced worker health and productivity.

AUTHORS' CONTRIBUTION

DAA: Principal Investigator and Lead Author. RAAR: Co-Investigator and Reviewer. TH: Co-investigator and Data Analyst. DIH: Student Trainee and Data Collection Assistant.

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