Chapter 2
Decision Tree for Manual Material Handling Tasks Using WEKA

R. Rajesh, J. Maiti and M. Reena

Abstract Manual material handling (MMH) is one of the most physically demanding operations where workers are exposed to repetitive movements, awkward postures, contact stresses, and forceful exertions. MMH results in biomechanical and physiological strain on material handlers. Numerous observational and direct methods are used for assessing MMH tasks. In industrial settings, observational methods are best suited for ergonomic assessments of MMH tasks. But issues such as unclear classification levels, need of expertise, obstructive and invasive nature of data collection procedures, and time and cost requirements create difficulty for safety and ergonomic engineers in using observational methods. The objective of the study is to propose a decision aid to help safety and ergonomic engineers in making an easy ergonomic assessment of MMH tasks for the case study plant in West Bengal. In the current study, WEKA is used to classify the MMH tasks using J48 algorithm. The input data for this study is obtained from our previous work on the development of Cube model-2 (Rajesh et al. in IIE Trans Occup Ergon Human Factors, 2(1):39–51, 2014), in which a field survey of MMH tasks is conducted and classified the MMH tasks into three categories. The output MMH task classifications in WEKA are also classified into three levels. Overall true-positive rate of 0.813, false-positive rate of 0.170, and ROC value of 0.851 are obtained. The weighted Kappa statistic is 0.715. The results from WEKA are encouraging and enable us to use the simple decision tree to judge the physical demands of material handlers. The practical relevance of the study is that the decision tree is helpful for industry practitioners in assessing the MMH tasks therein.

Keywords Manual material handling · Cube model-2 · Data mining · WEKA · Decision tree

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2.1 Introduction

Manual material handling (MMH) is an integral part of many industrial activities and is a major contributor of musculoskeletal disorders. MMH activities involve high physical demands, awkward postures, contact stresses, and forceful exertions, the contents of which vary significantly depending on the work situations and industrial sectors. MMH jobs previously composed of a high percentage of lift–lower–carry operations have gradually been replaced by pushing–pulling operations. The evolving nature of MMH exposure calls for not only better exposure measurement and assessment strategies, but also for methods that are easy use and implement.

Worksystem factors relevant for MMH exposure include worker characteristics, material characteristics, Task/workplace characteristics, and environment/organizational characteristics (Rajesh et al. 2014; Rajesh 2016). The physiological and biomechanical responses need to be examined to quantify the physical load and strain arising from the MMH exposure. For undertaking interventions to address ergonomic issues in workplaces engineers and Ergonomists resort to observational and direct measurement tools to quantify these responses (Takala et al. 2010). Ergonomic observational tools for assessing combined MMH tasks that are suitable for the on-field industrial environment are scarce, and newer tools are needed to be explored toward making ergonomic evaluations easier and simpler. For safety and health practitioners the current need is to make quick and easy qualitative ergonomic assessment of the work activity. These must complement the observational and quantitative ergonomic methods that are in place in the industries.

The objective of this paper is to highlight a decision tree devised for a case study plant. The methods section of the paper gives a brief description of the case study plant and description of ergonomic evaluation done by existing ergonomic tools. In the next section, the performance of decision tree with respect to the ergonomic tools is presented. Finally, conclusion section presents the performance summary, its limitation, and scope for future work.

2.2 Method

2.2.1 Dataset

The study was conducted in a bearing manufacturing plant in India. Ball bearing and roller bearings are the main products produced by the manufacturing plant. The plant has a diverse material handling system catering to the specific needs of different sections. The material handling system configuration coupled with worksite (i.e., location) layout, task–workplace characteristics shall produce different physical exposure doses on the material handlers. The work sampling study was conducted over 19 locations in Store section of the plant. At the completion of the study, 143 MMH tasks and 262 task elements were observed. Each of these MMH tasks was composed of multiple MMH task elements, consisting of lifting–lowering, carrying, and pushing–pulling activities. For each of the MMH tasks observed from the observational study, a biomechanical analysis is undertaken. Biomechanical analysis was done using digital human models in CATIA software (Version 5, Dassault Systems, and France). The most frequent posture observed for a particular activity was used for the analysis. Biomechanical analysis of postural activities was carried out for the starting and ending postures for each task element, and was limited to lower back and shoulder joints. To account for the time dimension, the cumulative loading concept (Callaghan et al. 2001) was applied over the representative static postures of the task elements. Details of the biomechanical analysis in Cube Model-2 can be found in Rajesh et al. (2014). Based on the instantaneous loads and the cumulative dose the exertion level for each task is classified into 'low', 'medium', or 'high' as per the biomechanical criteria (Rajesh et al. 2014). The exertion level 'low' implies that biomechanical load does not cause physical strain on the material handler and is acceptable. The exertion level 'medium' implies that the biomechanical load could cause physical strain when done continuously. Therefore, the task needs to be accepted conditionally. The exertion level 'high' implies that there is a high biomechanical load that would cause physical strain to the material handler, and hence is unacceptable. The data set so obtained from the biomechanical analysis forms the basis of this study. Details of the dataset are given in Table 2.1.

2.2.2 Decision Tree

A decision tree is a decision-modeling tool that graphically displays the classification process of a given input for given output class labels. The decision tree mechanism is transparent and allows one to follow the tree structure easily to see how the decision is made. A decision tree is a tree structure consisting of internal and external nodes connected by branches. An internal node is a decision-making unit that evaluates a decision function to determine which child node to visit next. The external node, on the other hand, has no child nodes and is associated with a label or value that characterizes the given data. A decision tree is a top-down induction method of classification that has three main steps. First, the root node at the top node of the tree considers all samples and passes through the samples information in the second node called 'branch node'. The branch node generates rules for a group of samples by considering all attribute values and finalizes the decision rule by pruning. After fixing the best rule, the branch nodes send the final target value in the last node called the 'leaf node'. Finally, it chooses the attribute that offers rules with minimum error and constructs the final decision tree. Decision tree classifier techniques have been used successfully for a wide range of classification problems, but none so far in MMH application. Software used in his study is

Table 2.1 Details about dataset

Attributes	Description	Type (unit)	Descriptive
Load	Total material moved manually between locations	Numeric (kg)	Min 5 to max 2625 kg. Mean 405 & Std Dev 454
Unit weight	Unit material handled manually	Numeric (kg)	Min 1 to max 1044 kg. Mean 155 & Std Dev 235
MMH	Type of MMH task, i.e., lifting or lowering, carrying, pushing or pulling	Nominal (no)	Lift–lower (n = 125), Carry (36), Push–pull (101)
Worker no	Number of workers undertaking the MMH task	Numeric (no)	Min 1 to max 4. Mean 1.447 & Std Dev 0.669
Working_height	Working height at which material is handled	Nominal (no)	Floor to shoulder height (n = 6), shoulder height (22), floor height (18), floor to waist height (97), waist to shoulder height (69), waist height (50)
Distance	Horizontal distance moved during MMH task	Numeric (m)	Min 0 to max 200 m. Mean 20.782 & Std Dev 40.824
Repetition	Number of times MMH activities are repeated	Numeric (no)	Min 1 to max 480. Mean 21.836 & Std Dev 44.818
Duration	Duration of the continuous MMH activity	Numeric (minutes)	Min 1 to max 32 min. Mean 7.378 & Std Dev 7.406
Exertion	Workers exertion level due to MMH task	Nominal (no)	Low (n = 72), Medium(147), High(43)

Waikato Environment for Knowledge Analysis (WEKA). WEKA has implemented data mining algorithms using the JAVA language. It is open-source software and contains tools for data preprocessing, classification, regression, clustering, association rules, and visualization.

2.2.3 Performance Measures

There are several terms that are used for estimating the performance measure. They are true-positive (TP), true-negative (TN), false-negative (FN), and false-positive (FP). The performance of the predictive model is calculated based on the precision, recall values of classification matrix. Precision is the fraction of retrieved instances that are relevant. Recall is a fraction of relevant instances that are retrieved.

True-positive rate:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}. \tag{2.1}$$

True-negative rate:

$$\mathrm{FPR} = \frac{\mathrm{FP}}{(\mathrm{FP} + \mathrm{TN})} \tag{2.2}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})} \tag{2.3}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}. \tag{2.4}$$

Other performance measures obtained from WEKA include Receiver operating characteristic (ROC) and Kappa statistic and root-mean-square error (RMSE). ROC provides comparison between predicted and actual target values in a classification. It describes the performance of a model with a complete range of classification thresholds. ROC area varies between 0 and 1 intervals. An increasing value indicates better classification, with an area of one representing perfect classification. The Kappa Statistic can be defined as measuring the degree of agreement between two sets of categorized data. Kappa statistic varies between 0 and 1 intervals; the higher the value, the stronger the agreement (Sim and Wright 2005). Root-mean-square error is defined as the square root of the sum of squares error divided by a number of predictions. It measures the differences between values predicted by a model and the values actually observed. The smaller the RMSE, the better the accuracy of the model. The performance of the learning techniques is dependent on the nature of the training data.

The current study is classified into three classes. For the multiclass problem, sok09 has presented a number of performance measures. The classifiers are evaluated by some the multiclass performance measures listed below.

Average accuracy:

$$\mathrm{ACC} = \frac{\sum_{i=1}^{\mathrm{N}} \frac{\mathrm{TP}_i + \mathrm{TN}_i}{\mathrm{TP}_i + \mathrm{FN}_i + \mathrm{FP}_i + \mathrm{TN}_i}}{\mathrm{N}}. \tag{2.5}$$

Average classification error:

$$\mathrm{ER} = \frac{\sum_{i=1}^{\mathrm{N}} \frac{\mathrm{FP}_i + \mathrm{FN}_i}{\mathrm{TP}_i + \mathrm{FN}_i + \mathrm{FP}_i + \mathrm{TN}_i}}{\mathrm{N}}. \tag{2.6}$$

An average per-class agreement of the data class labels with those of classifiers:

$$\mathrm{Precision_M} = \frac{\sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i}}{N}. \tag{2.7}$$

An average per-class effectiveness of a classifier to identify class labels:

$$\mathrm{Recall_M} = \frac{\sum_{i=1}^{N} \frac{TP_i}{TP_i + FN_i}}{N}. \tag{2.8}$$

Relation between data positive labels and those given by a classifier based on a per-class average:

$$\mathrm{Fscore_M} = \frac{(\beta^2 + 1)\mathrm{Precision_M Recall_M}}{\beta^2 \mathrm{Precision_M} + \mathrm{Recall_M}}. \tag{2.9}$$

Matthews correlation coefficient:

$$\mathrm{MCC} = \frac{F^2 + (N-2)TF - (N-1)F^2}{(T + (N-1)F)^2}. \tag{2.10}$$

Weighted Kappa statistic is obtained using the weights assigned for each class (Eq. 2.11). In the case of a task with true exertion 'Low' and classified as 'Medium' there is no physical strain on the worker, i.e., ergonomic cost is nil. It is likely that an operating cost exists if the ergonomist undertakes interventions, and on the other hand, a task with true exertion 'High' and classified as 'Medium'; there is a physical strain on the worker, i.e., ergonomic cost is present but ignored by the classifier. The weights are assigned based on author's judgment regarding penalties for incorrect classification and are shown in Table 2.2.

Weighted Kappa statistic based on ergonomic weights is as follows:

$$K_w = \frac{P_{e(o)} - P_{e(w)}}{1 - P_{e(w)}}, \tag{2.11}$$

Table 2.2 Weights for Kappa agreement analysis

Exertion level by biomechanical analysis	Exertion level predicted by classifier		
	Low	Medium	High
Low	1	0.75	0
Medium	0.25	1	0.75
High	0	0.25	1

where observed weighted proportion of agreement is

$$P_{e(o)} = \sum_{i=1}^{N=3} \sum_{j=1}^{N=3} w_{i,j}\, p_{i.} p_{j}.$$

Chance of expected weighted proportion of agreement is

$$P_{e(w)} = \sum_{i=1}^{N=3} \sum_{j=1}^{N=3} w_{i,j}\, p_{i.} p_{j}.$$

2.2.4 WEKA Procedure

In WEKA, all data is considered as instances and features in the data are known as attributes (Witten et al. 1999; Hall et al. 2009). The dataset with nine attributes (see Table 2.1) is preprocessed in WEKA and stored in a database. The data file normally used by WEKA is in ARFF file format, which consists of special tags to indicate different things in the data file. The refined data is given to the proposed prediction models as input, predicted class will be extracted and performance evaluation metrics of different algorithms. In this study J48, Random forest, REP and LMT algorithm are employed. For the test option tenfold cross-validation is used. Here the dataset is split by tenfold, each fold contains 90% of the samples to construct a model and the remaining 10% is used to evaluate the model performance. The performance measures from WEKA include TPR, FPR, Correct classification (%), MCC, ROC area, Kappa statistic, and RMSE. Confusion matrices are very useful for evaluating classifiers. In the confusion matrix, the columns represent the predictions, and the rows represent the actual class. Based on it the multiclass performance measures ACC, ER, Precision_M, Recall_M, F_{score}, MCC_M, and K_w are estimated (Sokolova and Lapalme 2009; Jurman et al. 2012).

2.3 Results and Discussion

2.3.1 Decision Tree Model Results

The results from J48, Random forest, and REP and LMT algorithm are shown in Table 2.3. We observe using the TPR and TNR measures that J48 was the best performing algorithm and the second best was Random Forest. By examining correct classification measure J48 performed best. Kappa statistic indicates that J48 and the Random Forest have a substantial agreement between biomechanical analysis and the classifiers. J48 returned the highest correct classification (81%) and

Table 2.3 Prediction performance measures (n = 262)

Performance measures	Algorithm			
	J48	Random forest	REP	REP
TPR	0.813	0.794	0.634	0.76
FPR	0.17	0.19	0.347	0.213
Precision	0.814	0.786	0.603	0.759
Recall	0.813	0.794	0.634	0.757
Correct classification (%)	81.3	79.4	63.3	75.9
ROC area	0.851	0.884	0.725	0.846
Kappa statistic	0.668	0.632	0.287	0.573
RMSE	0.332	0.324	0.418	0.361

Table 2.4 Confusion matrix from J48 and random forest algorithm in WEKA

Exertion level by biomechanical analysis	Predicted exertion level by J48			Predicted exertion level by random forest		
	Low	Medium	High	Low	Medium	High
Low	61	11	0	62	10	0
Medium	2	130	15	7	128	12
High	0	21	22	0	25	18

Table 2.5 Prediction performance using multiclass measures (n = 262)

Performance measures	Algorithm			
	J48	Random forest	REP	LMT
Accuracy (ACC)	0.872	0.856	0.823	0.829
Error rate (ER)	0.13	0.144	0.177	0.17
Precision_M	0.788	0.761	0.734	0.73
Recall_M	0.748	0.717	0.746	0.693
Fscore	0.768	0.738	0.74	0.711
Matthews correlation coefficient (MCCM)	0.563	0.536	0.446	0.473
Weighted Kappa (K_w)	0.715	0.649	0.647	0.631

the lowest RMSE. ROC values for J48, Random Forest, and LMT algorithm indicated good accuracy (ROC > 0.8). It appears that REP and LMT classifiers are not suitable for classifying MMH tasks as their correct classification %, Kappa statistic, and RMSE are lower than J48 and Random Forest algorithms. Confusion matrix from J48 and Random Forest algorithm is presented in Table 2.4. Though WEKA performance measures for J48 and Random Forest indicate only slight advantage for J48, multiclass measures in Table 2.5 indicate a distinct advantage for J48 classifier. Weighted kappa statistic for J48 is 0.715 against 0.649 for Random Forest, both of which indicates substantial agreement (Sim and Wright 2005). The lower value for Random Forest is due to the higher number of misclassification by Random forest as compared to J48 (Table 2.4). Among the four classifiers REP performed the worst and J48 returned the best results. Hence, J48 is more suited for prediction purpose.

2.3.2 Decision Tree Induced MMH Guidelines

Figure 2.1 shows the decision tree obtained using J48 algorithm. Figure 2.1 shows a simple decision tree that consists of a decision node, branches, and leaves. The root node in this example is 'MMH'. The results of the test at the root node (whether the MMH task type is 'push' or others) cause the tree to split into branches. The two branches in this case are '=push' indicating 'push–pull' MMH task and '! = push'.

Indicate 'lift-lower-carry' MMH task. The leaves are the decisions made and are found on at the end of the last branch. The size of the tree is 37 with 19 leaves. For example, the decision made for the task attributes, MMH = push (the task is push–pull MMH task), Repetition ≤ 1 (one time task), Duration = 4 min with Load ≤ 462 kg (material load using hand pallet truck is less than 462 kg), is 'Low'. Some of the useful decision rules that can be practically used in the case study company are presented in terms of MMH guidelines.

- Pushing tasks that are repeated more than 3 times are categorized as high exertion task and are unacceptable. An immediate solution to the above condition is to take a break after every 3 continuous push–pull task.
- Lifting–carrying–lowering tasks that are repeated more than 200 times are categorized as high exertion task and are unacceptable. An immediate solution to the above condition is to reduce repetitions below 200 or take a break at the end of 200 repetitions.
- In the case of lifting–carrying–lowering tasks where unit weight is above 36 kg and total material handling load is more than 80 kg, the MMH task is categorized as high exertion task and is unacceptable. An immediate solution to the above condition is to reduce the total MMH load to below 80 kg. In addition, a reduction of unit weight from 36 kg is likely to reduce the stress further and make the MMH task a medium exertion task. This can be seen from the node 'Unit Weight $\leq$ 36' to 'Load ≤ 300'.
- In the case of lifting–carrying–lowering tasks where unit weight is above 24 kg, total material handling load is more than 682 kg and working height is floor–waist height, the MMH task is categorized as high exertion task and is unacceptable. An immediate solution to the above condition is to reduce total MMH load to below 682 kg. This can be seen from the node 'Unit Weight > 24' to 'Load $\leq$ 682'. In addition, a reduction of unit weight to below 24 kg is likely to reduce the stress further and make the MMH task a medium exertion task.

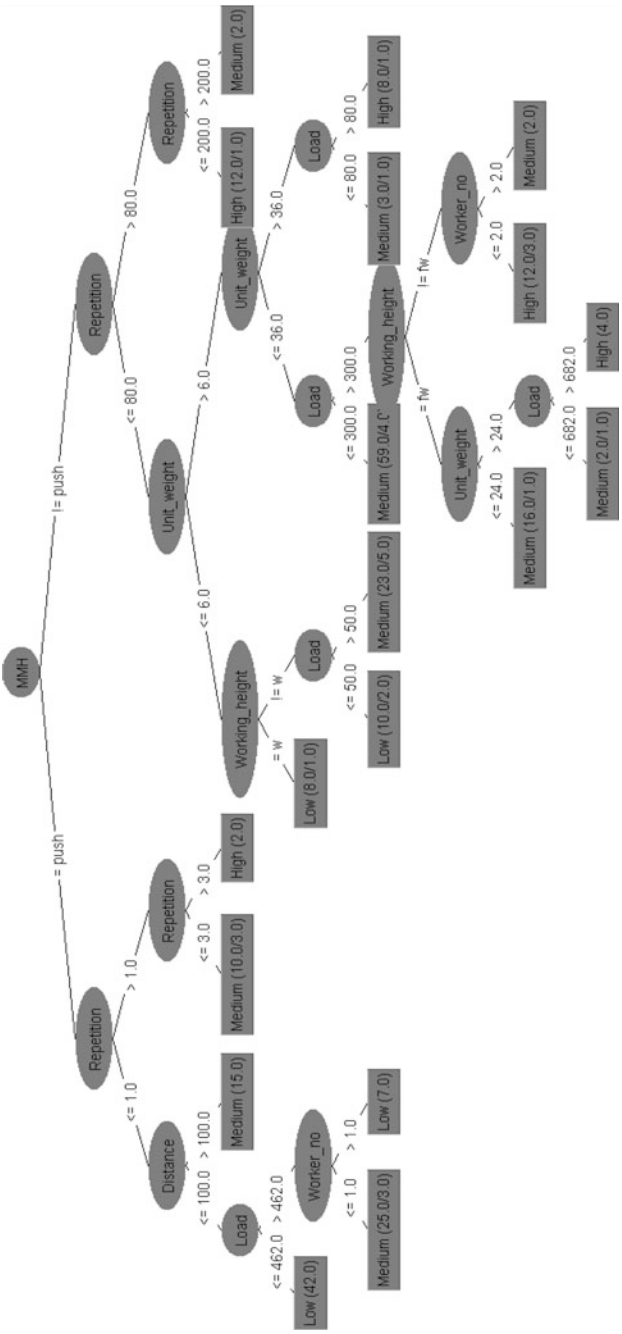

Fig. 2.1 Decision tree using J48 algorithm in WEKA

- In the case of lifting–carrying–lowering tasks where unit weight is between 25 and 36 kg, total material handling load is more than 300 kg and with 2 or lesser worker group; the MMH task is categorized as high exertion task and is unacceptable. An immediate solution to the above condition is to increase the number of workers in the group.

2.4 Conclusion

The output MMH task classifications in WEKA are also classified into three levels using WEKA-based classifiers J48, Random Forest, REP, and LMT. J48 and Random Forest performed better than the other two. Multiclass performance measures indicated J48 to be better than Random Forest classifier. Weighted Kappa statistic was the highest for J48. Among the four classifiers REP performed the worst and J48 gave the best results. J48 returned 81% correct classification. Overall true-positive rate of 0.813, false-positive rate of 0.170, and ROC value of 0.851 are obtained. The weighted Kappa statistic is 0.715. The results from WEKA are encouraging and enable us to use the simple decision tree to judge the physical demands of material handlers. The decision tree using J48 not only helps the industry practitioner in making quick ergonomic assessment of MMH task occurring in the plant but also provides insights toward intervention measured toward reducing the physical load in 'high' exertion tasks.

The practical relevance of the study is that the decision tree is helpful for industry practitioners in assessing the MMH tasks in the case study plant. The limitation of the study is that the sample size is small. Reasons for the misclassification need to be examined.

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