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DOI
10.1016/j.engappai.2023.106373

Publication date
2023

Document Version
Final published version

Published in
Engineering Applications of Artificial Intelligence

Engineering Applications of Artificial Intelligence 123 (2023) 106373

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A comparative neural networks and neuro-fuzzy based REBA methodology in ergonomic risk assessment: An application for service workers

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ARTICLE INFO

Keywords:
Artificial neural networks
Rapid Entire Body Assessment
Ergonomic
Service employees

ABSTRACT

Non-ergonomic working conditions are the leading causes of musculoskeletal disorders that seriously affect human health. REBA is widely used tool due to its convenience and consideration of all body parts. However, it heavily relies on the subjective judgments of the assessor, leading to inconsistencies in results, and lacks sensitivity in detecting small changes in ergonomic risk factors. Therefore, there is a need to improve the REBA method by integrating it with new technologies. While a few studies have proposed integrating ergonomic risk measurement tools with ANNs, there is a research gap in comparing different types of neural networks and membership functions to determine the most effective approach for improving the performance of REBA. Additionally, there is a need to apply these integrations to real-life case studies to demonstrate their effectiveness in practice. This study proposes a comparative neural network and neuro-fuzzy-based REBA method that includes various types of neural networks and membership functions. The proposed method is applied to service employee who have experienced increased workloads due to the Covid-19 pandemic. The results show that the neuro-fuzzy method is more accurate than the REBA and provides greater flexibility in defining which member belongs to which risk level cluster. This study is critical because it addresses research gaps in integrating neural networks and REBA and applies these integrations to a real-life case study. By comparing different types of neural networks and membership functions, the study provides insights into which approaches are most effective for improving the performance of REBA.

1. Introduction

Musculoskeletal disorders are among the most widespread occupational health problems caused by non-ergonomic working conditions in industrialized countries (Mattioli et al., 2006). In 2017, there were 138.7 million Disability-Adjusted Life Years, 1.3 billion extensive cases, and 121.3 thousand deaths globally associated with musculoskeletal disorders-related problems (Safiri et al., 2021) and besides these direct effects, decreased productivity, increased time waste, energy losses, and severe impacts of stress cause additional economic losses and psychological problems. For these reasons, it is crucial to identify ergonomic risk factors in a working environment and take preventive measures before they emerge (Boden et al., 2001; Goetsch, 2013). Accurate and comprehensive ergonomic risk detection using appropriate methods is an important starting point of this process.

Characteristics of ergonomic risk assessment include identifying ergonomic hazards in the workplace, evaluating the risk associated with these hazards, and recommending interventions to eliminate or reduce the risk of work-related musculoskeletal disorders. Ergonomic risk assessment often involves using standardized tools, such as NIOSH, RULA, OWAS, REBA, and WISHA, proposed for different work conditions by focusing on several parts of the human body. However, there are also some challenges and limitations associated with ergonomic risk assessment tasks. One of the main challenges is the subjectivity of the assessment, as different assessors may have different interpretations of the same task or hazard. There may also be limitations in the accuracy of the tools used, as some tools may not capture all relevant ergonomic risk factors or may not apply to all types of tasks or work environments (Boden et al., 2001; Goetsch, 2013). Another limitation is the feasibility and cost of implementing interventions to reduce ergonomic risks. Interventions may require significant resources and investment, and practical limitations in implementing changes to work processes or equipment may exist. Finally, ergonomic risk assessments may not always consider individual differences in factors such as body size, physical capabilities, and work experience, which can affect the level of risk associated with a task. Therefore, it is essential to consider these factors when conducting ergonomic risk assessments and designing interventions (Boden et al., 2001).

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https://doi.org/10.1016/j.engappai.2023.106373
Received 31 May 2022; Received in revised form 17 April 2023; Accepted 24 April 2023
Available online xxxx

The Rapid Entire Body Assessment (REBA) method is a widely used observational tool for musculoskeletal disorders to analyze the employee's posture and determine the operation's risk levels that are subject to measurement. Since REBA considers the whole body and provides analysts with a practical but systematic assessment procedure, it has become one of the most frequently used methods in many contexts (Erginel and Toptanci, 2019). There is an extensive body of literature focusing on different applications of REBA in various industries like transportation (Ahmed et al., 2012), manufacturing (Erginel and Toptanci, 2019), and health (Girard et al., 2016). Most of these applications consider an ergonomically risky task such as heavy lifting or repetitive movements of the hands and provide a case study by measuring risks and looking for preventive measurements. Also, comparing the performance of the REBA method with different risk assessment methods like RULA or OWAS is quite common. These studies contribute significantly to understanding various sources of risk in different industries, the performance of various methods, and prevention measures on different tasks. However, improving the assessment tools by considering the latest modern working environment's latest scientific developments and requirements as using them properly.

There has been an inevitable improvement in artificial intelligence applications in recent years, which is transformed numerous parts of traditional industries. In particular, machine learning and pattern recognition tools are widely used in different tasks. MLP (Multilayer Perceptron), GRNN (Generalized Regression Neural Network), RBF (Radial Basis Function), Convolutional Neural Network (CNN), and Fuzzy are the most popular types of Artificial Neural Networks (ANNs) used in these areas of application. MLP is a feedforward neural network architecture with one or more hidden layers of interconnected neurons. It is often used for classification and regression tasks. GRNN is a radial basis function neural network that uses a kernel function to estimate the conditional probability density function of the input data. It is often used for regression and function approximation tasks. RBF is another type of radial basis function neural network that uses radial basis functions to compute the output of each neuron. It is often used for function approximation, classification, and pattern recognition tasks. CNN is a deep learning algorithm well-suited for processing images and other multidimensional data types. CNNs have been used to achieve state-of-the-art performance on various computer vision tasks, including image classification, object detection, and image segmentation. Fuzzy logic is a mathematical framework that can handle data uncertainty by assigning degrees of truth to statements. Fuzzy logic can be used with artificial neural networks to improve their ability to handle uncertain and imprecise data. Especially CNN and fuzzy logic have been widely used in the health sector in recent years (Zhou et al., 2021; Almeida et al., 2020; Ghasemi and Mahdavi, 2020a). These methods will be discussed in detail in Section 3.

These promising developments also affect how we carry out our work tasks. While everything has been transforming in this direction, the assessment tools we use to measure ergonomic risks must also be improved. Although the conventional REBA is a user-friendly and systematic ergonomic risk assessment tool, its performance can be enhanced by using artificial intelligence applications. For instance, parallel to the motivation of our study, research that makes fuzzy and risk assessment is Ghasemi and Mahdavi (2020a) explores how technology is transforming work and its effects on workers' well-being, productivity, and job satisfaction. The authors examine the growing prevalence of telework, including its advantages and disadvantages, such as reduced commuting time and increased work-life balance, but also the potential for increased social isolation and decreased communication and collaboration. They also discuss the impact of automation on job displacement and the importance of reskilling and upskilling to help workers adapt to new technology and job requirements. Furthermore, the authors explore how the gig economy and the rise of independent contractors are changing the traditional employer–employee relationship, with benefits and job security implications.

From this point of view, this study focuses on ANNs and their possible integrations with the REBA method. The main objective is to improve the performance of the REBA steps by integrating them with neural networks and providing a more accurate and faster assessment tool. Combining the proven performance of the REBA method with promising artificial intelligence tools will provide important insights and valuable perspectives for ergonomic risk assessment by increasing the performance of the assessment.

With this motivation, we introduce comparative neural networks and neuro-fuzzy-based REBA methodology for ergonomic risk assessment. The performance of various neural network integrations with the REBA method is measured and compared regarding estimation performance, computation time, and errors. The proposed method is compared to other neural network methods and ANFIS with different membership functions. The study shows the potential of the proposed methodology to automate the assessment process and reduce the risk of musculoskeletal disorders in both service and manufacturing businesses. The proposed method is a successful decision support tool for identifying ergonomic risks and providing quick feedback to decision-makers. Future research can include incorporating biomechanical equations in the proposed methodology, adapting the method for employees in other work areas, and revising the parameters for different ergonomic risk assessment methods.

In doing so, we used a dataset of delivery service employees whose workload has increased significantly due to the Covid-19 pandemic and transformations in the online shopping industry. We calculated the ergonomic risk levels of the delivery task using different ANNs models with MLP, RBF, GRNN, and ANFIS and discussed their performances and integration capabilities for the ergonomic risk assessment. The proposed methodology contributes to ergonomic risk assessment literature by providing a flexible new tool integrated with artificial neural network methods. Since different combinations' performance is tested using a real-life case study, essential insights can help practitioners and researchers for future improvements.

The rest of the paper is organized into four sections. Section 2 presents a literature review by focusing on various REBA applications in different industries and discussing a few artificial intelligence-related applications in alignment with this study. Section 3 focuses on the materials and methods of the research and briefly discusses conventional REBA method steps, artificial neural networks, and adaptive neuro-fuzzy inference systems. While the application is given in Section 4, the results are discussed in Section 5. The conclusion and future directions of the study are discussed in Section 6.

2. Literature review

Rapid Entire Body Assessment (REBA) was presented in 2000 by Hignett and McAtamney (2000) and grabbed the attention of many researchers and practitioners in the coming years (Coyle, 2005; Motamedzade et al., 2011; Shirzaei et al., 2015). Thanks to its user-friendly calculation steps and observation-oriented nature, many people from different areas, such as agriculture and forestry (Enez and Nalbantoğlu, 2019), manufacturing (Erginel and Toptanci, 2019; Mukkamala et al., 2021), transportation and storage (Ahmed et al., 2012; Khan and Singh, 2018), construction (Li et al., 2018), health (Abdollahzade et al., 2016) and education (Hashim and Dawal, 2013), applied REBA to measure risk levels of various tasks. For instance, Abdollahzade and others (Abdollahzade et al., 2016) focused on the health domain and studied high-risk nurses in Iran with the help of a questionnaire and the REBA method. The application results indicated high-risk levels in the postures of nurses and discussed the requirements for urgent measures. They found a relationship between working postures, age, gender, experience, shift frequency and operational room types and pointed importance of not only physical conditions but also some additional variables on ergonomic risk assessment. Similar REBA applications for risk assessment of healthcare workers are proposed by other researchers

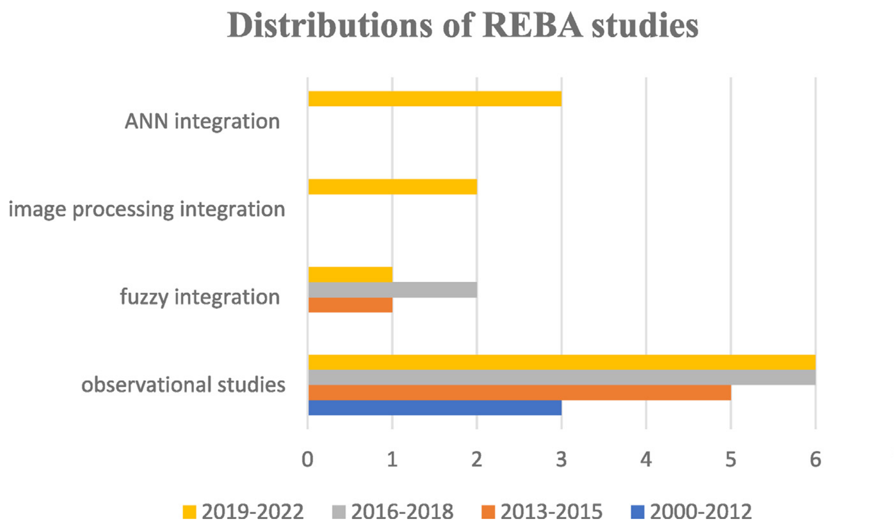

Fig. 1. Distribution of REBA studies.

using case studies, observations, and questionnaires (Torres et al., 2017; Ratzon et al., 2016; Carneiro et al., 2015). In addition, there are many REBA applications for dental hygienists (Kim et al., 2019; Noh and Roh, 2013; Rafeemanesh et al., 2013), radiologists (Yoo and Koo, 2004; Kim and Roh, 2014) and surgeons (Hignett et al., 2017; Dwyer et al., 2020) as various branches of healthcare tasks. Transportation is another application area that has a variety of REBA studies for operators, carriers and workers, sometimes integrated with other risk assessment tools (Ahmed et al., 2012; Gorde and Borade, 2019). For example, Ahmed et al. (2012) studied the ergonomic risk of bus drivers dealing with wheeled mobility devices by using three risk assessment tools besides REBA. The evaluation revealed that the current wheelchair tie-down and occupant restraint system (WTORS) in the US is highly risky for drivers and requires urgent improvement.

From a methodological point of view, when we look at REBA applications in the literature, it can be seen that many studies use the method for risk measuring or performance comparison aims. Even if most applications focus on the risk level definition of tasks using REBA or similar assessment methods like RULA, few studies consider neural network comparisons and fuzzy logic in alignment with this research. For example, Anghel et al. (2019) studied the RULA method by integrating neural networks and applied the proposed method to automotive workers. They structured an experiment in MATLAB in order to rank workstations according to their ergonomic risk levels. In another study, Bora et al. (2019) use an automated neural network search (ANS) approach for REBA and RULA integrated prediction system that is proposed for industrial vehicle drivers. They use CATIA software with other techniques to analyze the posture parameters of subjects and make a conclusion about the risk levels of the tasks. This application also presents some insights to improve the reliability of the system for drivers considering the findings of the experiments. Following a similar idea Ghasemi and Mahdavi (2020b) introduce a new scoring system based on Bayesian networks, fuzzy sets and REBA. In their study, they structure a network that consists of twenty-six nodes by following the logic of REBA assessment steps together with a fuzzy set. The application results showed that this new scoring system was more sensitive to changes in the body postures of the workers compared to the traditional method. The advantages of fuzzy logic and neural networks can improve the conventional REBA method and increase the sensitivity of the calculations.

In another study, Paudel and Choi (2020) also show the advantage of integrating promising methods to increase the reliability and performance of conventional risk assessment methods. They use the positions of the workers as input and estimate the body angles for postures to see whether the position is ergonomically safe or not. In doing so, they use REBA together with RULA to analyze videos that are taken from the working environment. The proposed integrated method plays a role as an early warning system by considering risky positions and presenting immediate output to analysts or decision-makers. In addition, few studies integrate image processing and different artificial intelligence methods with ergonomic assessment tools like REBA or RULA (Chatzis et al., 2022; Estrada-Lugo et al., 2022; Paudel and Choi, 2020).

Table 1 Illustrates some REBA studies from the literature systematically by focusing on their publication year, integrated, or compared methods if applicable and the approach used in the study. This classification aims to give an idea about the general trends in REBA studies and then introduce the literature gap we want to focus on by conducting this study.

It can be said that there is an increasing interest in the REBA method applications in various directions from 2007 to 2022. In order to show the integration of different approaches with the REBA method, we introduce Fig. 1, which focuses on the number of REBA studies together with other popular approaches like fuzzy sets or RULA.

The literature review analysis shows that many of the studies focus mainly on applications of REBA in different tasks. However, parallel to technological developments and increased performance of artificial intelligence applications, there are few promising integrations between ergonomic risk assessment tools and various network models, especially in recent years. These few applications revealed important results regarding with integration capability of the methods, performance levels and contributions. It has been shown that combining the REBA method with fuzzy sets and neural networks increases the performance of the assessment tools and provides practitioners with more reliable and efficient evaluation results. Also, they show the possibility and advantages of these combinations for practical reasons. However, since these studies generally consider one type of network or fuzzy sets, the comparisons between different methods or approaches still require further investigation. Even if we have some promising examples, we need to see the performances of the various network algorithms and learning styles together with the REBA method. With this motivation, our study proposes a comparative approach that covers all these literature gaps and presents a case study from the real world. In the next section, the proposed methodology that is proposed to integrate neural networks into the REBA method is presented and discussed step by step.

3. Materials and methods

The proposed methodology consists of four steps starting with data collection, as shown in Fig. 2. Here, as in the conventional REBA

Table 1
Literature review on REBA applications in various domains.

Author	Year	Focus	Method/Objective
Kee & Karwowski	2007	Comparison of REBA, RULA and OWAS	Observational study
Ahmed et.al.	2012	REBA on transportation mobility	Observational study
Torres & Vina	2012	REBA on vaccine production center	Observational study
Noh & Roh	2013	REBA on dental hygienists	Observational study
Rafeemanesh et.al.	2013	REBA on dentists.	Observational study
Kim & Roh	2014	REBA on radiologists	Observational study
Ansari & Sheikh	2014	REBA on small-scale industry	Observational study
Carneiro et.al.	2015	REBA on home-care nurses	Observational study
Can et.al.	2015	REBA on employees	Fuzzy-REBA
Abdollahzade et. al.	2016	REBA on nurses	Observational study
Ratzon et.al.	2016	REBA on nurses	Observational study
Balaji & Alphin	2016	REBA and RULA on industry	Observational study
Golabchi et.al.	2016	REBA on construction	Fuzzy- RULA
Torres et.al.	2017	REBA on nurses.	Observational study
Hignett et.al.	2017	REBA in the gynaecological field	Observational study
Khan & Singh	2018	REBA in the railway sector.	Observational study
Erginel et.al.	2018	REBA on furniture manufacturing employees	Fuzzy-REBA
Kim et.al.	2019	REBA, dental hygienists	Observational study
Schwartz et.al.	2019	REBA on Janitor	Observational study
Gorde & Borade	2019	REBA on cycle rickshaw operators	Observational study
Enez & Nalbantoğlu	2019	Comparison of REBA and OWAS	Observational study
Yaylı & Çalışkan	2019	REBA on forest nursery employees	Observational study
Bora et.al.	2019	REBA and RULA on industrial vehicle drivers	Prediction with ANS
Anghel et al.	2019	RULA on the automotive industry	Prediction with ANNs
Kee et.al.	2020	measure max holding time for REBA, RULA	Observational study
Paudel&Choi	2020	REBA and RULA in deep learning	Prediction with ANNs
Ghasemi&Mahdavi	2020	Fuzzy REBA and Bayesian networks	Fuzzy-REBA
Estrada-Lugo et. al	2022	RULA, REBA and image processing	Image processing integration
Chatsiz et.al.	2022	REBA and image processing	Image processing integration

method, there are observed and recorded body angle values and movement characteristics (rotation, bending, etc.). The next step is the REBA method application steps which depend on the employee's body angle values, and the Scores A, B and Activity are calculated in this part. The third step is the application part, where the ANNs structures and neuro-fuzzy methods are used. At this stage, different ANNs models are tried, such as MLP, RBF and GRNN, and the optimal result is obtained by changing the parameters of each model. In addition, the neuro-fuzzy method was used with different membership functions, and at the final stage, the results were compared with the results of the ANNs models.

3.1. Data collection

Ergonomic risk data is a unique type of data that refers to the risk of injury or discomfort resulting from the design or use of equipment, tools, or workstations. Compared to other data sets, such as financial or sales data, ergonomic risk data has some unique characteristics and challenges that make it difficult to collect, analyze, and apply.

One of the main challenges of ergonomic risk data is its subjectivity. Unlike financial or sales data, ergonomic risk data is often based on self-reported symptoms or discomfort experienced by workers. This can make it challenging to quantify and compare across different individuals or work environments, as different people may have different thresholds for pain or discomfort.

Another challenge of ergonomic risk data is its complexity. Ergonomic risk factors can involve multiple factors, such as posture, repetitive motions, force, and duration of exposure. Additionally, ergonomic risk factors can interact with physical, cognitive, and environmental factors, which can make it difficult to isolate specific risk factors. As a result, collecting and analyzing ergonomic risk data requires a multidisciplinary approach that involves expertise in ergonomics, human factors, and occupational health.

Contextual variability is another characteristic of ergonomic risk data that makes it unique. Ergonomic risk factors can vary depending on the context of the work environment, such as the type of work being performed, the equipment or tools being used, and the physical and environmental conditions. This variability can make it challenging to generalize findings across different work environments or tasks and highlights the importance of collecting data that is specific to the context of the workplace.

Lack of standardization is another challenge of ergonomic risk data. There is often a lack of standardization in the collection and analysis of ergonomic risk data, which can make it difficult to compare data across different studies or workplaces. This can also make it challenging to develop effective interventions or prevention strategies that can be applied across different work environments.

Finally, ergonomic risk data can raise ethical considerations related to worker privacy. Ergonomic risk data often involves the collection of sensitive health information, which must be collected and analyzed in a way that protects the privacy and confidentiality of workers.

In conclusion, ergonomic risk data is a unique type of data that presents several challenges compared to other data sets. To effectively collect, analyze, and apply ergonomic risk data, it is important to consider its subjectivity, complexity, contextual variability, lack of standardization, and ethical considerations. By taking a multidisciplinary approach to collecting and analyzing ergonomic risk data, we can better understand and mitigate ergonomic risks in the workplace.

After the task to be evaluated in terms of ergonomic risk is determined, appropriate equipment and measurement environment are prepared. All body angles required in the REBA method are measured and recorded by dividing the working body into two groups, Group A (Neck, Truck, Legs) and Group B (Upper arms, Lower arms, Wrists).

3.2. Rapid Entire Body Assessment (REBA) method

REBA is an observational method that allows the determination of the activities that may cause possible musculoskeletal disorders, based on evaluating the body shapes of the employees while performing an action (Hignett and McAtamney, 2000). REBA is a convenient method for risk assessment in manual tasks and is advantageous in terms of prioritizing the measures to be taken according to the outcome of the risk.

The REBA testbed involves a systematic approach that includes several steps. First, the work area is observed to identify the tasks and postures involved. Second, video recordings or photographs are taken of the workers performing these tasks. Third, the postures are

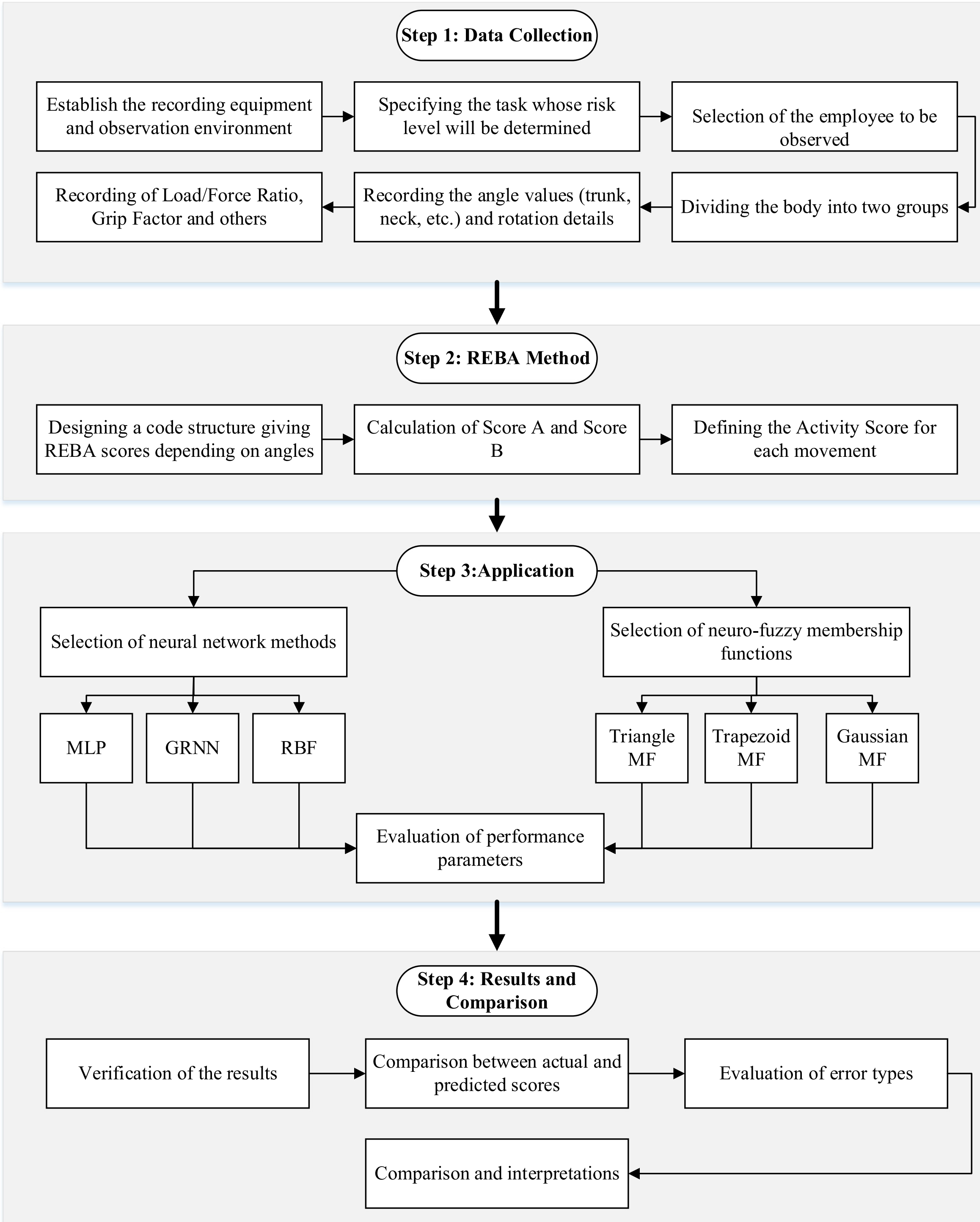

Fig. 2. The proposed methodology steps.

analyzed using established guidelines to determine the level of risk for developing WMSDs. Finally, recommendations are made to reduce the risk of injury.

For the application of the traditional REBA method, whole body parts are divided into two groups, A and B. As can be seen from Fig. 3, group A includes trunk–neck–legs, and group B includes upper arms–lower arms–wrists (Erginel and Toptanci, 2019). These groups are rated based on the degrees of angles and the body's vertical axis during work. The scores of Group A and B are calculated separately, using the REBA tables that can be seen in Fig. 4. The load/force score is added to the Group A score, and the load grip score is added to the Group B score to get the final scores of each group. Score C is obtained from the same table with the help of Score A and Score B. The final REBA score is obtained by adding Score C and activity scores (Hignett and McAtamney, 2000).

The final REBA scores are divided into five levels according to the degree of risk as shown in Table 2. The risk level of the work under examination determines the necessity of the measure to be taken.

The proposed method is designed to calculate Score A and Score B using the angle values observed and other required load ratings. Thus,

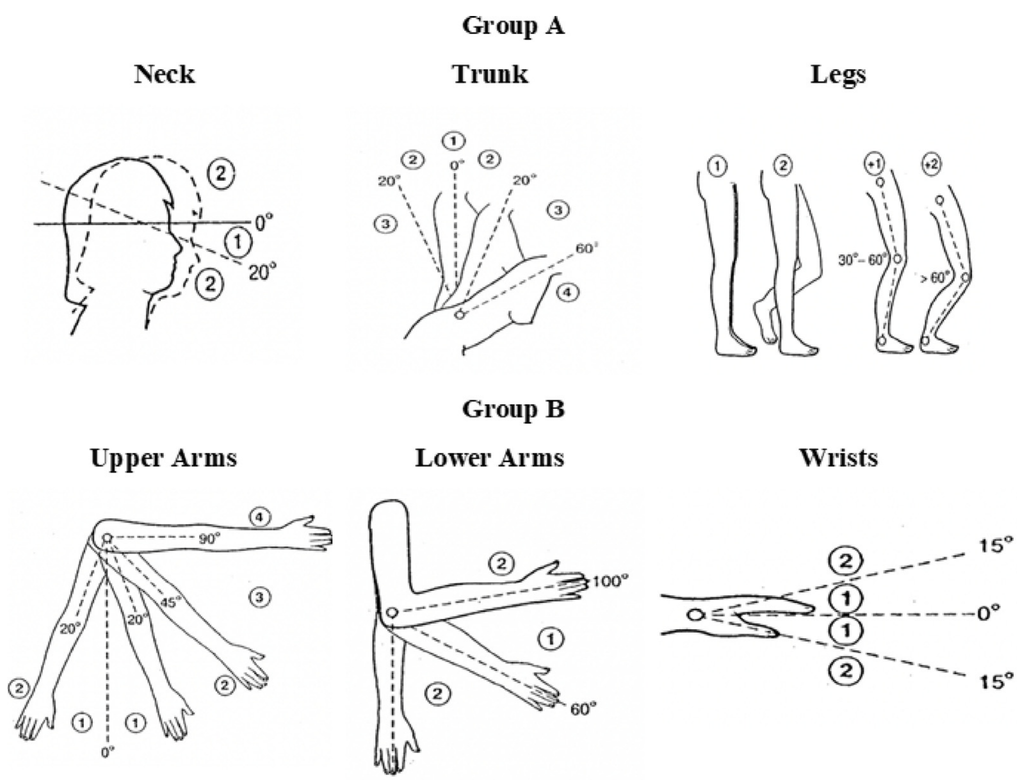

Fig. 3. Body angles for the REBA method (Paudel and Choi, 2020).

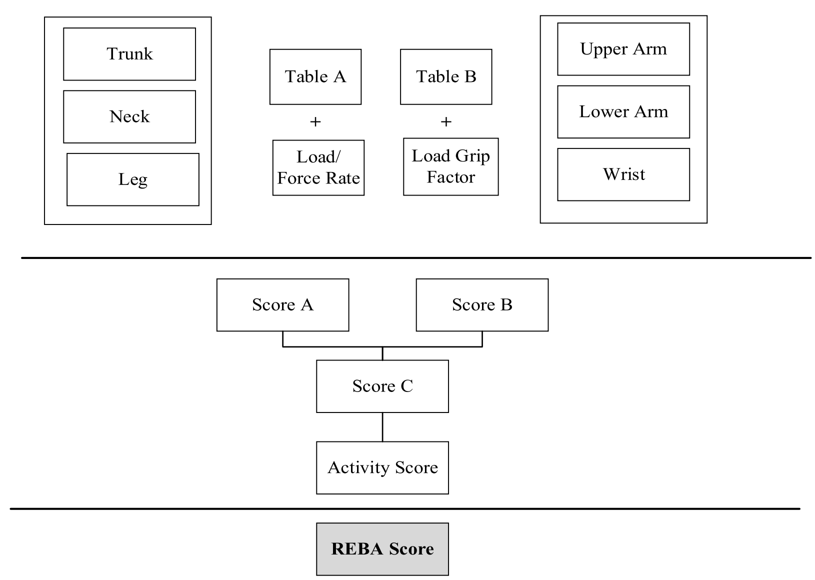

Fig. 4. REBA calculations steps (Hignett and McAtamney, 2000).

Table 2
Prevention levels depending on REBA risk scores.

Degree	REBA score	Risk level	Precaution
0	1	Negligible	Not necessary
1	2–3	Low	May be necessary
2	4–7	Middle	Necessary
3	8–10	High	Necessary in a short time
4	11–15	Very high	Immediately necessary

three input values (Score A, Score B and Activity Score) to be used in the next step are obtained in a faster way in this step.

3.3. Artificial neural networks (ANNs)

Artificial neural networks (ANNs) were first proposed by Warren McCulloch and Walter Pitts by following the learning, inference and prediction principles of the human brain (Chatzis et al., 2022). Its structure is inspired by neural networks and presented with mathematical principles for input, output and hidden layers. The most basic unit of an ANNs is a single artificial neuron, and they have entry pathways like biological neurons, and the networks balance inputs with the help of transfer functions via hidden layers (Hill et al., 1994). There is at least one neuron in each layer, and the transfer function only exists in the hidden and output nodes. The most frequently used ANNs model is the backpropagation learning rule which detects patterns and relationships in data and collects information in that direction (Basheer and Hajmeer, 2000). This means that it learns not through network programming but through experiences.

Artificial neural networks (ANNs) have several parameters that can be adjusted during training. These parameters include the number of hidden layers and nodes per hidden layer, the activation function, learning rate, regularization, optimization algorithm, and batch size. Adjusting these parameters can influence the capacity of the network to learn complex patterns, the convergence rate, and the quality of the final solution. It is important to select and adjust these parameters carefully to optimize the performance of the network on the given task. Hyperparameter optimization techniques such as grid search and randomized search can be used to find the optimal set of parameters.

For ANNs analysis, the dataset with possible inputs and corresponding targets is divided into three parts: Training dataset, validation dataset and testing dataset. The training process optimizes the connections between neurons in different layers, while the testing process aims to approximate the real data by making predictions. The validation dataset is used to prove that the method used is accurate and can consistently achieve what is expected (Liu et al., 2015).

ANNs process a series of input data by updating the weights recursively. The signals collected from the input layer are combined after being multiplied by their weight values and passed through an activation function to obtain an output value for the neuron. This function represents the sum of the weights of the input values, most of the time, the sigmoid function is preferred (Basheer and Hajmeer, 2000). ANNs read the input and output values given to them for training and determine the difference between the predicted value and the target value. It updates the weight values backwards to reduce the resulting difference. This cycle is repeated until the target accuracy level is reached.

A multilayer perceptron (MLP) is a class of feedforward ANNs which are suitable for regression prediction problems where a real-valued quantity is predicted given input value. A multilayer perceptron (MLP) is a class of feedforward ANNs. MLPs are suitable for regression prediction problems where a real-valued quantity is predicted given input value. The mathematical notations used to describe MLP:

Input Layer The input layer consists of the input features. Let X be the input vector, where $X = [x_1, x_2, x_3, \ldots, x_n]$.

Hidden Layer: An MLP may have one or more hidden layers. Let H be the hidden layer, where $H = [h_1, h_2, h_3, \ldots, h_n]$, and the number of neurons in the hidden layer is denoted by the letter 'm'.

Weight Matrices: MLP uses a set of weight matrices to connect the input and hidden layers, as well as the hidden and output layers. Let W_1 be the weight matrix between the input layer and the hidden layer, where $W_1 = [w_{1,1}, w_{1,2}, w_{1,3}, \ldots, w_{1,m}]$, and W_2 be the weight matrix between the hidden layer and the output layer, where $W_2 = [w_{2,1}, w_{2,2}, w_{2,3}, \ldots, w_{2,p.}]$ Here, '*p*' is the number of output neurons.

Bias Terms: MLP also uses bias terms to adjust the output of each neuron. Let b_1 be the bias term for the hidden layer, where $b_1 = [b_{1,1}, b_{1,2}, b_{1,3}, \ldots, b_{1,m}]$, and b_2 be the bias term for the output layer, where $b_2 = [b_{2,1}, b_{2,2}, b_{2,3}, \ldots, b_{2,p}]$.

Activation Function: Each neuron in the MLP uses an activation function to introduce non-linearity into the network. Let f be the activation function, where f(x) = 1/(1 + e^-x) is the commonly used sigmoid function.

Output: The output of the MLP is denoted by Y, where $Y = [y_1, y_2, y_3, \ldots, y_p]$. The predicted output is obtained by applying the activation function to the weighted sum of the input features and bias term for each neuron in the hidden and output layers. Mathematical Formulation: The mathematical formulation of MLP can be represented as:

$$H = f\,(X * W_1 + b_1)$$

$$Y = f\,(H * W_2 + b_2) \tag{1}$$

where '*' denotes the dot product of two matrices, and f() denotes the activation function.

There are also methods other than MLP that provide a lot of flexibility and reliability in problems. Radial Basis Function Neural Networks (RBF) is one of these methods. RBF proposed by Kung and Hwang (1988). RBF and MLP belong to the same class of neural networks called feed-forward networks. RBF is a mathematical function commonly used in machine learning and other fields. The general mathematical notation for a Radial Basis Function is:

$$\phi(\mathrm{r}) = \phi(||\mathrm{x} - \mathrm{c}||) \tag{2}$$

where:

ϕ is the Radial Basis Function

r is the distance between the input vector x and the center point c

‖x-c‖ is the Euclidean distance between the input vector x and the center point c.

RBF is used as an alternative to MLP. It reduces the time used for network training. RBF consists of three layers: an input layer, a hidden layer, and an output layer. While RBF uses Euclidean distances, MLP uses point products between inputs and weights. Also, MLP uses sigmoidal activation functions, while RBF uses Gaussian activation functions that make neurons more locally sensitive. With these differences, RBF facilitates the growth of new neurons during training (Frost, 2017b).

Generalized Regression Neural Networks (GRNN) is a variation of RBF based on kernel regression networks and was introduced by Specht (1991). Here are the mathematical notations used in GRNN:

Input vector: The input vector is denoted by x, where $x = [x_1, x_2, \ldots, x_n]$, and x_i is the ith input variable.

Target output: The target output is denoted by y.

Hidden layer: The hidden layer consists of the RBF neurons. The output of each RBF neuron is a function of the distance between the input vector and the center of the neuron. The RBF is denoted by ϕ(r), which is a function that computes the similarity between the input vector and each training example. The most used RBF is the Gaussian function:

$$\phi(\mathrm{r}) = \exp\frac{-\|\mathrm{x} - \mathrm{c}\|2}{2\sigma^2}, \tag{3}$$

where c is the center of the RBF, σ is the width of the RBF

Weight: The weight between the input vector and the RBF is denoted by w.

Normalized weight: The normalized weight between the input vector and the RBF is denoted by a, which is computed as:

$$\mathrm{a} = \frac{\mathrm{w}}{\sum w_i.} \tag{4}$$

Output: The output of the GRNN is denoted by ȳ, which is computed as:

$$\bar{\mathrm{y}} = \frac{\sum \mathrm{a}\phi(x_i)y_i}{\sum \mathrm{a}\phi(x_i)} \tag{5}$$

Training dataset: The training dataset consists of a set of input vectors $X = \{x_1, x_2, \ldots, x_m\}$ and their corresponding target outputs $Y = \{y_1, y_2, \ldots, y_m\}$.

Test dataset: The test dataset consists of a set of input vectors $X' = \{x1', x2', \ldots, xn'\}$ for which we want to predict the target outputs $Y' = \{y_1', y_2', \ldots, y_n'\}$.

Learning algorithm: The learning algorithm is used to train the GRNN on the training dataset. The most used learning algorithm for GRNN is the Gaussian mixture model (GMM) algorithm.

GRNN does not require an iterative training procedure, since it approximates any arbitrary function between input and output. Its main advantages are that it can learn quickly and rapidly converge to the optimal regression surface with a large number of datasets. Although GRNN and RBF models are motivated by different principles, they have similar applications. The main difference is that the GRNN output layer performs a weighted average while RBF performs a weighted sum (Zadeh, 1965).

In the proposed methodology, a feedforward backpropagation learning rule is used that allows the weights to be updated according to the error rate achieved in the previous epoch. ANNs is designed as a network that accepts Score A, Score B and Activity Score as inputs, and the final REBA Score as output. The explanation of every unit is given below:

Score A (input): Score A is calculated from trunk, neck and leg angles and is an input value for the proposed ANNs model that predicts the final REBA score.

Score B (input): Score B is calculated from the upper arm, lower arm and wrist angles and is an input value to.

Score C (input): Score C constitutes the third input value as a value derived from the combination of Scores A and B.

Final REBA Score (output): It is the final score value introduced to ANNs depending on the input values.

3.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

In fuzzy sets introduced by Zadeh (1965), the state of an entity belonging to any set is represented by the concept of "membership degree". While in classical sets, whether it belongs to the set or not is expressed with certain values such as 0 and 1, there is no such distinction in fuzzy sets, and the membership degree takes a value in the range of [0,1].

Most of the hybrid systems, in which fuzzy logic and ANNs are integrated, are made with the principles in the categories of putting fuzziness into the neural network framework and changing the basic properties of neurons. The neuro-fuzzy systems used for this purpose can be listed as ANFIS, FALCON, FuNe, etc. In this study, Adaptive Neural Fuzzy Inference System (ANFIS) method will be used due to its practicality and promising performance for this type of network model. ANFIS is a type of artificial neural network that is based on the Takagi–Sugeno fuzzy inference system developed in the early 1990s by taking the benefits of both, as it uses both neural networks and fuzzy logic principles together (Zadeh, 1965).

We assume the fuzzy inference system under consideration has two inputs (x and y), and one output (z). Usually input variable represents as a polynomial. In that case, a typical rule set of first-order polynomial, Takagi and Sugeno fuzzy if-then rules can be expressed as in Eq. (6) (Kung and Hwang, 1988):

$$\textbf{Rule 1}: \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1$$
$$\textbf{Rule 2}: \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \tag{6}$$

where Rule i denotes ith fuzzy rule ($i = 1, 2, \ldots$), x is the input, y^i is the output and A_i and B_i are fuzzy membership functions in the then-part (consequent part of the first-order Sugeno fuzzy model. The architecture of ANFIS consists of five layers, and a brief introduction of the model is given as follows.

Layer 1 The first layer is called the fuzzification layer. It uses Jang's ANFIS model to separate the input values into fuzzy sets, and the Triangle, Trapezoid and Gaussian activation function as a form of membership function. Here, the output of each node consists of the membership degrees that depend on the input values and the membership function used. The output of the node is a square node membership function given in Eq. (7).

$$O_i^1 = \mu \mathrm{A}_i(x) \tag{7}$$

where x values are the inputs of node i, and A_i is the linguistic label characterized by membership function μ.

Layer 2: The second layer is called rule layer. Each node in this layer represents the number and rules created according to the Sugeno fuzzy logic inference system. The output μi of each rule node is the product of the membership degrees from the first layer. Each node output indicates the firing strength of a rule. Firing strength means the degrees to which the prior part of the fuzzy rule is satisfied and it shapes the output function for the rule.

$$w_i = \mu \mathrm{A}_i(x) * \mu \mathrm{B}_i(y) \qquad (i = 1, 2, \ldots) \tag{8}$$

Layer 3: The third layer is called the normalization layer. Each node in this layer accepts all nodes from the rule layer as input values and calculates the normalized value of each of them. The outputs of this layer are called the normalized firing level (Eq. (9)). That is, each node in this layer is a fixed node labeled *N*.

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad (i = 1, 2, \ldots) \tag{9}$$

Layer 4: This layer is called the clarification layer. The weighted result values of a given rule are calculated at each node in this layer. The parameters are called result parameters. Every node i in this layer is a square node. The node output is the output membership function given by Eq. (10).

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i\mathrm{x} + \mathrm{q}_i\mathrm{y} + r_i) \tag{10}$$

Layer 5: This layer is called the total layer. There is only one node in this layer and it is labeled with a summation. Here, the output value of each node in the 4th layer is summed to obtain the actual value of the ANFIS system. As a result, the ANFIS structure is functionally identical to a Sugeno-type FIS structure.

4. The application

The proposed methodology is applied to supermarket delivery employees, who were exposed to higher risks due to the operational circumstances during the pandemic. In addition to affecting all working conditions worldwide, the COVID-19 pandemic has also been a transformative factor in people's consumption habits. Due to the development and widespread use of e-commerce, online shopping has become more popular during COVID-19 lockdown days. Most countries banned going out for days to prevent the virus from spreading. During these periods, especially online shopping systems of supermarkets were used to meet consumption needs in Turkey. People order and supply their needs quickly and safely through these platforms. Thus, needs were met without going to supermarkets. To meet these demands most of the time, supermarket employees work more than their regular working hours and deliver orders to be handled ergonomically. Repetitive movements of supermarket employees, such as lifting, carrying and climbing stairs with shopping bags, can cause ergonomic problems. A series of operations are carried out, such as taking customer orders from the supply points, loading them to the vehicles, unloading them at the delivery point, moving them to the buildings and moving them to the upper floors with or without elevators. These operations may negatively affect the musculoskeletal system of service employees, and skeletal system disorders may occur if measures are not taken in the long term. To prevent this, in the proposed approach, while service employees are performing the task of "order delivery", the shapes their bodies take are analyzed with the REBA method, and the observations are recorded. These observations are used in the proposed new methodology to determine the risk scores of the movements.

ANNs methods can be used to predict the ergonomic risk level based on input factors. It can help to identify potential risks before they become actual issues, allowing for early intervention and prevention. Also, these methods can be used to optimize ergonomic factors in the

Fig. 5. Image of a market employee while lifting the bags.

Table 3
Body angles of some of the real employees measured.

			E1	E2	E3	E4	E5
C Score	A Score	Trunk	35′	50′	48′	45′	65′
		Neck	10′	20′	25′	32′	25′
		Leg	55′	40′	42′	45′	35′
	B Score	Upper Arm	55′	12′	87′	90′	90′
		Lower Arm	75′	88′	90′	180′	85′
		Wrist	13′	10′	12′	18′	12′
		Activity score	0	0	1	2	2
		REBA	10	9	12	11	12

workplace. By analyzing various aspects, a neural network can suggest changes or adjustments to workstations or processes that minimize ergonomic risks. ANNs methods help to improve the efficiency and accuracy of REBA assessments. By automating the analysis and prediction of ergonomic risks, the process can be streamlined and standardized, reducing potential errors or inconsistencies. Overall, ANNs methods can be a valuable tool for analyzing and predicting ergonomic risks in the workplace, allowing for more proactive and effective management of these risks.

This study uses comparative neural networks and neuro-fuzzy-based REBA methodology for ergonomic risk assessment. The classical REBA method eliminates processing redundancy and makes a faster and more precise estimation. Different ANNs models were established with the obtained data set and continued with specific models that gave more meaningful results. These models are MLP, RBF, GRNN. At the same time, ANFIS was used to classify movements and remove uncertainty.

Due to the Covid-19 pandemic, tracking each employee individually for the case study was impossible, which created some problems in obtaining the data needed for the study. To overcome this problem, 25 random order delivery employees' body angles were obtained by recording and measuring. It was not possible to get the entire data set by measuring due to pandemic restrictions and social distance rules. For example, Fig. 5 shows the image of a market employee while lifting the bags. Some factors, such as bending, waist angle and knee angle, as seen in Fig. 5, are essential for the load on the person. Also, the load on the arms and the angle of the arms are crucial when delivering bags. Climbing stairs with heavy bags and continuous isometric arm muscle contraction are not ergonomic for supermarket employees.

The real-life measurements of the study were made with 25 random volunteers and the relevant parameters were collected. As an example of these measurements, the body angles (Trunk, Neck, Leg, Upper Arm, Lower Arm and Wrist) of five employees (E1, M2, E3, E4 and E5) are given in Table 3.

Table 4
Correlation coefficients between the input variables determined.

Variable	A_Score	B_Score	C_Score
A_Score	1	−0.169	0.047
B_Score	−0.169	1	0.046
C_Score	0.047	0.046	1

Based on the data collected from 25 employees, 75 more data were produced randomly which based on the body angles of the real workers with the MATLAB R2021b program. This study worked with a total of 100 data (25 real-life and 75 produced). Random data are generated by adhering to certain rules such as human body limits, REBA upper and lower angle values. These values are restricted according to the limits given in the Step-by-step REBA guide and task records. In addition, expert opinions are consulted for the angle ranges of different body parts in accordance with human ergonomics, and the dataset is generated randomly according to the following ranges.

The trunk data are generated between 0–90 degrees according to the flexion–extension state and the side bending of the trunk. The leg data are generated between 0–90 degrees according to the movement of double leg or single leg use. The wrist data are generated between 0–75 degrees of bending from the midline. The arm data are generated between 0–180 degrees according to shoulder raise, upper arm abducting, supporting arms, leaning and front and back movement of the arm.

Firstly, the correlation coefficients of input variables are calculated and given in Table 4. The correlation coefficient of −0.169 indicates a weak negative correlation between A Score and B score. The correlation coefficient of 0.047 and 0.046 indicates a weak positive correlation between A Score and C Score, and B Score and C Score, respectively. However, when interpreting correlation, it is important to remember that correlation is not causation. There may or may not be a causal relationship between the two related variables. The weak correlation coefficients do not have a negative effect on the independent variables' explanation ($R^2 = 0.95$) of the REBA Score.

Relationship analysis is conducted with the IBM SPSS AMOS program. The diagram and results are given in Fig. 6 as follows:

Fig. 6 shows the inputs and output, arrows extending from inputs to output to indicates the regression coefficient of each input. These coefficients show how each input affects the REBA output; with error variable which is denoted by "e1". In the structural model, 3 inputs and 1 output are examined. By checking Fig. 6, it can be interpreted that all the inputs have a significant effect on the target variable.

4.1. The ANNs based REBA model

The proposed ANNs model is structured considering several procedures; first, the dataset consisting of scores based on angles generated

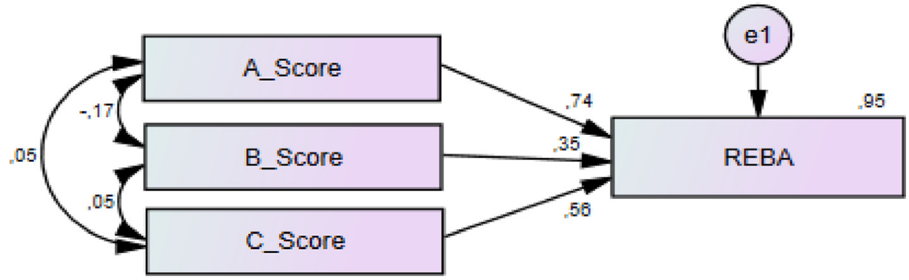

Fig. 6. The diagram and results of relationship analysis.

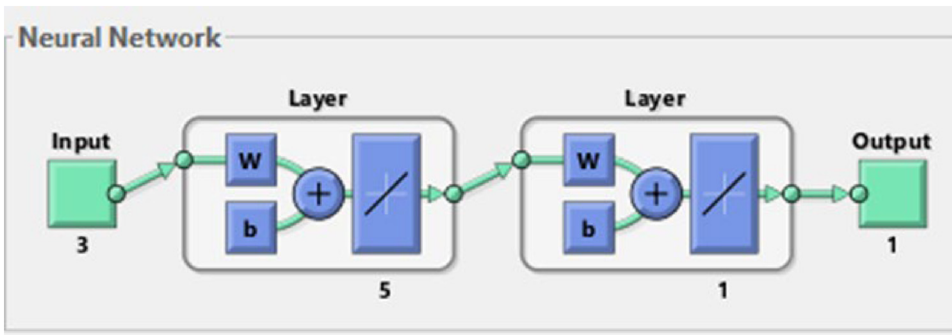

Fig. 7. The proposed MLP neural network model.

randomly is divided into training (80%) and test (20%) datasets. The training dataset is used to construct the network that matches parameters. The testing dataset is used to provide an independent assessment of the final unbiased fitted model. In this study, the proposed ANNs model is trained and tested with 80 and 20 samples, respectively. In the ANNs procedure, the network with 3 input neurons and 1 output neuron is trained for 1000 epochs. Two different rules are applied for the training process as; "stop it after a certain number of epochs" or "stop it when the error tolerance value reaches to 0.01". The proposed model is trained by the learning algorithm of "Gradient descent with momentum and adaptive learning rate backpropagation (GDX)".

Although there are different approaches in literature to determine the required number of hidden layers and the number of neurons in hidden layers, there is not a general rule (Zadeh, 1965). In this study, the number of hidden layers and the number of neurons in these layers are determined by trial and error in order to minimize the error rate (Kung and Hwang, 1988). For this purpose, the network is simulated for various number of hidden layers and hidden neurons in order to minimize the mean square error (MSE) between the actual and predicted values. As a result of the experiments, the range of hidden layers and hidden neurons are selected as 1–2 and 5–10, respectively, to give the best output. Studies in the literature have shown that the momentum factor should be less than one in order to stabilize the back propagation. Therefore, a constant momentum coefficient value of 0.9 and various learning rate values (0.1, 0.5 and 0.9) are used for the network model. In order to determine the optimum neural network performance, trial and error method is used by changing one factor at a time (Frost, 2017a). Some combinations of this experimental work on predicting REBA values are summarized in Table 5.

In this study, different network models designed to find the optimum value are run and MSE, MAPE, RMSE and validation values are computed for each model. Considering an unused dataset is an important principle when generalizing a network model (Frost, 2017a). The network is created by the MLP with the training function of "traingdx" and the learning function of "traingdm". With these functions, learning rates, weight and bias values can be changed.

Different ANNs models are designed with predefined input and output values. Also, they are designed using combinations of different values of parameters, which are hidden layer, hidden neuron, learning rate, momentum rate and activation function. Each model is run at least 10 times and the value with the lowest error is taken into account. To measure the model performance, MSE, MAPE and RMSE are used. A brief comparison of different ANNs models is designed here and, their MSE, MAPE, RMSE and Validation values can be seen in Table 6.

Table 5
The proposed neural network model definition.

Architecture	• Multi-layer perceptron neural networks (MLP) • Input neurons: 3 • Output neuron: 1 • Training function: GDX • Hidden layers 1 or 2 • Hidden neurons: 5 or 10 • Activation functions: purelin or tansig or logsig functions in hidden and output layers • Learning rates: 0.1 or 0.5 or 0.9 • Momentum rate: 0.9
Computation	• Training: Backpropagation rule • Training termination: Stop training when reaches a specified number of epochs or 0.01 error tolerance

Model #10 is selected as the best model because it has the lowest MSE value. The ANNs structure of Model #10 is shown in Fig. 7. This structure has 3 inputs, 1 output and one hidden layer containing 5 neurons. The hidden layer activation function is "purelin", the output layer activation function is "purelin", the learning coefficient equals to 0.9 and the momentum ratio equals to 0.9.

80% of the dataset is used for training and 20% for testing, here. Training is continued till the error tolerance reaches to a specified number of epochs or 0.01. Fig. 8 shows the coefficient of correlation (R) graph for training, validation, test and overall targets data. The coefficient of correlation is used to measure the correlation between actual output and predicted output and show the direction and strength of the linear relationship between these values. For this reason, if R-value is high enough, the constructed ANNs model is considered to be good (Detienne et al., 2003). In Fig. 8, it can be seen that R-values are 0.972, 0.983, 0.974 and 0.973 for training, validation, test and overall

Table 6
ANNs models with combinations of different parameter values.

#	Hidden Layer	Learning Rate	# of Hidden Neurons		Activation Function			MSE	MAPE	RMSE	Val. (%)
			HN-1	HN-2	HL-1 AF	HL-2 AF	Output Layer AF				
1	1	0.1	10	-	purelin	-	purelin	0.1433	0.0260	0.3785	97
2	1	0.1	10	-	purelin	-	tansig	1.1815	0.9165	1.0869	47
3	1	0.1	10	-	tansig	-	logsig	1.1815	0.9165	1.0869	40
4	1	0.5	5	-	purelin	-	purelin	0.1411	0.2570	0.3756	97
5	1	0.5	5	-	tansig	-	logsig	1.1839	0.9165	1.0880	36
6	1	0.5	10	-	purelin	-	purelin	0.1834	0.0288	0.4282	97
7	1	0.9	10	-	tansig	-	tansig	1.1185	0.9165	1.0575	32
8	1	0.9	10	-	purelin	-	purelin	0.1514	0.0269	0.3891	97
9	1	0.9	10	-	purelin	-	tansig	1.1985	0.9165	1.0947	58
10	**1**	**0.9**	**5**	**-**	**purelin**	**-**	**purelin**	**0.1410**	**0.0256**	**0.3754**	**98**
11	2	0.1	5	5	purelin	purelin	purelin	0.6681	0.0517	0.8173	96
12	2	0.1	5	10	purelin	purelin	purelin	0.1471	0.0263	0.3835	97
13	2	0.1	5	10	purelin	logsig	tansig	1.1886	0.9165	1.0902	20
14	2	0.1	10	10	purelin	purelin	purelin	0.1571	0.0257	0.3963	97
15	2	0.1	10	10	purelin	logsig	tansig	1.190	0.9165	1,0908	49
16	2	0.5	5	5	purelin	purelin	purelin	0.3211	0.0367	0.5667	96
17	2	0.5	5	10	purelin	purelin	purelin	0.1529	0.0266	0.3910	97
18	2	0.5	5	10	logsig	logsig	logsig	1.1901	0.9160	1.0909	28
19	2	0.5	10	10	purelin	purelin	purelin	0.1809	0.0286	0.4253	97
20	2	0.9	5	5	purelin	purelin	purelin	0.163	0.0276	0.4037	97
21	2	0.9	5	5	logsig	logsig	logsig	1.1835	0.9190	1.0878	35
22	2	0.9	5	10	purelin	purelin	purelin	0.1691	0.0278	0.4112	97
23	2	0.9	10	10	purelin	purelin	purelin	0.1439	0.0260	0.3793	97

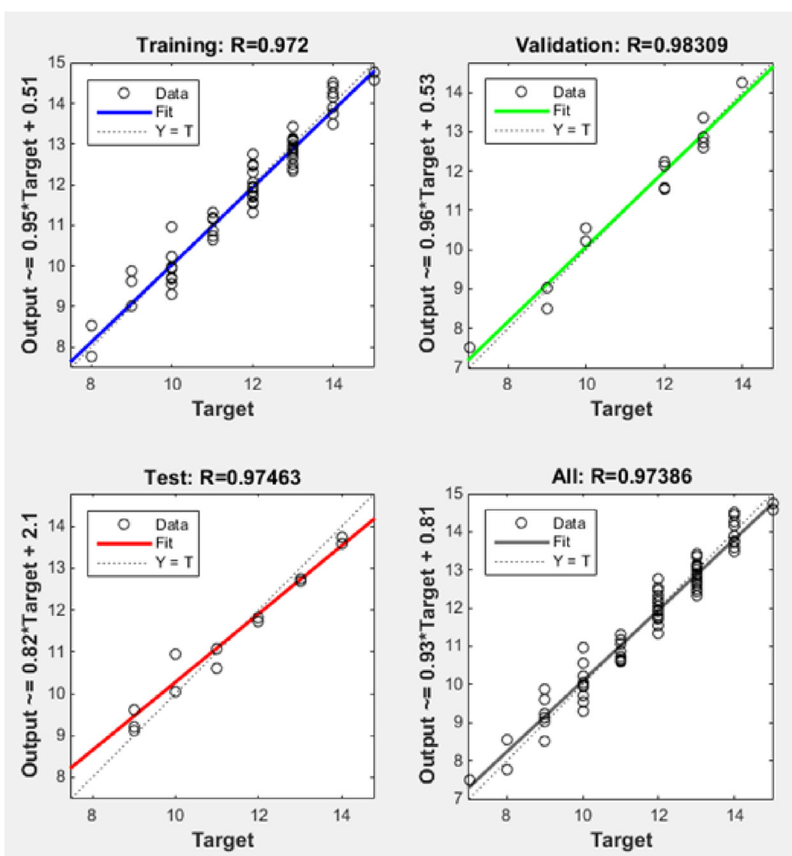

Fig. 8. The coefficient of correlation values for Model#10.

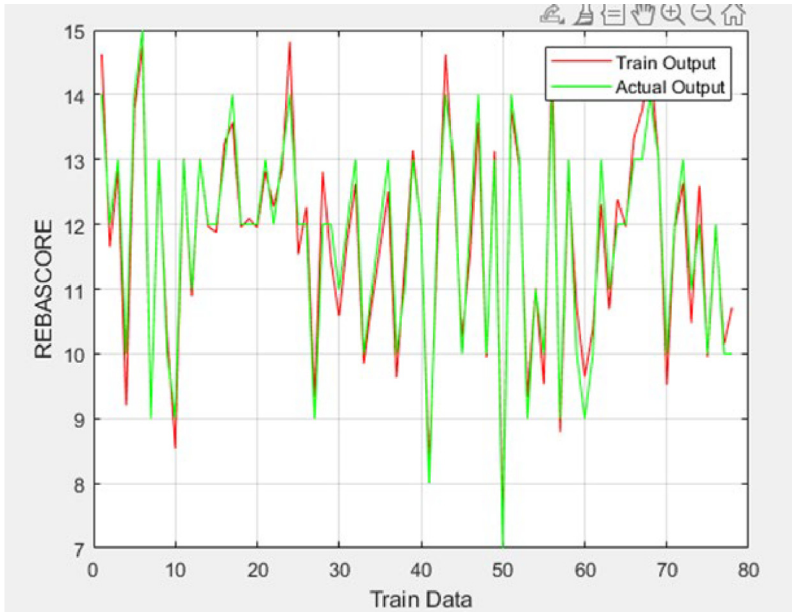

Fig. 9. The MLP fitness chart for the train data.

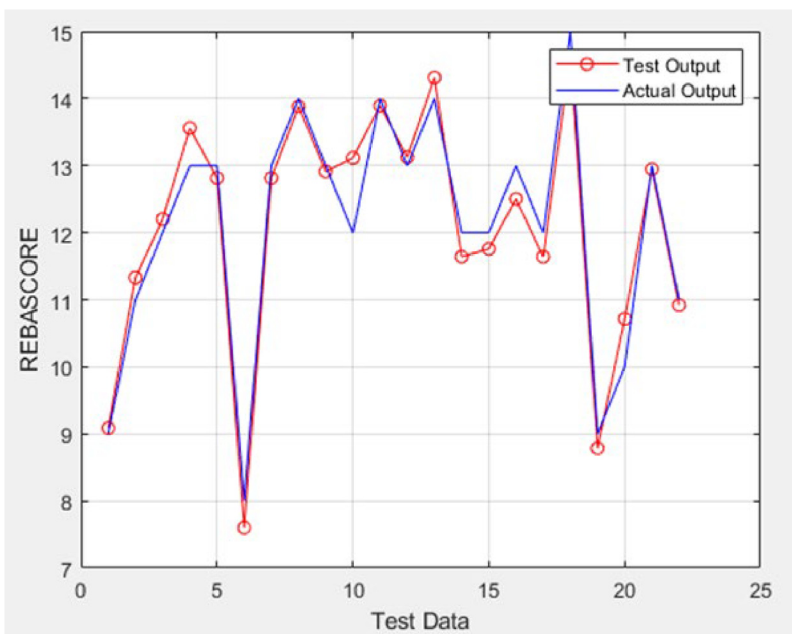

Fig. 10. The MLP fitness chart for the test data.

targets data, respectively (Lee, 1997). The estimated values represent the real values very well as seen in Fig. 8.

The fitness charts for the actual and predicted data are shown in Figs. 9 and 10, respectively. The graphs show the relationship between outputs.

Fig. 9 shows the estimation values for the training data. Actual outputs and estimated outputs are shown in green and red, respectively. It is seen that these two output graphs are very close to each other and even overlap some points. Good prediction results mean that the learning of the network with the training data will be better. Then the test data is estimated with the trained network and the result can be seen in Fig. 10.

In Fig. 11, the test outputs and the actual outputs are shown in red and blue, respectively. The graph shows that the data are very close to each other. In this case, it can be said that the established ANNs model is well trained and makes good predictions.

4.2. The Neuro-Fuzzy based REBA model

In this study, Neuro Fuzzy integration ANFIS method is used. The scores used in the classical REBA are expressed as Triangle fuzzy number, Trapezoidal fuzzy number and Gaussian fuzzy number. The fuzzy operations that deal with two different calculation methodologies are performed, and the ergonomic risk score of the job is determined by using the Fuzzy REBA tables obtained by Detienne et al. (2003). A Score, B Score and Activity Score input variables are considered as fuzzy numbers to create REBA Score values. The Triangle, Trapezoid and Gaussian fuzzy forms of the scores used in classical REBA are given in Table 7.

Table 7
Fuzzy scores and their associated fuzzy numbers.

FN	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{6}$
Triangle MF	(1,1,2)	(1,2,3)	(2,3,4)	(3,4,5)	(4,5,6)	(5,6,7)
Trapezoid MF	(0,0,1,2)	(0,1,2,3)	(1,2,3,4)	(2,3,4,5)	(3,4,5,6)	(4,5,6,7)
Gaussian MF	(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
FN	$\tilde{7}$	$\tilde{8}$	$\tilde{9}$	$\widetilde{10}$	$\widetilde{11}$	$\widetilde{12}$
Triangle MF	(6,7,8)	(7,8,9)	(8,9,10)	(9,10,11)	(10,11,12)	(11,12,12)
Trapezoid MF	(5,6,7,8)	(6,7,8,9)	(7,8,9,10)	(8,9,10,11)	(9,10,11,12)	(10,11,12,12)
Gaussian MF	(1,7)	(1,8)	(1,9)	(1,10)	(1,11)	(1,12)

Table 8
The results of the sensitivity analysis.

#	Input MF Type	Output MF Type	Optimization Method	Train error	Test Error
1	Trampmf	Linear	hybrid	2.65e-06	0.3359
2	Trampmf	Linear	backpropa.	0.0114	0.3365
3	Trampmf	Constant	hybrid	2.65e-06	0.3359
4	Trampmf	Constant	backpropa	0.7613	0.8117
5	**Trimf**	**Linear**	**hybrid**	**4.13e-07**	**0.3363**
6	Trimf	Linear	backpropa.	0.0096	0.3387
7	Trimf	Constant	hybrid	1.42e-06	0.3365
8	Trimf	Constant	backpropa.	0.7671	0.8161
9	Gaussmf	Linear	hybrid	4.22e-07	0.3386
10	Gaussmf	Linear	backpropa.	0.0109	0.3372
11	Gaussmf	Constant	hybrid	1.31e-06	0.3175
12	Gaussmf	Constant	backpropa.	0.0075	0.3170

The graphical membership functions of each fuzzy scores are shown in Fig. 11. Fuzzy Logic Designer Apps of the MATLAB R2021b is used for Fuzzy REBA calculations. Data set values with 3 inputs and 1 output are normalized with *x/max(x)*. The "wtaver" method is used for defuzzification in the ANFIS system containing 432 rules. Some rules are shown below.

(1) If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf1)

(2) If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out1mf2)

(3) If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf3) then (output is out1mf3)

A sensitivity analysis is carried out by changing the parameters in order to determine the configuration with the lowest error. Table 8 shows the result of the sensitivity analysis for the linear and constant membership functions. The parameters are changed during the analysis including input MF type (trampmf, trimf and gaussmf), output MF type and Optimization type (hybrid and backpropagation). In total, 12 cases are developed and for each case the train and test errors are calculated. The most accurate configuration consists of triangle and gaussian membership functions. Among them, the model that gives the best results is triangle input, linear output and hybrid optimization method with the train error of 4.13e−07 and test error of 0.3363.

5. Results and discussion

In this section, the results of the established ANNs models (MLP, RBF and GRNN) and ANFIS models (trampmf, trimf and gaussmf) are compared. The GRNN model, that gives the best results among the ANNs models, is trained by the learning algorithm of "GDX". The model structure has a two-layer network with 3 inputs and 1 output. The transfer function of the first layer is the "radial basis" and weights to inputs with the help of a spread rate of 0.6. The transfer function of the second layer is "purelin". The learning rate equals to 0.5 and the momentum ratio equals to 0.9. The best result among the neuro-fuzzy models is given by "trimf ANFIS model" with triangular membership function.

Table 9
Comparison of neural network and neuro-fuzzy models.

Type	MSE	MAPE	RMSE
MLP	0.1410	0.0256	0.3754
RBF	0.1340	0.0801	0.3660
GRNN	**0.0163**	0.0247	0.1276
Triangle MF	**0.0054**	0.0011	0.0735
Trapezoid MF	0.4392	0.0117	0.6627
Gaussian MF	0.7113	0.0105	0.8433

The MSE, MAPE and RMSE values obtained from all model types are given in Table 9.

According to the results in Table 9, the lowest MSE value between ANNs models belongs to GRNN with 0.0163. Although there is not a big difference between GRNN and MLP, it is seen as GRNN is a more suitable method for the dataset we have. The reason is that, GRNN Train error is very low (0.0016) compared to the other methods. It can be seen in Fig. 12 that the overlap ratio with the real data in the train part is very well.

The lowest MSE value between ANFIS belongs to Triangle membership function with 0.0054. It can be said that, triangle membership function is a more suitable method for the dataset we have. It can be seen in Fig. 13 that the overlap ratio with the real data in the train part is very well compared to others.

If we compare the ANNs and ANFIS error results, triangular MF ANFIS model obtains the best results for all error types. This shows that in REBA score calculation, fuzzy logic predictions are more suitable for real calculations and more realistic results can be obtained with fuzzy logic.

In order to better see the difference between these three methods, the five real employee data given in Table 3 are estimated with MLP, GRNN, RBF and the ANFIS models with different MFs, and the results are presented in Table 10. For example, an employee's body angles to be used in estimating REBA output are trunk (45′), neck (32′), leg (45′), upper arm (90′), lower arm (180′), and wrist (18′). In addition to this, the employee who has 2 activity points has a REBA score of 11

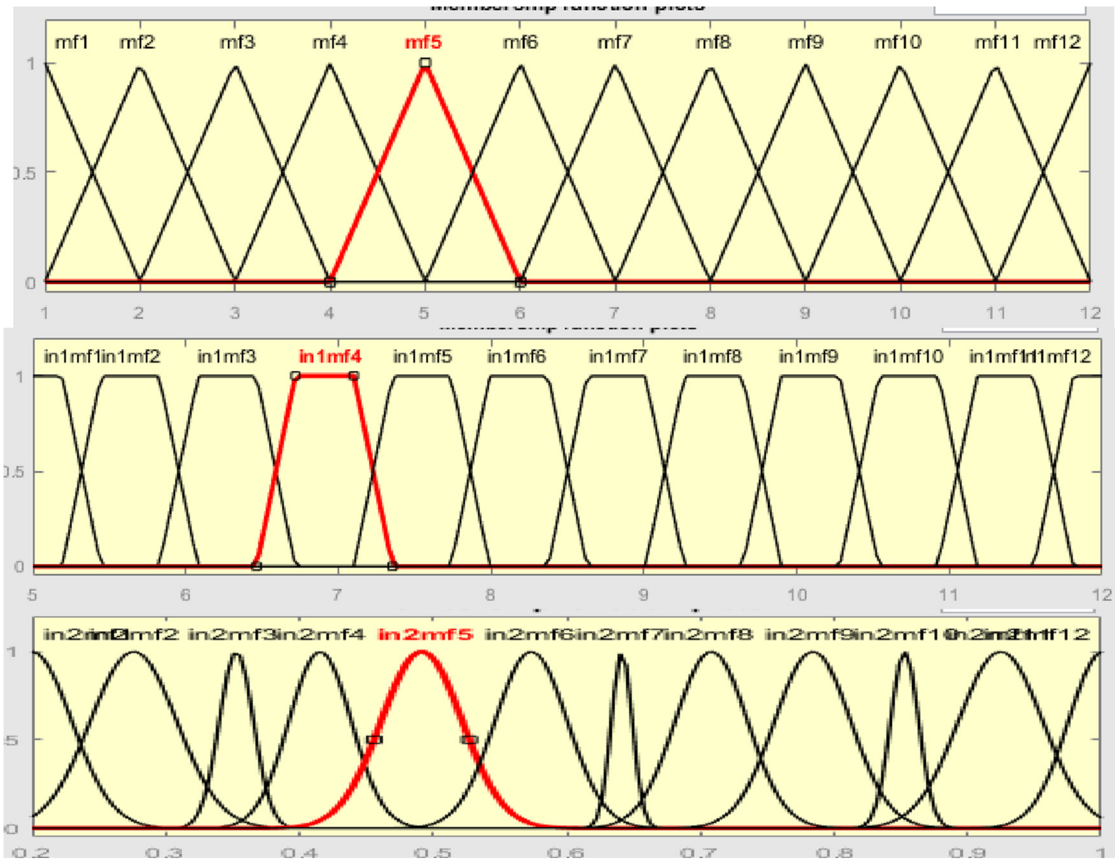

Fig. 11. Membership functions representing triangle, trapezoid and gaussian fuzzy scores, respectively.

Table 10
Actual REBA score and the predicted values with neural networks and neuro-fuzzy models.

	REBA score	Predicted score					
		MLP	GRNN	RBF	Triangle MF	Trapezoid MF	Gaussian MF
E1	10	9.7888	**10**	10.001	**10**	9.999	9.999
E2	9	10.8043	**9**	9	**9**	8.999	8.999
E3	12	10.8569	**12**	11.999	**12**	11.999	11.999
E4	11	9.6323	**11**	11.1273	**11**	10.999	10.999
E5	12	9.8400	**12**	11.8727	**12**	10.999	10.999

considering traditional REBA tables. He/she can be classified as in the high-risk group.

These predicted REBA scores show that the employee is in the high-risk group. It is seen that, the predicted score with GRNN model is closer to the actual value compared to the one predicted with MLP and RBF model. GRNN handles the data with a single-pass neural network which uses Gaussian activation hidden layer function. Therefore, GRNN makes more precise predictions on linear datasets. Since our dataset has linear features, the scores predicted with RBF are equal to the actual REBA Scores (Can et al., 2015).

On the other hand, the solution time is shorter in GRNN than other methods for a dataset of 100 units. The computational complexity is the amount of resources required to run it. Particular focus is given to computation time and memory storage requirements https://www.mathworks.com/matlabcentral/answers/108121-how-to-calculate-the-computational-complexity. Therefore, the short duration of the analyses is an important decision method. Elapsed time for MLP is 3.528 s, for GRNN is 2.249 s, for RBF is 2.537 s, for Triangle MF 2.356 s, for Trapezoid MF 3.462 s and for Gaussian MF 3.381 s. As the size of the problem increases, time becomes an important factor for the researcher. For this reason, by comparing prediction errors and time, the researcher will be able to decide which method to apply.

At the same time, the ANFIS model with a triangular membership function is also closer to the actual value compared to the other predicted MFs. Although the GRNN and triangular MF ANFIS prediction scores are the same, the errors of triangular MF ANFIS are found to be smaller because of the fuzzy logic is providing a more appropriate modeling here. It is seen that the ANFIS model is better in performance comparison.

6. Conclusions and future directions

In recent years, there has been an increasing interest in automating ergonomic evaluations using artificial intelligence techniques such as ANNs. ANNs-based REBA is a modified version of the REBA method that uses ANNs to predict REBA scores automatically. However, like any other artificial intelligence-based technique, ANNs-based REBA has certain limitations that need to be considered. This study is aimed to develop a framework in which ANNs and neuro-fuzzy models are integrated into REBA in order to determine the risk levels of the works in a faster and more consistent way. Thus, a structure that predicts a more realistic risk score is established depending on the observed body angles and movement characteristics.

One of the limitations of the proposed method is the quality and quantity of input data. The accuracy of the predictions depends on

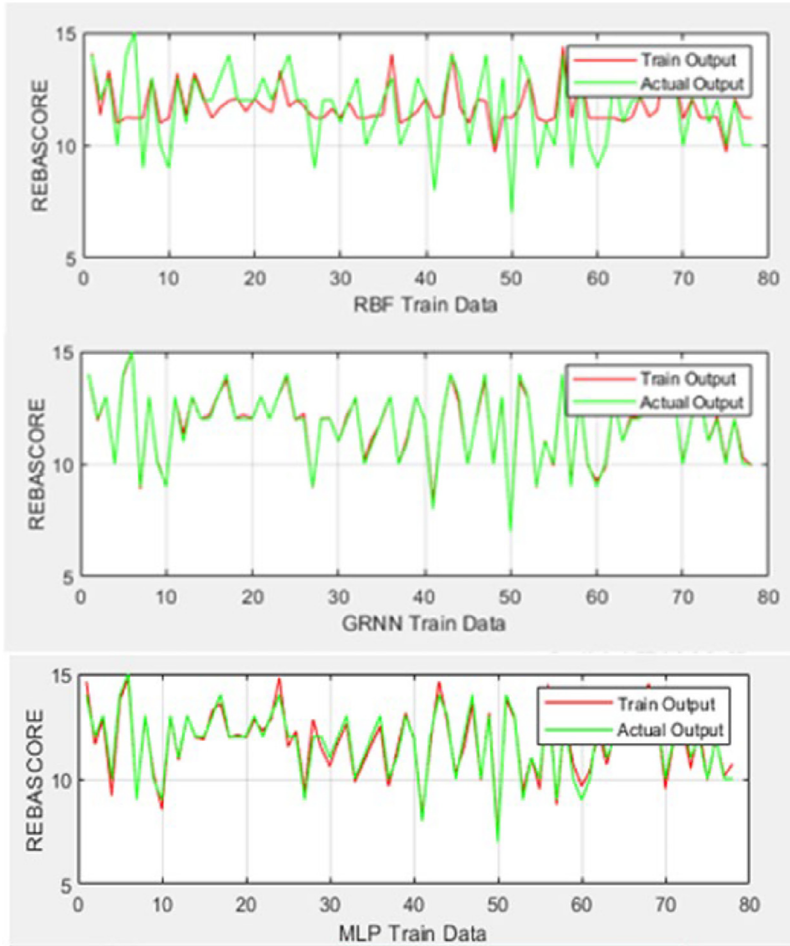

Fig. 12. The fitness charts of train data for RBF, GRNN and MLP.

the availability of complete and accurate input data. It is not possible to observe all employees individually for the case study due to the Covid-19 pandemic. To improve the accuracy of the predictions, it is crucial to ensure the input data is complete and accurate. Another limitation of the proposed method is its limited applicability. The method has been trained on a specific set of tasks and populations, and may not be suitable for evaluating tasks and populations that differ from those used in training the algorithm. This can limit the usefulness of the method in certain settings. To make the proposed method more applicable to different tasks and populations, it is necessary to expand the training data. This can be achieved by collecting data from a wider range of tasks and populations, including individuals with different physical characteristics and abilities. The expanded training data will improve the accuracy of the predictions for a broader range of tasks and populations.

Another limitation of the proposed method is its lack of consideration for individual differences. The method does not account for individual characteristics such as age, gender, and physical ability, which can result in inaccurate predictions for individuals who fall outside the average range of the population used to train the algorithm. Finally, the proposed method can be costly. It requires specialized software and hardware, which can be expensive for smaller organizations with limited resources. To reduce the cost of the method, it is essential to develop more affordable software and hardware solutions. This can be achieved by using open-source software and cloud-based solutions, which can reduce the cost of hardware and licensing fees.

To our knowledge, this is the first study in the literature to present a risk score calculation methodology by integrating neural networks and neuro-fuzzy models with REBA method. In addition, it presents a comparative analysis with MLP, GRNN, RBF neural network methods and three different membership functions of ANFIS. In this respect, it offers a new perspective in terms of handling the ergonomic risks of the works with artificial intelligence techniques in future studies. The proposed method will form the basis for the study of more advanced ANNs techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to predict REBA scores based on input data from motion capture sensors or video recordings. Additionally, in terms of a real-world application, this methodology has shown great potential in automating the assessment process and reducing the risk of musculoskeletal disorders in both service and manufacturing businesses, allowing a quick and practical estimation. With the motivation of this study, the proposed ANNs and neuro-fuzzy integrated REBA methodology can be considered as a successful decision support tool to identify the ergonomic risks of the works and get quick feedbacks to decision makers for non-ergonomic situations. As a future direction, fuzzy logic approach can be included as a comparative and multi-dimensional study. The methodology proposed here can be applied by revising the parameters for different ergonomic risk assessment methods such as RULA or OWAS. At the same time, different data sets can be obtained by making observations for the REBA method. These datasets can be analyzed and compared to the methods in this study.

Alternatively, for future research the biomechanical equations can be incorporated into the proposed methodology in the laboratory environment after the pandemic restrictions have ended. The proposed method can also be adapted for employees in other work areas (for manufacturing workers, cargo personnel, etc.), where REBA-based risk assessment can be performed, due to its generalizability.

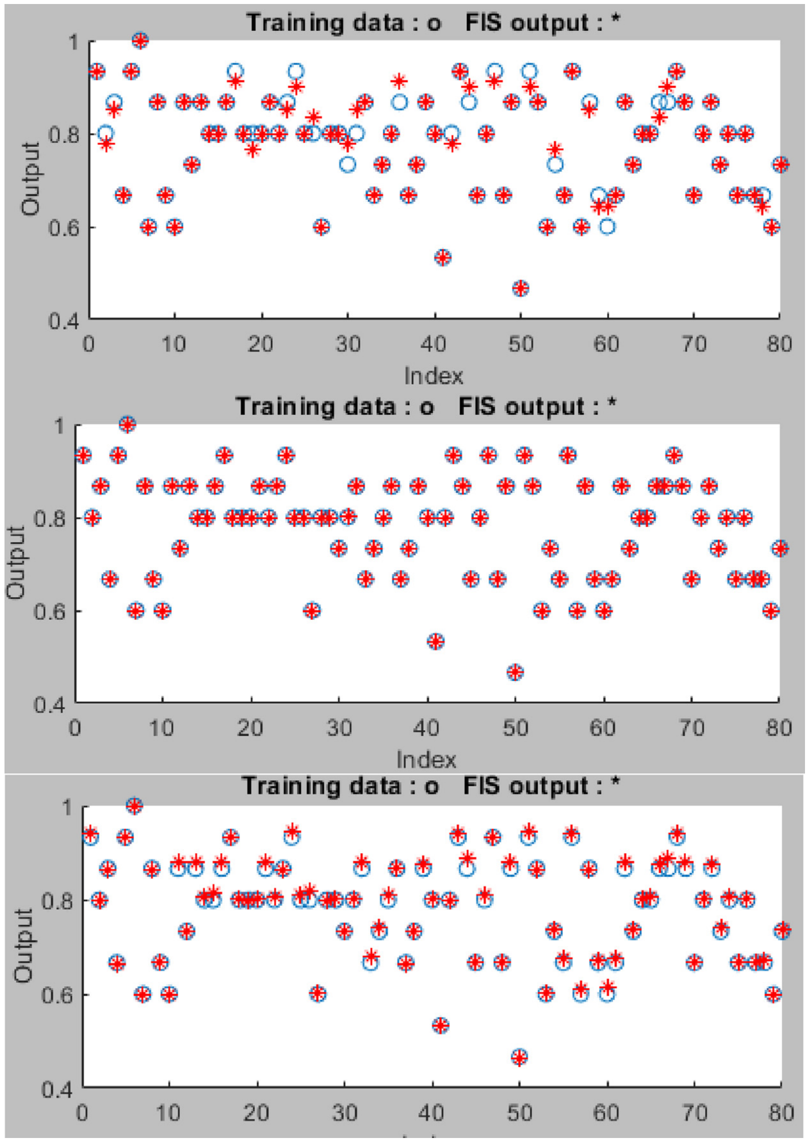

Fig. 13. The fitness charts of train data for trampmf, trimf and gaussmf ANFIS, respectively.

CRediT authorship contribution statement

Bahar Yalcin Kavus: Writing – original draft, Validation, Formal analysis. **Pelin Gulum Tas:** Writing – original draft, Investigation, Methodology. **Alev Taskin:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Funding

No funding was received to assist with the preparation of this manuscript.

Code availability: It can be shared on demand

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