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Reviewing Current Trends: Machine Learning for Risk Assessments of Occupational Exoskeletons †

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Abstract: With the increase in musculoskeletal injuries caused by poor posture and excessive physical exertion at work, assistive wearable solutions such as occupational exoskeletons have been developed. These exoskeletons are paired with advanced wearable sensors that monitor physical exertion and provide real-time data on muscle activity and movement trajectory. In recent years, there has been a significant increase in efforts to create innovative tools that incorporate machine learning (ML) systems and sensor technologies into the risk assessment prediction of exoskeletons. The objective of this mini-literature review is to present a comprehensive outline of sensor-integrated ML models in risk assessors of occupational exoskeletons.

Keywords: occupation exoskeletons; machine learning; risk assessment; review

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1. Introduction

Today, many work environments are becoming more and more complex, forcing many humans around the world working in factories and other physically demanding work environments to put a lot of physical duress on their bodies. This physical stress can lead to a range of musculoskeletal disorders and further worsen one's mental state [1].

In order to decrease a human's risk in a work setting many tailored solutions are innovated. One solution currently being implemented are industrial exoskeletons which have proven to be very successful in decreasing cognitive stress and musculoskeletal disorders. Exoskeletons are wearable devices designed to support and improve the physical abilities of workers [2]. Research on exoskeletons has promoted many solutions for applications particularly in the military and healthcare sectors. For instance, the Wilmington Robotic Exoskeleton displayed in Figure 1 (WREX) is a passive orthosis with two segments and four degrees of freedom (DOF), designed to be mounted on a wheelchair [9]. The WREX uses elastic elements to counteract gravity. Another useful exoskeleton is The Hybrid Assistive Limb (HAL), developed by the University of Tsukuba and Cyberdyne [9]. This exoskeleton is an active exoskeleton that improves physical functions by detecting bioelectric signals and translating the signals into actuator movements. HAL has been commercialized in many European countries for treating lower-limb paralysis. A third example is the ARMin III, which is an arm therapy exoskeleton with four degrees of freedom, and it has been designed to help many stroke patients with their rehabilitation process [9].

Furthermore, exoskeletons reduce the physical strain associated with heavy lifting, awkward postures, and repetitive tasks [2]. Industrial exoskeletons can be classified into two specific groups: active and passive. Active exoskeletons are generally more expensive, consist of electrical components, and help extensively in dynamic situations [5]. On the other hand, passive exoskeletons do not require a power source; instead, they relieve human movement and assist the user with elastic materials such as springs [5].

Figure 1. Examples of exoskeletons for various functions: (1) Passive arm exoskeleton WREX, (2) HAL from Cyberdyne, Japan, (3) ARMin III rehabilitation arm, (4) ActiveLinks Powerloader Ninja exoskeleton suit, (5) NaTUre-gaits, and (6) E-leg exoskeleton from Ekso Bionics.

While passive exoskeletons are used prominently today due to their simplicity and cost, active exoskeletons are still in the nascent stages of development and face challenges such as high cost, complexity for the user, and the need for regular electrical maintenance. Despite these limitations, active exoskeletons have greater scope for enhancing human capabilities in industrial applications. Overall, there are a wide range of exoskeletons that can be chosen based on the task that is required to be carried out [3].

Many exoskeleton systems use sensors and artificial intelligence systems to understand the user's complete response upon using the assistive device. Given the recent advancements in machine learning systems, several research studies in human-exoskeleton interaction are also exploring the use and development of machine learning algorithms and systems that can predict the response of a user to a certain exoskeleton based on various data and existing responses. This mini-literature review aims to provide a summary on the existing implementation of machine learning systems aiding the user training in exoskeleton research and risk assessments of industrial exoskeletons, giving an overview of the benefits and disadvantages.

2. Method

In the past, implementing a Machine Learning System into existing exoskeleton technology and risk assessment has shown promising results. Existing systems have enhanced effectiveness and safety by predicting a risk assessment for numerous lifting tasks [6]. Specifically, in this section of the report, some vital publications have been analyzed, highlighting existing problems in their machine learning system and giving an overview of why a more effective machine learning system is necessary for industrial exoskeletons. There is a clear lack of existing research done on risk assessment for industrial operations. However, these five studies have specifically been analyzed due to the integration of sensors and data processing of sensors with the machine learning models. Every machine learning model requires data to make predictions and assess risk, but there is a significant lack of papers that expand upon both the sensor's data processing and integrating this data for risk prediction algorithms. These studies have been analyzed to understand the integration of machine learning models with sensor data.

3. Literature Review

3.1.1. Machine Learning for Detection and Risk Assessment of Lifting Action [6]

The Machine Learning for Detection and Risk Assessment of Lifting Action system implements data from embedded sensors in exoskeletons to predict muscle fatigue. This system primarily focuses on the Inertial Measurement Unit (IMU) data along with the NIOSH dataset to successfully output an accurate risk assessment for the user. NIOSH is The National Institute for Occupational Safety and Health (NIOSH) system [6]. It offers guidelines and tools to reduce danger for workers in the work environment. For exoskeleton recommendations, the NIOSH system has been beneficial as it provides proven methods and criteria that evaluates the effectiveness and safety of exoskeletons in the workplace. This specific machine learning system only focuses on lifting actions. Based on the data from the sensors and the dataset the system can give feedback to prevent overexertion by the human.

One significant limitation with this study is that the data comes only from two sources: the NIOSH dataset and IMU sensors. Instead, the risk assessor would be much more efficient if more measures were considered such as muscle activation patterns. Electromyography (EMG) measures the electrical activity produced by skeletal muscles and gives data on muscle activation and fatigue levels. In the context of exoskeletons, EMG sensors can be combined with a device to monitor the user's muscle signals, allowing the exoskeleton user to adjust the support dynamically based on the muscle activity. This improves the efficiency of the exoskeleton, further ensuring that it gives the correct amount of assistance to reduce strain and prevent injury [6]. To further improve, the system can take data regarding the type of action, duration of physical activity, and breaks being taken as more measures would be considered [3]. Implementing a transfer learning machine learning method would achieve this aim of training the system with a wider range of data and merging multiple datasets. Similarly, two other studies have also proposed different systems in different applications to decrease the risk of musculoskeletal disorders.

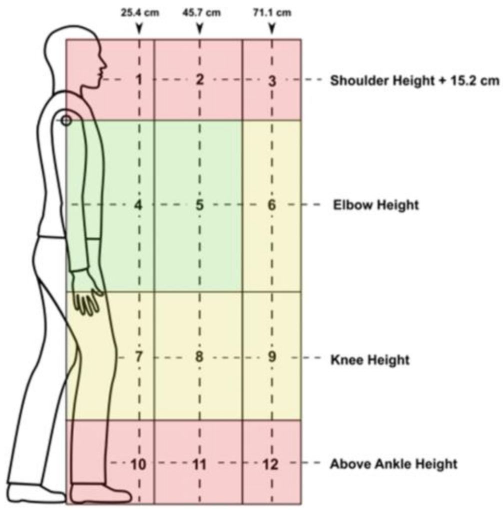

Figure 2. Lifting zones defined by ACGIH Lifting TLV. Green zones (4–5) are considered Low Risk, yellow zones (6–9) are Medium Risk, and red zones (1–3, 10–12) are High Risk. Intersections of dashed lines indicate where in the zone the object is lifted from. (Source: NIOSH).

3.1.2. The Risk Classification of Ergonomic Musculoskeletal Disorders in Work-Related Repetitive Manual Handling Operations with Deep Learning Approaches [7]

The past machine learning system was able to predict risk assessment for only lifting tasks based upon one dataset and sensor output data. This study written by Chan [7] merges multiple datasets to provide an accurate risk assessment for manual handling operations. In this case, a deep learning algorithm has been constructed to receive inputs of position of lifting, posture, number of working hours, total distance worked, and more. All this data is extracted from the Central Florida dataset which is filled with action videos of existing workers carrying out manual operations [7]. Then, this system uses data augmentation on the existing action video dataset. Data augmentation is a deep learning approach which eliminates a lack of resources for training as it makes many copies of existing data for the machine learning system to be trained with. This system extracts historical data from the video and combines this existing information with sensor data [7]. By achieving this, the machine learning system is trained with logistical regression to identify patterns and potential dangers within a given scenario, resulting in the valuable feedback that helps build more effective exoskeletons. However, the issue with this model is the drawback of Data Augmentation and lack of video data sets. By using Data Augmentation only replicates of existing data are made, so the system is trained to a lesser accuracy than it would be with more raw video data. To further improve this system, transfer learning should be implemented where different and unique datasets should be combined with the system's existing ones.

3.1.3. A Machine Learning System for Classification of EMG Signals to Assist Exoskeleton Performance [8]

This study has implemented a machine learning system for signal classification for exoskeleton control and has focused on developing algorithms that can predict muscle activity and help with controlling orthotic devices [8]. The flowchart of the presented study is displayed in figure three below. Orthotic devices have been used extensively in the medical industry as a support to correct the function of moving body parts. This study's main aim is to create a system which converts complex neuromuscular signals into commands for exoskeletons. This system would help greatly in applications such as rehabilitation of injuries and improve productivity of humans.

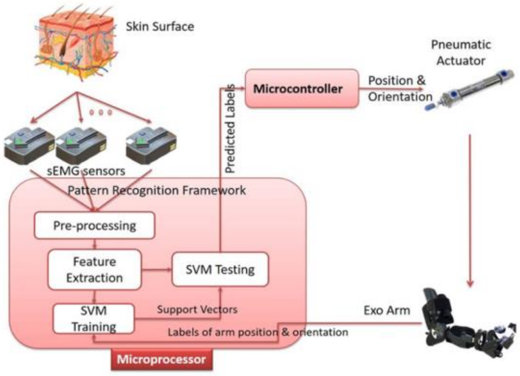

Figure 3. Flowchart of the machine learning enhanced exoskeleton system. The flowchart utilizes variety of techniques with the emg sensors.

The machine learning focus of this study is around feature extraction, classification accuracy. The authors of this paper aimed to identify which features of EMG signals are relevant for the classification, how to pre-process and convert the signals effectively, and which machine learning model would obtain the highest accuracy in classifying different hand gestures or movements. The main advantage for this system is the high classification accuracy [8]. The use of a multiclass support vector machine classifier with a kernel is highly accurate. The support vector machine classifier is an existing machine learning algorithm which is used to solve regression, classification tasks, and group the data into two groups.

One limitation of the proposed system is the use of the ML model to new subjects and different conditions not covered in the training data. Specifically, this study doesn't use a large database for the machine learning model to predict based on.

One way to improve this system would be to focus on developing a more adaptive and personalized ML system that can learn from the user's EMG patterns over a time. The system can potentially use transfer learning to adapt a pre-trained model to the specific characteristics of individual users. For example, the pre-trained model provided by reference number [7] can be used in the transfer learning. This is because the model suggested in reference [7] already includes the core component of data augmentation. This approach will improve the system's prediction on the variability that EMG sensor signals have across different users and conditions.

3.1.4. AI-Based Methodologies for Exoskeleton-Assisted Rehabilitation of the Lower Limb: A Review [10]

This study is an existing literature review which gives an analysis of the use of Artificial Intelligence (AI) methodologies in exoskeleton-assisted lower-limb rehabilitation. The authors researched 31 papers that implemented AI algorithms for exoskeleton-assisted rehabilitation [10]. These papers were categorized based on the AI methodologies, which include Reinforcement Learning (RL), Support Vector Machine (SVM), and Neural Networks (NN).

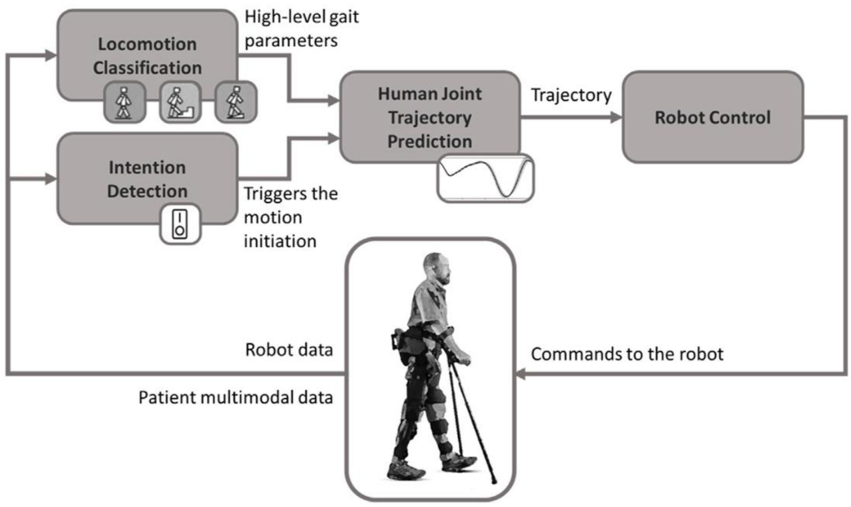

Figure 3. Flowchart of the machine learning enhanced exoskeleton system. The flowchart includes the data driven to predict within the algorithm.

Reinforcement Learning (RL) has been used for robot control tasks. It is a type of machine learning where the existing algorithm learns to make decisions by performing actions and receiving rewards or penalties based on if the prediction is correct. It is used to train systems to perform tasks or achieve goals in specific environments. The Reinforcement Learning algorithm's advantage is its ability to learn from interactions and optimize the decision-making processes [10]. Furthermore, this makes it suitable for adapting to human intentions, data, and commands in real-time.

According to this study, Support Vector Machine (SVM) is more effective in handling non-linear classification tasks. Since handling non-linear classification is when the algorithm directly predicts between two outcomes, the SVM method has been widely used in gait analysis and intention detection. SVM has a high accuracy in binary classification and this makes it an optimum choice for real-time classification of human intentions from sensor data [10].

Another Artificial Intelligence method that can be implemented in rehabilitation robotics is Neural Networks (NN). Neural Networks are efficient at observing complex patterns and have been extensively used in human joints trajectory prediction (HJTP) in the past. The main advantage of NNs is that they can learn from large datasets and model human joint movements over time, later giving accurate predictions of where the future joint positions would be [10]. This method's unique attribute is crucial for exoskeletons to adapt to human movements and with its implementation can ensure safer and more efficient human-robot combination. The existing use of NNs in HJTP research is huge but expanding NNs to exoskeleton risk assessors can increase overall accuracy by predicting future positions of joints in movement.

Overall, this review expands upon the numerous Artificial Intelligence methods that can be combined to form an optimum risk assessor for exoskeleton usage. When partaking in dangerous actions, humans require validation of safety. Many of the existing solutions are either confined to simulation environments or validated only on healthy individuals. This gap is highlighted in this study and promotes the importance of creating a solution that would be useful for individuals to use around the world. This review paper emphasizes the need for further research, in the areas of implementing AI for exoskeletons and the development of publicly available datasets to improve research progress and train AI models to greater accuracy.

3.1.5. Machine Learning Techniques for Motion Analysis of Fatigue from Manual Material Handling Operations Using 3D Motion Capture Data [11]

This study is different from the other four as it implements 3D motion capture data and biometric information collected from participants wearing a Hexoskin Shirt and reflective markers. The data is then preprocessed and split into training and testing sets to develop Machine Learning models. The researchers experimented with the setup of three different models: using data from all participants to create one prediction model, creating a prediction model for each specific participant, and developing personalized models and training the model based on each subject.

This study uses both supervised and unsupervised learning techniques. Supervised learning uses the Borg scale, a scale measuring intensity of an exercise, as the target value to predict fatigue. On the other hand the unsupervised learning algorithm focuses on joint angles after applying principal component analysis during preprocessing. Principal component analysis is a machine learning method that reduces the dimensionality of large data sets, by transforming a large set of data into a smaller one that still contains most of the information in the large set.

One of the drawbacks of this system is the optical motion capture systems for data capture. These are not practical for the real-world in the Manual Material Handling industry because of the space constraints and the complexity of data collection in the real world. The researchers in this study suggested future work involving inertial motion capture systems, which are more portable and better suited in the real-world scenario.

Another potential drawback is the use of recurrent neural networks, which have a short-term memory. This can lead to difficulties in carrying over previous observations for later subjects' accurate fatigue prediction. The study proposes to address this by considering Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, which are designed to handle time-series data for a longer time and more efficiently.

4. Summary and Findings

The five studies reviewed in this report review the use of machine learning systems to improve safety and efficiency in physical tasks and reduce risk, with a particular focus on the exoskeletons and manual handling operations industry. Study 1 [6] uses data from IMUs and the NIOSH dataset to predict muscle fatigue and assess risks during lifting actions. Study 2 [7] broadens this by merging multiple datasets and using deep learning to classify the risks in manual handling tasks. The study also highlights the limitations of data augmentation and recommends transfer learning for better accuracy [7], which is a technique that could also benefit Study 1 [6].

On the other hand, Study 3 [8] uses EMG signals and signal classification to improve hand orthotic device performance. It proposes a unique and personalized machine learning method which uses transfer learning from previously trained models to adapt to individual users' patterns faster than the model in study 1 and 2. This personalized approach could improve Study 1 and Study 2's risk assessments by accounting for user-specific data rather than just the generalized NIOSH dataset [6,7].

Study 4 is the most insightful as it reviews numerous AI methodologies for lower-limb exoskeleton-assisted rehabilitation rather than only one model [10]. The study also emphasizes the need for real-world validation and publicly available datasets. This recommendation applies across all the 5 studies as more data would improve model accuracy and ability to predict.

Study 5 is the one study that is quite different from the others as it examines the prediction of fatigue in manual material handling operations using 3D motion capture data and biometric information [11]. In the other studies, EMG signals and datasets were used to train the models for prediction. This study combines both supervised and unsupervised learning techniques rather than only using one to understand the better method for this study's scenario.

Although each study has different focuses and methodologies, the five studies have a common point regarding the importance of unique and extensive datasets, and the potential that transfer learning has to improve model accuracy [7]. The combination of the accurate data sources (as suggested in Study 1 and Study 5 [6,11]) such as the NIOSH with a transfer learning method (proposed in Studies 2 and 3 [7,8]), and the use of advanced AI methodologies like RL, SVM, and NN (reviewed in Study 4 [10]) could improve the effectiveness and accuracy of machine learning systems in predicting risks and improving the performance of exoskeletons and manual handling operations. These combined improvements would help create a safer work environment ultimately reducing the risk of musculoskeletal disorders and improving safety and efficiency in physical tasks.

5. Conclusion and Limitations

Although given the scope of this mini-review only five publications have been discussed, these studies support integrations of exoskeletons with advanced wearable sensors that monitor physical exertion and provide real-time data on muscle activity can be beneficial. The ML systems which work with the sensors data enhance the accuracy of the risk assessments. For example, in one of the studies electromyography (EMG) sensors have been used by the exoskeletons to measure muscle activation levels and muscle strain and fatigue during a lifting task. Paring the data provided by the EMG sensors with the ML model has shown to accurately predict risk [8]. Furthermore, the five studies analyzed in this paper establish that current systems show substantial benefits such as accurately predicting risk for a certain muscle group while carrying out a particular action. However, the studies have also expanded upon the significant limitation in the scope of these ML models because of a lack in experimented data. To compensate, many of the ML models have extensively used data augmentation which hinders the system's overall accuracy. The studies have suggested that integrating more sophisticated sensors with real-time insights can help reduce the reliance on data augmentation by providing real-world and immediate data [6–11].

Next, this section of the paper will discuss several notable limitations. Firsly, this analysis is confined to only five studies, which does not provide a comprehensive overview of the field of machine learning applications in exoskeleton technology and risk assessment. Future research must discuss the real-world applicability and validation of the machine learning models presented, as most studies were conducted in controlled environments or with limited datasets. Secondly, although this mini-review attempted to summarize findings based on potential application of ML for sensor based data that can aid exoskeleton technology, this review does not provide a comparative analysis of the performance metrics of different machine learning approaches across the studies. Future research must compare the efficacy of these systems and must also address the ethical implications and potential risks associated with the implementation of AI and machine learning in industrial safety contexts. However, given the summary and limitations of this work, there is a need for continued research and development in machine learning applications for sensor development to aid human-exoskeleton interaction evaluation, which can significantly contribute to reducing workplace injuries and enhancing worker performance.

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