Titre: Title:	WMSDsNet: A Sensor-Based Deep Learning Framework for Real-Time Ergonomic Risk Assessment in Human-Robot Collaborative Disassembly
Auteur: Author:	Marziyeh Mirzahosseininejad
Date:	2025
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Mirzahosseininejad, M. (2025). WMSDsNet: A Sensor-Based Deep Learning Framework for Real-Time Ergonomic Risk Assessment in Human-Robot Collaborative Disassembly [Master's thesis, Polytechnique Montréal]. PolyPublie. https://publications.polymtl.ca/70062/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/70062/
Directeurs de recherche: Advisors:	Samira Keivanpour, & Firdaous Sekkay
Programme: Program:	Maîtrise recherche en génie industriel

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

WMSDsNet: A Sensor-Based Deep Learning Framework for Real-Time Ergonomic Risk Assessment in Human-Robot Collaborative Disassembly

MARZIYEH MIRZAHOSSEININEJAD

Département de mathématiques et de génie industriel

Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

Génie industriel

Septembre 2025

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Ce mémoire intitulé :

WMSDsNet: A Sensor-Based Deep Learning Framework for Real-Time Ergonomic Risk Assessment in Human-Robot Collaborative Disassembly

présenté par **Marziyeh MIRZAHOSSEININEJAD**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

a été dûment accepté par le jury d'examen constitué de :

Camélia DADOUCHI présidente

Firdaous SEKKAY, membre et directrice de recherche

Samira KEIVANPOUR, membre et codirectrice de recherche

Abdelhak OULMANE, membre

DEDICATION

To all the courageous women of Iran, whose unwavering bravery and resistance in the face of oppression inspire the pursuit of freedom and justice.

To my husband, my little daughter, and my dear parents, your unconditional love, sacrifices, and steadfast support have carried me through every challenge. This journey has never been mine alone, but ours, a shared dream, realized together.

ACKNOWLEDGMENTS

This work would not have been possible without the invaluable guidance, support, and encouragement of many individuals. I would first like to express my deepest gratitude to Dr. Firdaous Sekkay, my supervisor, for her continuous mentorship, insightful feedback, and unwavering support throughout this research journey. Her academic rigor and constructive guidance have been instrumental in shaping the direction and quality of this thesis. I am equally grateful to Dr. Samira Keivanpour, my co-supervisor, for her exceptional encouragement, generous time, and valuable insights that helped strengthen the interdisciplinary dimensions of this work.

Special thanks are extended to Dr. Soumaya Yacout and her research group for providing access to laboratory resources and technical facilities that made the experimental setup possible. I also gratefully acknowledge the financial support received in part from the PIED program (Parrainage, Intégration, Émergence et Démarrage) at Polytechnique Montréal, which contributed to the successful completion of this research.

RÉSUMÉ

Les troubles musculosquelettiques liés au travail (TMS) demeurent l'une des principales causes de blessures professionnelles dans le monde, en particulier dans les environnements industriels où les tâches répétitives et les postures contraignantes sont fréquentes. Avec l'essor de la collaboration homme-robot (HRC) dans les processus de fabrication et de désassemblage, le besoin d'outils intelligents de surveillance ergonomique en temps réel, capables de s'adapter à des conditions de travail dynamiques et de soutenir des pratiques de travail durables, devient de plus en plus important.

Ce mémoire propose **WMSDsNet**, un cadre novateur d'évaluation des risques de TMS basé sur l'apprentissage profond, qui combine une architecture à double sortie avec des unités de mesure inertielle (IMU) portables pour l'application spécifique du désassemblage collaboratif homme-robot. Le système effectue simultanément la classification des sous-tâches physiques et des niveaux de risque ergonomique, avec un étiquetage basé sur deux méthodes d'évaluation de TMS: RULA (Rapid Upper Limb Assessment) et REBA (Rapid Entire Body Assessment). Le cadre comprend également une analyse comparative de six modèles d'apprentissage automatique, réseau de neurones convolutifs (CNN), réseau de neurones profonds (DNN), machine à vecteurs de support (SVM), K plus proches voisins (KNN), arbre de décision (DT) et forêt aléatoire (RF), afin de déterminer le modèle optimal pour ces deux tâches. Cette intégration assure une évaluation complète et validée, permettant une surveillance ergonomique précise et en temps réel dans des environnements industriels collaboratifs. Les données expérimentales ont été collectées dans un scénario de HRC en laboratoire, où un participant a exécuté une série de sous-tâches de désassemblage, telles que le dévissage, le tri des composants et la manipulation d'outils, tout en portant un ensemble de capteurs IMU.

Le modèle le plus performant (DNN) a atteint une précision macro-moyenne de 92 % pour la classification des sous-tâches et de 90 % pour la classification des risques ergonomiques. Une carte thermique a été utilisée pour identifier les relations posture-risque, mettant en évidence les tâches présentant un niveau plus élevé de sollicitation biomécanique. Les résultats démontrent que l'intégration de la technologie des capteurs portables avec des modèles d'apprentissage automatique permet des évaluations ergonomiques précises et en temps réel. Le cadre proposé, WMSDsNet, permet une identification précoce des situations à haut risque, offrant aux ingénieurs industriels un outil proactif pour la prévention des blessures et l'optimisation des flux de travail.

Ce travail contribue aux domaines de l'ergonomie professionnelle, de la fabrication intelligente et de l'Industrie 4.0, en présentant une solution évolutive, interprétable et adaptée à l'automatisation pour la gestion des risques ergonomiques dans les environnements collaboratifs homme-robot. Les travaux futurs porteront sur une validation multi-sujets et un déploiement en milieu industriel réel afin d'évaluer plus en profondeur la généralisabilité et l'intégration pratique du cadre proposé.

ABSTRACT

Work-related musculoskeletal disorders (WMSDs) remain a leading cause of workplace injuries worldwide, particularly in industrial environments where repetitive tasks and awkward postures are common. With the rise of human-robot collaboration (HRC) in manufacturing and disassembly, there is an increasing need for intelligent, real-time ergonomic monitoring systems that can adapt to dynamic working conditions and support sustainable labour practices. This thesis proposes WMSDsNet is a novel deep learning-based ergonomic risk assessment framework that combines a dual-output architecture with wearable inertial measurement units (IMUs) for the specific application of human-robot collaborative (HRC) disassembly. It performs simultaneous classification of physical subtasks and ergonomic risk levels, with risks labelled using two methods: RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment). The framework also includes a comparative analysis of six machine learning models, Convolutional Neural Network (CNN), Deep Neural Network (DNN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF), to determine the optimal model for both tasks. This integration ensures a comprehensive and validated assessment, supporting accurate, real-time ergonomic monitoring in collaborative industrial environments. Experimental data were collected from a laboratory-based HRC scenario in which a participant performed a series of disassembly subtasks, such as unscrewing, sorting components, and handling tools, while wearing a set of IMU sensors.

The best-performing model (DNN) achieved a macro-average accuracy of 92% for subtask classification and 90% for ergonomic risk classification. A heatmap visualization was used to identify posture-risk relationships, highlighting which tasks involved higher levels of biomechanical strain. The findings demonstrate that integrating wearable sensor technology with machine learning models can lead to accurate, real-time assessments of ergonomic conditions. The proposed WMSDsNet framework enables early identification of high-risk conditions, offering industrial engineers a proactive tool for injury prevention and workflow optimization. This work contributes to the fields of occupational ergonomics, smart manufacturing, and Industry 4.0 by presenting a scalable, interpretable, and automation-friendly solution for ergonomic risk management in human-robot collaborative settings. Future work will focus on multi-subject validation and real-world industrial deployment to further assess the framework’s generalizability and practical integration.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

1.1 Background and Context

The disassembly of end-of-life (EoL) products is a key enabler of sustainable manufacturing, contributing to the circular economy by facilitating component reuse, material recovery, and reducing landfill waste [1]. As industries adopt more circular strategies, disassembly is increasingly recognized as a critical stage for improving resource efficiency. Traditionally, disassembly operations have been performed manually, requiring workers to carry out repetitive, physically demanding actions under diverse ergonomic conditions.

Recent advances in human-robot collaboration (HRC) have introduced a hybrid approach that combines human adaptability, dexterity, and decision-making with the speed, precision, and strength of collaborative robots [2]. This integration has shown potential to improve productivity, flexibility, and even aspects of safety, with robots undertaking strenuous or hazardous activities while humans focus on judgment-intensive tasks.

However, despite these benefits, HRC does not inherently eliminate physical ergonomic risks. Workers remain exposed to awkward postures, repetitive subtasks, and static loading, all of which contribute to work-related musculoskeletal disorders (WMSDs). WMSDs are among the most prevalent occupational health problems globally, accounting for nearly half of all work-related injuries [3,4]. Their economic burden is significant, resulting in lost productivity, absenteeism, and long-term disability.

To address these challenges, effective methods for assessing MSD risks are needed that operate in fast-paced, dynamic, and collaborative industrial environments. Methods, such as RULA and REBA, are widely used [5]. Still, they rely on manual observation, making them time-consuming, subjective, and impractical for continuous or real-time monitoring in HRC disassembly contexts.

The emergence of wearable inertial measurement units (IMUs) offers an opportunity to capture high-resolution, continuous motion data [6,7]. When combined with machine learning (ML), these sensors enable automated, objective, and potentially predictive ergonomic assessments, critical capabilities for proactive prevention of WMSDs in Industry 4.0 environments.

1.2 Problem statement

Despite progress in ergonomics and automation, three major limitations persist in current approaches:

Limitations of traditional ergonomic tools

Standardized observational tools (e.g., RULA, REBA) are effective for static or snapshot evaluations but unsuitable for dynamic, repetitive environments. They depend on expert judgment, are labour-intensive, and fail to account for cumulative strain from repeated or prolonged postures.

Gaps in sensor-based systems

While IMUs can provide continuous and accurate motion capture, most existing sensor-based ergonomic studies, particularly in disassembly, still report high physical strain, even with robotic assistance. Certain subtasks, such as cable detachment or component sorting, frequently exceed ergonomic safety thresholds, demonstrating that HRC does not automatically eliminate biomechanical risk.

Deficiencies in machine learning models

Current ML-based ergonomic systems often focus narrowly on posture recognition, neglecting cumulative risk factors such as repetition frequency and posture duration, critical drivers of WMSD development. These models are typically trained on isolated postures, which limits their applicability in real-world disassembly workflows where tasks are sequential and variable. Comparative benchmarking of multiple ML models under unified experimental conditions is also rare.

Research gap

To date, no existing framework integrates real-time IMU sensor data with a dual-output deep learning model capable of simultaneously classifying disassembly subtasks and assessing cumulative ergonomic risk in an HRC setting. This gap limits the ability to provide timely, actionable feedback for injury prevention.

1.3 Research questions

Primary research question

Can a dual-output deep learning framework (WMSDsNet) accurately and simultaneously classify disassembly subtasks and their ergonomic risk levels from raw IMU data in real time?

Secondary research questions

- How does WMSDsNet's performance compare to other commonly used machine learning models in ergonomic risk classification?
- Can this framework effectively quantify cumulative ergonomic risk, incorporating factors such as posture duration and repetition, and enable proactive feedback for WMSD prevention?

1.4 Research objectives

The overarching goal of this research is to design, implement, and validate WMSDsNet, a sensor-based machine learning framework for real-time ergonomic risk prediction in human-robot collaborative (HRC) disassembly environments.

Rather than proposing a purely conceptual system, this study emphasizes the practical development and experimental validation of a labeled dataset and a dual-output learning model capable of classifying both disassembly subtasks and associated ergonomic risk levels.

To achieve this aim, the research pursued the following four objectives, each corresponding to the work effectively completed and validated:

1. Development of an Ergonomically Labeled Dataset
    - Design and execute a controlled HRC disassembly experiment replicating realistic ergonomic risks.
    - Collect motion data from multiple body segments using wearable IMU sensors and label them systematically with RULA and REBA scores to create a structured, reproducible learning base for ergonomic applications.
2. Demonstration of Sensor Data Usability for Machine Learning
    - Establish a full data-processing pipeline, from raw IMU acquisition to preprocessing and labeling, to demonstrate that wearable-sensor signals can effectively support supervised learning for ergonomic risk analysis.

3. Comparative Classification of Disassembly Subtasks and Risk Levels
   - Train and evaluate six machine-learning models (CNN, DNN, SVM, KNN, DT, RF) on the same dataset to classify disassembly subtasks and ergonomic risk levels.
   - Benchmark model performances through accuracy and macro-average F1-scores, validating the generalizability and robustness of the best-performing model (DNN).
4. Integration into a Unified Framework for Real-Time Ergonomic Assessment
   - Consolidate the full process, from ergonomic labeling to real-time classification, into the WMSDsNet framework, illustrating its applicability for proactive monitoring and early detection of work-related musculoskeletal disorder (WMSD) risks in collaborative industrial settings.

1.5 Contributions of the thesis

Each research objective outlined in Section 1.4 directly corresponds to a tangible contribution achieved throughout the development of this thesis. Together, these contributions establish WMSDsNet — a unified, sensor-based deep learning framework for real-time ergonomic risk prediction in human-robot collaborative (HRC) disassembly environments.

Contribution 1 Development of an Ergonomically Labeled Dataset

A controlled laboratory experiment was designed and executed to simulate realistic HRC disassembly conditions and capture representative ergonomic risks. Ten wearable inertial measurement unit (IMU) sensors were deployed across multiple body segments to collect high-resolution motion data. Each data segment was systematically labeled using standardized ergonomic assessment tools (RULA and REBA), generating a reproducible dataset that links disassembly subtasks with corresponding ergonomic risk levels. This dataset forms the foundation for supervised machine-learning applications in physical ergonomics.

Contribution 2 Demonstration of Sensor Data Usability for Machine Learning

A complete data-processing pipeline was established, including signal synchronization, filtering, segmentation, and normalization, to transform raw IMU signals into machine-learning-ready inputs. This contribution demonstrates the feasibility of using wearable-sensor data to train ML algorithms for ergonomic evaluation. The resulting pipeline enables objective, continuous, and scalable monitoring of biomechanical exposure, replacing traditional observation-based methods.

Contribution 3 Comparative Classification of Disassembly Subtasks and Risk Levels

Six machine-learning models—CNN, DNN, SVM, KNN, Decision Tree, and Random Forest—were trained and evaluated using the same labeled dataset. Their performance was systematically benchmarked through accuracy, macro-average F1-scores, and confusion-matrix analysis. This comparative evaluation identifies the DNN as the most reliable model for dual-task classification, highlighting the strengths and trade-offs of deep and classical learning approaches in ergonomic applications.

Contribution 4 Integration into a Unified Framework for Real-Time Ergonomic Assessment

All previous stages were consolidated into a single integrated system—**WMSDsNet**—that combines data acquisition, labeling, and dual-output classification within one end-to-end framework. WMSDsNet simultaneously predicts both the physical subtask and its ergonomic risk level in real time, providing industrial engineers with an interpretable, proactive tool for early WMSD detection and prevention in collaborative disassembly operations.

Together, these four contributions establish a coherent progression from data generation to practical application, ensuring that each research objective is fully achieved and that the proposed WMSDsNet framework advances ergonomic intelligence within Industry 4.0 manufacturing environments.

Figure 1-1 illustrates how the four main contributions of this thesis are interconnected across three conceptual layers. The framework evolves from the creation of an ergonomically labeled dataset to its integration into a real-time risk-prediction system, forming a coherent process that connects ergonomic theory, data science, and industrial application.

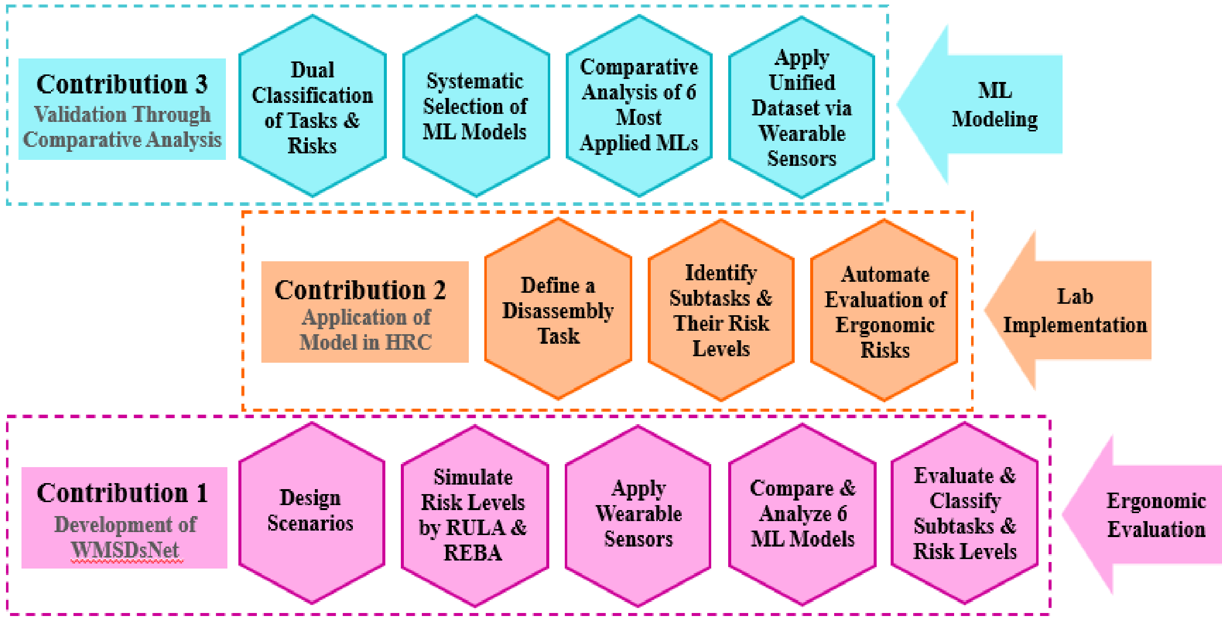


Figure 1-1. *Overall framework and four key contributions across three interconnected layers.* The bottom layer (data foundation) represents Contribution 1 and Contribution 2, where the ergonomically labeled dataset and data-processing pipeline were developed using wearable IMUs.

The middle layer (modeling and analysis) corresponds to Contribution 3, which focuses on comparative classification of subtasks and ergonomic risk levels using six ML models.

The top layer (integration and application) embodies Contribution 4, where all components were unified into WMSDsNet, a real-time dual-output framework for ergonomic risk prediction in human-robot collaborative disassembly.

CHAPTER 2 LITERATURE REVIEW

2.1 Work-Related Musculoskeletal Disorders (WMSDs) in Industry 4.0 and Disassembly

Work-related musculoskeletal disorders (WMSDs) are injuries or disorders affecting muscles, tendons, ligaments, joints, nerves, or supporting blood vessels, typically caused or aggravated by workplace activities [ref]. They remain a widespread occupational health issue, even in modern industrial settings where technological advancements have introduced robotics and automation. In human-robot collaboration (HRC), particularly in disassembly lines, workers are still required to perform physically intensive tasks such as unscrewing, part separation, cable detachment, and inspection [1],[2]. These tasks frequently involve awkward or constrained postures, repetitive hand and arm motions, and sustained force application, all primary risk factors for WMSDs [11].

The global economic burden of WMSDs is substantial. According to the World Health Organization (WHO), WMSDs are among the most prevalent occupational disorders worldwide and are associated with absenteeism, decreased productivity, and long-term disability [12]. In Canada alone, WMSDs account for over 40% of lost-time claims, as reported by national compensation boards [13].

While ergonomics has been studied extensively in high-risk sectors such as manufacturing, healthcare, and construction, the disassembly domain is relatively underrepresented. In contrast to assembly lines, where standardized parts and sequences are common, disassembly tasks often involve unpredictable geometries and degraded components, leading to postural variability and high biomechanical demands [14]. Even when robotic arms are present to assist, their support is often limited to heavy lifting or predefined motions, while workers handle tasks that are unstructured and nuanced.

In HRC-enabled disassembly settings, humans contribute flexibility, adaptability, and dexterity, while robots provide consistency and strength. However, this partnership can inadvertently increase ergonomic risk due to synchronized task pacing, workspace sharing, and frequent handovers [15]. These factors justify the need for intelligent systems capable of monitoring and predicting ergonomic risks in real-time, beyond the limitations of traditional assessment tools.

2.2 Limitations of Manual Ergonomic Assessment Methods

Several standardized methods have been widely used to evaluate postural and task-related ergonomic risks, notably RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), and OCRA (Occupational Repetitive Actions) [5]. These checklists and scoring systems are based on observed joint angles, body postures, task frequency, and force application, typically assessed visually by trained ergonomists.

While these methods provide structured frameworks for evaluating physical demands, they are limited by several drawbacks, particularly in the context of fast-paced or collaborative industrial tasks. First, they are inherently subjective and susceptible to observer bias, especially when ergonomic evaluators disagree on joint angle estimates or exposure frequencies [16]. Second, these tools are primarily designed for snapshot evaluations and cannot account for posture duration, task variability, or sequential risk accumulation.

Moreover, traditional tools are often impractical for environments like HRC disassembly, where subtasks change quickly, and access to operators is obstructed by machinery or tooling. The manual nature of these tools limits their use for real-time feedback, making them unsuitable for dynamic task conditions or for integration into Industry 4.0 feedback loops [17].

Several studies have demonstrated the underperformance of these manual tools when applied in HRC settings. For instance, Takala et al. (2010) noted that manual posture scoring systems failed to detect high-risk cumulative exposure in tasks involving alternating hand movements and torso rotation [18]. These insights have accelerated the push toward sensor-based and AI-driven ergonomic evaluation systems that can operate autonomously and continuously [10].

In summary, while tools like RULA and REBA remain useful as baseline ergonomic standards, they are increasingly being augmented, or replaced, by data-driven approaches that can track risk with greater precision and adaptability.

2.3 Emergence of Wearable IMUs for Postural Monitoring

To address the limitations of visual and manual ergonomic tools, researchers have increasingly adopted wearable inertial measurement units (IMUs) for continuous, objective monitoring of human motion. These devices, typically comprising accelerometers, gyroscopes, and magnetometers, can capture 3D motion, body orientation, and angular velocity without requiring a direct line of sight, making them ideal for cluttered or enclosed workspaces, such as disassembly cells [6]; [19].

IMUs are unobtrusive, lightweight, and cost-effective compared to optical motion capture systems. Unlike vision-based systems that require fixed camera setups, IMUs can be worn directly on body segments (e.g., forearm, trunk, thigh), enabling detailed postural analysis during real-world tasks [20]. This flexibility makes them especially suitable for dynamic environments such as HRC stations, where camera obstruction and lighting variability often interfere with visual tracking.

Recent advancements in wireless synchronization and sensor fusion algorithms have significantly improved the accuracy and reliability of IMU-based systems. Studies have validated the agreement of IMU-derived joint angles with gold-standard optical systems [21]. In practical terms, IMUs enable multi-segment motion capture, which is crucial for understanding how different body parts interact and compensate during tasks that involve forceful exertion or constrained reach [7].

Prior ergonomic studies have employed inertial measurement units (IMUs) to capture detailed motion data across multiple body segments, enabling analysis of both sustained and short-duration movements[97],[98].

The integration of IMUs into ergonomic analysis also enables real-time risk monitoring when combined with machine learning models. Continuous posture streams can be labelled using ergonomic scores (e.g., RULA, REBA) and used to train classifiers that infer risk levels automatically [5],[97]. This approach is crucial for implementing smart feedback systems that help prevent WMSDs in high-risk environments like collaborative disassembly.

2.4 Machine Learning for Posture-Based Risk Classification

Integrating wearable IMUs into industrial settings has paved the way for automated ergonomic risk classification using machine learning (ML). By leveraging patterns in multivariate sensor data, ML models can detect postural deviations, classify task segments, and predict ergonomic risk levels in real time [97]. Compared to manual assessment methods, ML-based systems provide higher throughput, reduced subjectivity, and scalable deployment across workstations. Traditional supervised ML algorithms, such as Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN), are widely used in ergonomic studies to classify postures or task phases based on IMU-derived features [22]. These models typically rely on handcrafted features extracted from sensor data, such as peak joint angles, angular velocity ranges, or signal vector magnitudes [98]. The success of ML models in ergonomic risk prediction has been demonstrated across various industrial domains. For instance, Llop-Harillo et al. (2020) employed Random Forest classifiers to detect ergonomic risks during order picking, achieving over 85% classification accuracy [23], and Lee et al. [24] used SVMs to evaluate lower back postures and achieved high agreement with manual REBA scoring.

However, ML performance is sensitive to feature selection, sensor placement, and task variability. The lack of transferability between models trained on specific subtasks and new untrained environments remains a critical challenge. Moreover, these models often require domain expertise to engineer effective features, introducing bottlenecks in scalability and generalization [25]. In our study [7], Comparative studies in the literature have examined the performance of various machine learning classifiers, such as CNN, DNN, RF, DT, SVM, and KNN, using consistent data preprocessing and labeling protocols. These approaches allow for an unbiased assessment of classification performance across ergonomic risk levels and physical subtasks in HRC disassembly contexts.

Comparative evaluations in prior research provide valuable guidance for identifying model architectures that can address the dual challenges of ergonomic risk classification and subtask recognition in disassembly work.

2.5 Deep Learning in Ergonomic Prediction

Deep learning (DL) models have emerged as powerful alternatives to handcrafted feature engineering and classical machine learning (ML) approaches for ergonomic risk assessment. Among them, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are notable for their ability to capture spatial and temporal patterns in human motion data [8,9].

CNNs excel at learning local and hierarchical features from structured inputs such as multichannel inertial measurement unit (IMU) signals or posture matrices. Liang et al. (2021) applied a CNN to extract posture representations from 3D skeletal data, achieving higher classification accuracy and generalizability than conventional methods [26]. Similarly, Baskar et al. (2021) trained a 1D CNN on IMU signals for workplace posture classification, reporting robust cross-subject performance [27].

LSTM networks, in contrast, are designed to process sequential data by retaining information across time steps, making them suitable for modeling dynamic movement patterns [28]. Ergonomic applications have included motion segmentation, activity recognition, and physiological monitoring. For instance, Ghani et al. (2021) used LSTMs to predict work stress and fatigue from wearable sensor data, demonstrating their utility in continuous monitoring contexts [29].

From a biomechanical perspective, work-related musculoskeletal disorders (WMSDs) are often linked not only to isolated postures but also to repetitive or sustained exposure to suboptimal positions, high force exertion, and inadequate recovery time [31]. While traditional ergonomic tools such as RULA and REBA incorporate frequency into their scoring, they do so in broad categories without fine-grained temporal tracking [32]. Wearable sensor systems offer the potential to monitor and quantify such exposure patterns in real time. Nevertheless, as highlighted in a systematic review by Tkachuk et al. (2022), fewer than 15% of IMU-based ergonomic studies addressed exposure duration, and only a small fraction implemented sequence-aware models such as LSTMs [33].

Although the present study focuses on static-window risk classification using multiple ML and DL models, the integration of time-dependent risk indicators and sequence-based modeling remains an important and underexplored research direction [10].

2.6 Multi-Model Comparisons in Ergonomics Literature

One of the overlooked aspects in ergonomic modelling is the lack of a comprehensive comparative analysis between different machine learning approaches. Many studies validate their proposed method in isolation, on limited datasets or under specific conditions, without benchmarking against other well-established models. This restricts the ability of researchers and practitioners to objectively determine which models are best suited for ergonomic risk classification in varied industrial scenarios [7].

The value of multi-model evaluation has been emphasized in related fields such as human activity recognition and gait analysis, where performance across tasks, environments, and populations can vary significantly depending on model complexity and data representation [34In ergonomics, however, comprehensive comparative studies remain uncommon. Existing research often concentrates on a single classifier or, at most, compares two closely related algorithms, typically without a thorough examination of important trade-offs such as interpretability, suitability for real-time deployment, or robustness under varying task and sensor conditions.

In the context of wearable sensor–based ergonomics, comparative studies do exist but often face notable limitations. Many examine only a small set of models, focus on narrowly defined tasks, or omit discussion of trade-offs such as interpretability, computational efficiency, and robustness across varied conditions. These limitations hinder the identification of models best suited for deployment across diverse ergonomic scenarios, including lifting, sorting, or disassembling. For example, Karvekar et al. (2022) compared CNN and SVM for posture classification but restricted their analysis to a single repetitive task, limiting generalizability [35]. Similarly, Cho et al. (2020) applied Random Forests and ANN to lifting-risk evaluation but did not benchmark against temporal models or provide justification for model selection [36]. Addressing these constraints is essential for developing ergonomic assessment systems that are adaptable, reliable, and optimized for real-world industrial environments.

Our study addresses this shortfall by systematically comparing six commonly used models, CNN, DNN, RF, DT, SVM, and KNN, on a shared, labeled dataset derived from IMU sensors during human-robot disassembly tasks [7]. All models were trained and validated under uniform data preprocessing, feature extraction, and labeling conditions, enabling unbiased benchmarking. The results not only reveal performance strengths but also clarify the limitations of each model type across task classification and ergonomic risk prediction.

Such comparative insight is critical for practical deployment, where real-time performance, explainability, and hardware constraints must be balanced. By reporting on both task and risk classification accuracies, our multi-model analysis provides actionable guidance for selecting appropriate models in future ergonomic systems.

2.7 Underrepresentation of Disassembly Ergonomics in HRC Research

Within the broader field of human-robot collaboration (HRC), most ergonomic assessments and system developments have focused on assembly rather than disassembly contexts [1]; [2]. Disassembly tasks, an increasingly vital part of the circular economy, remanufacturing, and sustainable waste management, are fundamentally different from assembly in both structure and ergonomic demands.

Unlike assembly tasks, which are often optimized for robotic compatibility and designed for ease of access, disassembly involves reversed processes where parts may be hidden, damaged, or unstructured. This results in unpredictable task flows, frequent tool changes, awkward postures, and higher exposure to repetitive actions, all contributing to elevated ergonomic risks [37]. Moreover, as automation in disassembly remains limited, the human contribution remains dominant, particularly for tasks involving delicate or high-judgment decisions.

In addition, the variability in component sizes and joint configurations in EoL products forces operators into non-standardized positions, often exceeding safe ranges of motion [38]. Disassembly thus requires not only flexible cognitive strategies but also adaptive physical responses, something not adequately captured by existing ergonomic models developed for structured assembly workstations.

Despite these known differences, few studies have focused on sensor-based ergonomic assessment tailored to disassembly workflows. Most wearable sensor studies are set in controlled, repetitive environments such as packaging, lifting, or assembly lines [39]. In our work [1]; [7], we address this gap by applying IMU-based monitoring and machine learning classification specifically to disassembly subtasks in an HRC environment. Tasks such as part separation, cable detachment, and sorting are segmented and evaluated independently to understand posture-specific and cumulative ergonomic risks.

This underrepresentation in literature points to the urgent need for ergonomic models and risk detection frameworks that account for the unique complexity and unpredictability of disassembly tasks, particularly as robotics becomes more integrated into circular manufacturing systems.

2.8 Justification for the WMSDsNet Framework

The convergence of gaps identified in previous sections, namely, the overreliance on snapshot posture assessments [16],[17],[18], the underuse of temporal models [28],[29],[40], the absence of cumulative risk tracking [12],[31],[55], and the lack of disassembly-specific ergonomics [36],[37],[38], motivates the design of our proposed architecture, WMSDsNet.

WMSDsNet integrates CNNs and LSTMs into a hybrid deep learning model that performs dual classification of (1) physical subtasks and (2) ergonomic risk levels using wearable IMU signals. The CNN layers extract spatial features from high-resolution time windows, while the LSTM layers capture sequence patterns to assess frequency and duration-based risk accumulation. This dual-stream structure enables the system to function as both a real-time classifier and a temporal exposure monitor, allowing for the early detection and prevention of WMSDs.

This design aligns with the trend toward multitask learning architectures in wearable health monitoring, where a single model addresses multiple outputs to enhance system efficiency and consistency [40]. Additionally, our model aligns with the growing focus on interpretable deep learning in industrial applications, where safety-critical decisions must be transparent and explainable to operators and supervisors [41].

Furthermore, WMSDsNet is among the first models to be trained on IMU data collected during actual HRC disassembly tasks, under three risk scenarios (safe, moderate, and high). The framework supports real-time deployment and personalization through task-specific labelling and motion-aware subtask recognition.

In this way, WMSDsNet not only advances the state of the art in ergonomic modelling but also demonstrates how AI-driven approaches can support proactive health and safety interventions in industrial settings, especially in the high-risk, underexplored domain of human-robot disassembly collaboration.

CHAPTER 3 RESEARCH APPROACH AND STRUCTURE OF THE THESIS

Research Methodology

This chapter outlines the research process applied to design, implement, and validate WMSDsNet, a real-time sensor-based framework for ergonomic risk prediction in human-robot collaborative (HRC) disassembly environments. The overall methodology draws inspiration from the CRISP-DM process model, adapted here to the context of ergonomic machine-learning applications. The sequence of steps, business understanding, data generation, data preparation, modeling, and evaluation, ensures a transparent, reproducible approach from problem definition to experimental validation.

3.1 Business Understanding: Ergonomic Context and Objectives

- Work-related musculoskeletal disorders (WMSDs) are a major concern in industrial environments where human–robot collaboration is increasingly adopted for disassembly operations.
  The study begins by defining the ergonomic goals underpinning WMSDsNet:
- To identify postures and repetitive actions that contribute to cumulative strain.
- To enable data-driven prediction of ergonomic risk levels in real time.
- To bridge ergonomic evaluation tools (RULA and REBA) with sensor-based machine learning methods for proactive prevention.
- This phase translates ergonomic concepts into measurable learning objectives, where RULA and REBA scores act as ergonomic ground-truth labels guiding model training and evaluation.

3.2 Data Generation: Experimental Design and Sensor Configuration

- A laboratory-based HRC disassembly scenario was designed to reproduce typical ergonomic risks found in industrial environments. One trained participant executed four subtasks, unscrewing components, detaching cables, sorting parts, and changing tools, under three predefined ergonomic risk levels (low, moderate, and high).

- Each subtask-risk combination was repeated multiple times to ensure data sufficiency and balanced representation across classes. Although this balanced design facilitates reliable model training, it is recognized that real-world conditions often present imbalanced risk exposure, an important limitation discussed later.
- Ten T-Sens Motion v9.0 IMU sensors were placed on key body segments (head, shoulders, upper arms, forearms, waist, lower back, and legs). Each sensor recorded tri-axial acceleration and angular velocity at 100 Hz, producing high-resolution motion data synchronized across all segments. The configuration ensured complete kinematic coverage of body movements relevant to WMSD risk factors such as awkward posture, repetition, and asymmetry.

3.3 Data Preparation: Preprocessing and Labeling

- Raw IMU signals were first synchronized, filtered, and segmented into fixed-length windows representing continuous movement sequences. Each segment was labeled using RULA (for upper-body subtasks) or REBA (for full-body subtasks) scores, resulting in structured and standardized risk categories: *safe, moderate,* and *high*.
- This step produced a clean, reproducible dataset that constitutes the ergonomic learning base for subsequent model training. The dataset integrates both physical-task labels (subtasks) and ergonomic-risk labels, enabling dual-output classification central to the WMSDsNet framework.

3.4 Modeling: Machine Learning Framework Design

Model Selection

- Six supervised machine-learning models were developed and evaluated to determine the most suitable algorithm for ergonomic risk prediction:
- Deep Learning Models: Convolutional Neural Network (CNN) and Deep Neural Network (DNN)
- Classical Machine-Learning Models: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF)

- These models were chosen to represent both deep and classical paradigms, allowing a balanced comparison of accuracy, interpretability, and computational cost.

Architecture Rationale

- The DNN architecture was selected as the primary backbone for WMSDsNet due to its ability to learn from raw IMU signals without manual feature engineering. Its dense layers capture high-dimensional nonlinear relationships between motion signals and ergonomic scores. The CNN architecture was tested to evaluate spatial-pattern extraction capability across sensor channels. Hyperparameters, number of layers, dropout rate, activation functions, and batch size, were tuned through iterative experimentation to maximize generalization.

Dual-Output Learning

- WMSDsNet integrates two parallel output heads:

1. Subtask Classification: Recognizes the specific physical activity being performed.
2. Risk Classification: Predicts the corresponding ergonomic risk level.

This dual structure allows the model to provide *context-aware feedback*, where risk prediction is informed by the nature of the subtask.

3.5 Evaluation: Validation, Metrics, and Interpretation

- Model performance was evaluated using both aggregate and class-specific metrics:
- Accuracy to measure overall correctness.
- Macro-average and per-class F1-scores to assess model robustness across imbalanced categories.
- Confusion matrices to visualize misclassifications between subtasks and risk levels.
- Complementary visualizations, including heatmaps and radar charts, were used to highlight inter-class relationships and posture-risk interactions. For clarity, all confusion matrices are now displayed two per page maximum, following consistent orientation and labeling standards.

- The DNN achieved the best overall performance, reaching 92 % accuracy for subtask classification and 90 % for ergonomic-risk classification. This confirmed the framework's feasibility for real-time, sensor-based ergonomic monitoring in collaborative disassembly environments.

3.6 Summary of Methodological Flow

- The methodology integrates ergonomic theory, sensor technology, and machine learning into a unified framework that progresses through five interdependent stages:

1. Business Understanding: Translate ergonomic risks into measurable learning goals using RULA/REBA.
2. Data Generation: Collect multi-segment IMU data from HRC disassembly tasks under controlled conditions.
3. Data Preparation: Clean, segment, and label data to create an ergonomic learning base.
4. Modeling: Train and compare six ML algorithms, implement the dual-output WMSDsNet model.
5. Evaluation: Quantitatively assess performance and interpret ergonomic implications through visualization and metrics.

3.7. Structure of the Thesis

This thesis is organized as follows:

Chapter 1: Introduction

Presents the background, research motivation, problem statement, and objectives. Emphasizes the significance of WMSDs in HRC environments and introduces the proposed WMSDsNet framework.

Chapter 2: Literature Review

Reviews prior work on wearable sensor-based ergonomic risk assessment, machine learning in ergonomics, and ergonomics in HRC disassembly contexts. Identifies research gaps that motivate this study.

Chapter 3: Research Approach and Structure of the Thesis

Details the overall methodology applied in both stages of the research and outlines the thesis structure.

Chapter 4: Journal Paper

Presents the journal article containing the extended study, including the comparative evaluation of six ML models (CNN, DNN, SVM, KNN, DT, RF), deeper analysis, and trade-off discussion.

Chapter 5: Discussion

Interprets findings in light of the literature, examines strengths and limitations, and outlines potential directions for further research.

Chapter 6: Conclusion and Recommendations for Future Work

Summarizes the key outcomes of the research and provides practical recommendations for applying the WMSDsNet framework in real-world industrial settings.

CHAPTER 4 ARTICLE 1: Development of a Sensor-Based Ergonomic Risk Assessment Framework Using Machine Learning: Application to Human-Robot Collaborative Disassembly

Authors: Marziyeh Mirzahosseininejad, Firdaous Sekkay, Elham Ghorbani, Ashkan Amirnia, Samira Keivanpour

The paper was submitted on July 31, 2025, and is currently under review in the *International Journal of Industrial Ergonomics*.

Abstract, Despite advances in automation, work-related musculoskeletal disorders (WMSDs) remain common in industrial environments, especially in human-robot collaboration (HRC) systems where physical subtasks continue to pose ergonomic risks. This study introduces WMSDsNet, a real-time framework that uses wearable inertial measurement unit (IMU) sensors to classify ergonomic risk levels and recognize physical subtasks during collaborative disassembly operations. The system captures motion patterns from key body segments and labels them using two widely accepted ergonomic tools: Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA).

Unlike previous approaches that focus on either posture or task recognition alone, WMSDsNet handles both within a consistent and reproducible setup. A labeled dataset was collected and used to train six machine learning models: Convolutional Neural Network (CNN), Deep Neural Network (DNN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF). Among these, the DNN performed best, reaching 92% accuracy in subtask classification and 90% in ergonomic risk prediction, with strong F1-scores across all categories.

The framework not only compares the models across accuracy and class balance but also considers their speed and ability to generalize. Results show that deep learning and ensemble methods (DNN, CNN, RF) are especially effective for this dual-task classification. WMSDsNet offers a practical, repeatable approach for evaluating ergonomic risk with machine learning and helps bring intelligent, worker-centered safety solutions into modern industrial environments.

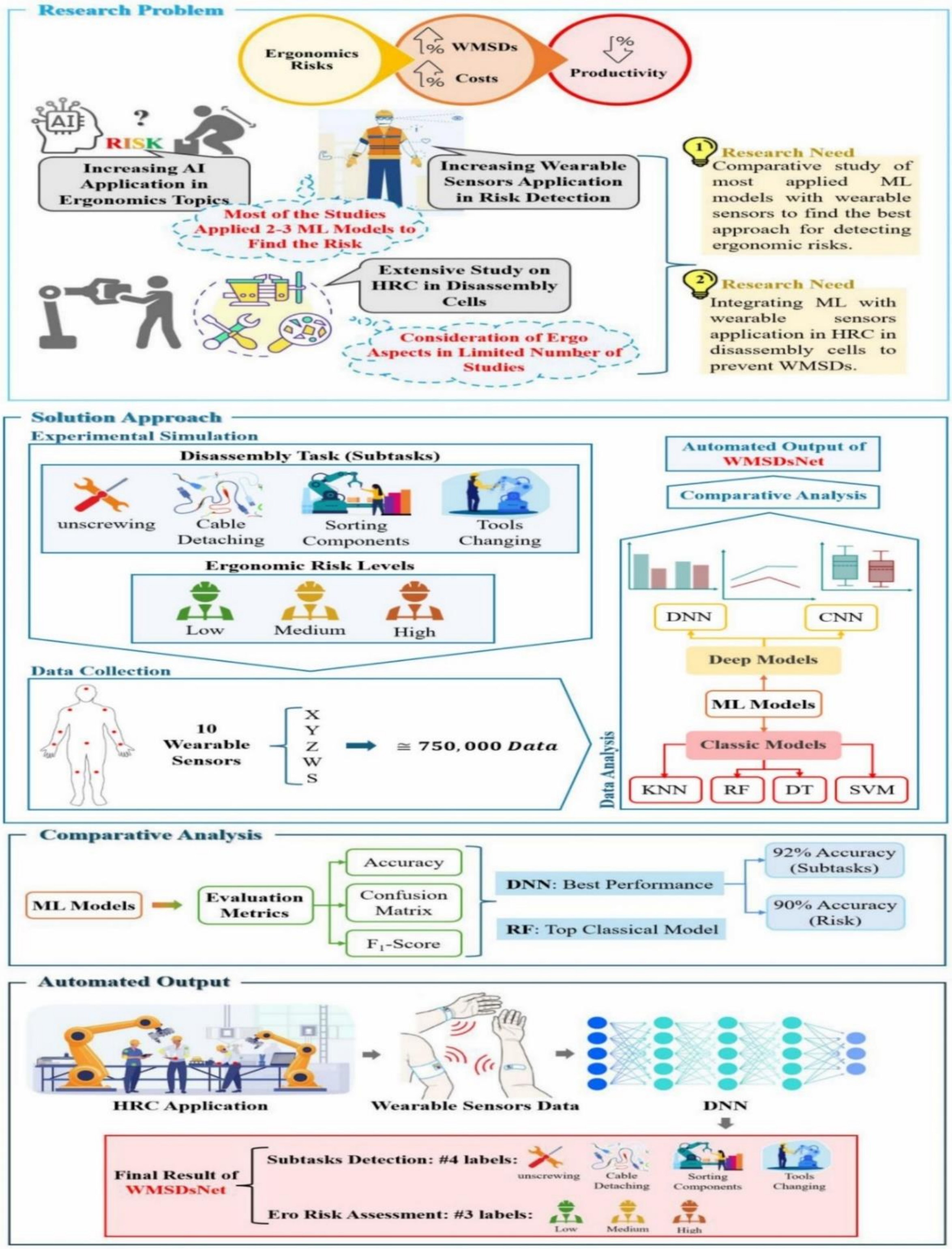


Figure 4-1: Graphical abstract

4.1. Introduction

In the era of Industry 4.0, where intelligent automation and human-robot collaboration are transforming industrial workflows, work-related musculoskeletal disorders (WMSDs) are among the leading causes of occupational injuries and remain a major public health concern in industrialized nations [1,2].They are responsible for nearly half of all work-related health problems, significantly affecting worker well-being and quality of life [9,53]. Beyond personal health, WMSDs impose substantial costs on organizations through productivity loss and increased absenteeism [5]. A study involving 197 participants showed that over 77% experienced discomfort-related productivity loss, with high rates of absenteeism and presenteeism [8]. In 2017 alone, musculoskeletal conditions were associated with 138.7 million Disability-Adjusted Life Years (DALYs) across more than 1.3 billion cases globally, underlining their vast societal impact [54].

Common risk factors for WMSDs include high-force exertion, repetitive motion, and awkward postures such as bending, twisting, or kneeling [55]. Early detection of ergonomic risks is essential for mitigating long-term consequences. Conventional ergonomic assessments rely on standardized tools like RULA and REBA, which require manual expert observation aligned with ISO guidelines. While well-established, these methods are time-consuming, subjective, and poorly suited to dynamic industrial conditions [10]. Effective prevention demands accurate identification of ergonomic risk factors through systematic assessment and real-time monitoring. A recent review by Siddhaiyan et al. [7] further emphasizes the limitations of these traditional approaches and highlights the need for more intelligent, automated, and scalable risk assessment systems within Industry 4.0 frameworks.

Recent advances in artificial intelligence (AI) and machine learning (ML) have opened new pathways for automating ergonomic evaluations [56]. A review of 188 papers, including 28 selected studies, highlighted the increasing use of AI to assess ergonomic risks and support flexible, intelligent industrial systems [56]. Commonly used ML models include support vector machines (SVMs), convolutional neural networks (CNNs), and random forests (RFs), primarily for classifying postures and predicting WMSDs [30,38,57,59]. More recent work has expanded to deep learning approaches such as long short-term memory (LSTM) networks, especially for sequence modeling in dynamic tasks [60,61].

The integration of wearable motion capture systems, particularly inertial measurement units (IMUs), has transformed physical ergonomics, an area focused on optimizing human physical interaction with tasks, tools, and environments, by enabling accurate, continuous monitoring of biomechanical parameters [61,45]. IMUs, consisting of tri-axial accelerometers, gyroscopes, and magnetometers, offer reliable kinematic data during complex movements [61]. They are more practical than vision-based methods in cluttered or constrained environments [62], and are non-invasive, cost-effective, and scalable for industrial use [63,64]. IMUs have been used for both posture classification and real-time ergonomic risk detection [65]. Studies show they outperform depth cameras like Kinect in capturing fine-grained motion and provide effective analysis for various body segments [66,67]. Some frameworks have integrated IMUs with additional sensors, such as pressure, EMG, or inclinometers, for a more comprehensive biomechanical evaluation [68]. However, validation in real industrial environments remains limited [62].

4.1.1 ML Applications in Ergonomic Risk Prediction

The application of machine learning (ML) in ergonomic risk prediction has gained significant momentum in recent years, driven by the increasing adoption of Industry 4.0 technologies that facilitate real-time monitoring, intelligent feedback systems, and data-driven decision-making in dynamic work environments. Traditional observational methods for assessing work-related musculoskeletal disorders (WMSDs), such as the Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA), are widely used but present several limitations. These include subjectivity, dependency on expert observation, and a lack of scalability for continuous and objective risk evaluation in complex, fast-paced industrial settings [60].

In response to these challenges, ML-based approaches have emerged as powerful alternatives that can identify and mitigate ergonomic risks more proactively. A comprehensive scoping review by Chan et al. analyzed 130 primary studies and found a substantial rise in the use of ML techniques for WMSD prevention, with nearly one-quarter of the studies published in 2020 alone [69]. Commonly used models included artificial neural networks (ANNs), decision trees, and support vector machines (SVMs), which were applied primarily for classification and regression tasks aimed at identifying risk factors and developing intervention strategies [69].

Beyond classical techniques, recent experimental studies have adopted more advanced and diverse ML methods to improve predictive accuracy and support real-time risk detection. These include random forests (RF), convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and other sequence-aware models. For instance, Fernandes et al. proposed an LSTM-based deep learning model to predict shoulder movements using sensor-derived orientation angles. Their results showed that sequence-to-sequence models outperformed classical ML algorithms in forecasting potentially harmful motion patterns associated with WMSDs, particularly in tasks involving repetition or awkward postures [61].

Matos et al. extended this approach by integrating a motion capture system with a time series forecasting (TSF) module and a WMSD risk classifier [70]. Their framework used historical angular trajectory data to train forecasting algorithms such as SVM, XGBoost, LSTM, and multilayer perceptron (MLP), enabling the system to anticipate future movement patterns and assess ergonomic risk against ISO-defined thresholds. Among the models evaluated, SVM offered a favorable balance between computational efficiency and predictive performance, particularly for assessing shoulder abduction and rotation in textile manufacturing [70].

Despite these advances, Sherafat et al. noted in their review of ML-based activity recognition in industrial construction that many existing models were not suitable for real-time deployment. They often relied on offline video analysis or manually annotated post-task data, which limited scalability and practical implementation [71]. Their work highlighted the urgent need for sensor-based ergonomic monitoring systems that can function autonomously without constant expert supervision, aligning with the broader goals of wearable ML approaches.

Supporting the trend toward temporal modeling, Dey and Schilling applied a temporal convolutional neural network (TCN) to predict foot angle trajectories in powered prosthetics using a single IMU sensor [72]. Although their focus was not on ergonomics, the study demonstrated the effectiveness of low-latency sequence modeling for real-time biomechanical prediction tasks, reinforcing the value of deep temporal architectures in wearable sensor applications.

In summary, recent advancements illustrate the growing role of deep learning and temporal modeling in ergonomic risk prediction. Models like CNN and LSTM are particularly well-suited for capturing dynamic movement patterns that static feature-based methods often miss. However, several limitations persist across current studies, including a narrow focus on specific postures, limited comparison of ML models under unified experimental setups, and an overrepresentation of applications in construction or healthcare. There remains a significant research gap in ergonomic risk prediction for collaborative disassembly tasks in human-robot environments, an emerging but underexplored domain in the context of Industry 4.0 [60,69,70,71,72].

4.1.2 Wearable Sensor Systems

The integration of wearable sensors, particularly inertial measurement units (IMUs), has significantly advanced the field of physical ergonomics by enabling objective, real-time, and continuous monitoring of posture, motion, and ergonomic risk factors. IMUs typically consist of tri-axial accelerometers, gyroscopes, and magnetometers, which allow for the capture of detailed kinematic data during a variety of industrial tasks [61,73]. Compared to vision-based systems, IMUs are less intrusive, more practical for deployment in the field, and especially effective in cluttered or constrained environments where optical tracking systems like Kinect often fail [45,65]. Their compact form factor and high sensitivity make them particularly suitable for monitoring awkward or repetitive postures that may otherwise be missed by observational methods [65]. Clark et al. [74] highlighted that 3D vision-based tracking systems such as Kinect often face limitations in depth accuracy, occlusion handling, and constrained environments, which underscores the need for alternative sensing modalities like IMUs in ergonomic monitoring.

Studies have demonstrated the effectiveness of IMUs in capturing fine-grained motor patterns, [61,62,63,66]. They have been successfully used across various body segments, including the upper and lower limbs and trunk, to assess complex full-body movements during industrial tasks [67]. IMU-based systems have also been integrated with machine learning (ML) algorithms to automate posture classification and WMSD risk detection. For instance, a multi-step deep learning pipeline incorporating a Seq2Seq LSTM architecture was used to forecast angular posture trajectories and detect high-risk movements, demonstrating strong performance on data collected via shoulder-mounted IMUs [60].

IMUs are not only useful for classification but also for regression-based motion prediction, supporting both real-time feedback and long-term ergonomic planning [60]. Furthermore, IMU-based risk classification frameworks have been developed to detect postural deviations and estimate ergonomic strain, effectively replacing traditional observational tools like RULA and REBA with more scalable, sensor-driven solutions [65].

To improve biomechanical accuracy, some studies have proposed hybrid systems that combine IMUs with complementary sensors such as pressure sensors, inclinometers, or electromyography

(EMG) [67]. These multimodal setups allow for more comprehensive assessments by correlating movement patterns with muscular activity or load distribution. However, while these data fusion approaches hold promise, many remain at the experimental stage and are seldom validated under realistic industrial constraints [62,68]. Additionally, although multimodal combinations can theoretically enhance biomechanical coverage, few studies have deployed such systems in actual workplaces, often limiting trials to lab-based environments or small sample sizes [62].

Overall, wearable sensor-based ergonomic monitoring, especially when using IMUs, offers a promising alternative to subjective observational methods. By enabling real-time WMSD risk detection and supporting long-term ergonomic improvements, these technologies help bridge the gap between laboratory research and practical workplace applications [65,75].

4.1.3 Human-Robot Collaboration in Disassembly Tasks

Human-Robot Collaboration (HRC) has emerged as a core feature of Industry 4.0, enabling flexible, adaptive manufacturing systems where human and robotic agents share tasks dynamically. In these hybrid environments, robots often assume responsibility for physically demanding or repetitive operations, theoretically reducing the ergonomic burden on human workers. However, research shows that ergonomic risks, particularly those related to posture and repetition, are not fully eliminated. In disassembly tasks, for example, humans still perform physically static or awkward subtasks such as unscrewing components, disconnecting cables, or sorting materials [44,76,77,78]. These actions can contribute to cumulative strain and work-related musculoskeletal disorders (WMSDs), especially when repeated over long shifts. Despite this, physical ergonomic concerns in HRC settings are often overlooked under the assumption that automation inherently resolves such risks.

Disassembly lines, in particular, benefit greatly from HRC by enabling faster processing of end-of-life products and supporting circular economy initiatives [6,43]. However, even in cobot-assisted systems, ergonomic strain is not entirely mitigated. For instance, Siew et al. found that while collaborative disassembly improved ergonomic outcomes compared to manual operations, suboptimal task allocation could still lead to joint overloading [76,79].

While interest in ergonomics within HRC is growing, the majority of recent research has concentrated on cognitive ergonomics, including stress, mental workload, and human-robot trust. For instance, Rajavenkatanarayanan et al. developed a real-time cognitive load monitoring system using ECG and EDA sensors to support adaptive robotic behavior based on user stress levels [40]. Similarly, studies by Antonino et al. [81], Wu et al. [82], and Xie et al. [83] have explored cognitive fatigue, human-robot interaction strategies, and reinforcement learning for enhancing worker well-being. These contributions have advanced adaptive HRC systems, but they primarily address the psychological and perceptual dimensions of ergonomic comfort.

In contrast, research targeting physical ergonomic risks, especially in the context of subtasks involving awkward posture, force exertion, or sustained static positions, remains comparatively limited. Lorenzini et al. provided a comprehensive review of ergonomic HRC, concluding that although both physical and cognitive ergonomics have received increased attention, several core challenges remain unresolved. Specifically, they highlighted the absence of real-time ergonomic risk monitoring, cost-effective sensor integration, and systems capable of detecting biomechanical strain during human-robot cooperation [77].

Although several frameworks have proposed integrating tools like RULA, REBA, or biomechanical estimations into collaborative robotic systems, most of these studies focus on narrow use cases, simulated movements, or early-stage lab experiments [78,84,85]. For example, Meregalli Falerni et al. introduced an adaptive HRC system that modified robot behavior based on ergonomic posture classification, but the system was tested only in single-arm tasks within constrained lab setups [78]. Similarly, Kim et al. proposed biomechanical joint torque estimation during shared tool usage, but their model lacked generalizability to broader, real-world task sequences [85].

4.1.4. Research Gaps

Disassembly-specific HRC environments remain underexplored, despite their growing industrial relevance. Unlike high-risk sectors like construction or agriculture, ergonomic strain in semi-automated disassembly is less visible and often under-prioritized [80.81]. Another challenge in the literature is the lack of standardized comparative evaluation of ML models for ergonomic risk classification. Many prior studies evaluate a limited number of algorithms (e.g., two or three)[61,69,70]. This narrow scope limits the generalizability of findings, overlooks potentially better-performing models, and makes it difficult to draw consistent conclusions across studies.

Despite growing interest in ergonomics within human-robot collaboration, most recent research still prioritizes cognitive metrics, such as mental workload, stress, and user trust, or focuses on generalized coordination frameworks. In contrast, posture-specific physical ergonomic risks in collaborative settings remain critically underexplored [77,80,83]. This gap is particularly evident in disassembly tasks, where workers continue to perform static or awkward motions, despite robotic assistance. Few studies have addressed real-time physical ergonomic risk classification within these task contexts, especially using wearable IMUs combined with standardized risk labeling tools like RULA and REBA. As a result, there is a clear need for sensor-based frameworks that go beyond general posture classification and specifically target physical ergonomic risks during subtasks in collaborative industrial environments.

Labeling methods are frequently subjective, relying on expert ratings or self-reported discomfort, which limits generalizability [88]. Others use survey-based data without sensor input or ground-truth ergonomic scoring, such as RULA or REBA [88]. For example, Kiraz & Geçici used pose images and deep learning to classify REBA risk levels, but without task-specific segmentation or real-time context [90]. Fernandes et al. proposed sequential modeling for ergonomic hazard prediction, but did not address dual-task classification in collaborative settings [45]. Luo et al. and Hanumegowda et al. relied on questionnaires and classical ML methods but did not incorporate sensor-based motion data [61]. Matos et al. and Barkallah et al. applied LSTM and hybrid neural networks to ergonomic classification using motion and force sensors, but their datasets were limited in domain and complexity [70,32]. Chen et al. used 1D CNN to classify ergonomic risk from IMU signals but lacked simultaneous task identification [95].

4.1.5. Objectives

This study addresses these gaps by proposing a sensor-based framework for ergonomic risk detection in collaborative disassembly. A controlled lab setup is used to simulate realistic subtasks, each labeled using standardized RULA and REBA scores. This unified and replicable setup ensures consistent risk labeling across subtasks while maintaining methodological control over experimental variables. IMU data is captured in real time to construct a multi-class dataset. Six machine learning models, CNN, DNN, SVM, KNN, Decision Tree, and Random Forest, are then evaluated using consistent preprocessing, task segmentation, and dual classification outputs. Prior work confirms that joint overloading persists during HRC tasks [79] and that even when simulation tools are available, manual disassembly poses significant ergonomic risks [36].

In summary, machine learning has been increasingly applied to ergonomic risk classification, particularly through wearable sensor data and posture recognition. Yet, key limitations persist in prior studies, including subjective labeling, lack of task-specific risk modeling, and settings that are non-industrial or non-collaborative. Comparative benchmarking is also limited, with most approaches focusing solely on posture classification, neglecting task identification and multi-phase subtasks. Moreover, cognitive ergonomics in HRC has received more attention than physical risk modeling, especially in real-time contexts. To address these gaps, our study proposes a dual-output classification model, predicting ergonomic risk levels and subtasks in an HRC disassembly setting, using structured sensor data and evaluating six ML algorithms based on accuracy, precision, recall, and F1-score. It is important to note that this study was conducted using a single-subject dataset in a controlled environment, which supports reproducibility but may limit generalizability, an aspect further discussed in Section 4.3.

To express the novelty of our proposed model, we compare it to recent studies in Table 4-1, which summarizes key characteristics such as task focus, labeling strategy, application domain, ML model selection, dataset design, and evaluation metrics. As shown in the table, most existing works focus on posture-based risk recognition, often in high-risk physical domains, with limited application to collaborative, task-based environments. In contrast, our work integrates real-time sensor data, subtask-specific risk labeling using RULA and REBA, and dual classification of both task and ergonomic risk in an HRC disassembly context, offering a structured and reproducible contribution to the field.

Table 4-1: Comparative Evaluation Toward Previous Studies

Index	Study	Task Focus	Labeling Method	Application Domain	ML Models Compared	Dataset Consistency	Risk Levels Predefined	Data Source	ML Task	Measure
1	Hida et al. (2022) [92]	OWAS-based posture evaluation	Manual posture coding from 3D→2D	Lab-based simulated postures	k-NN, SVM	✓	✓	Motion capture (2D)	Classification	Accuracy
2	Villalobos & Mac Cawley (2022) [93]	RULA score + knife sharpness prediction	Post-task expert rating	Slaughterhouse	DT, RF, ET, SVM	✓	✓	Wearable IMU	Classification	Accuracy, F1

Table 4-1: Comparative Evaluation Toward Previous Studies (continued)

3	Zhao & Obonyo (2020)	Posture recognition	Manual video-based	Construction	CNN, LSTM, CNN-LSTM	✓	✗	IMUs	Classification	Accuracy
4	Luo et al. (2024) [94]	WMSD risk prediction	Self-reported questionnaire	Healthcare	RF, SVM, MLP, ENet, XGBoost	✓	✗	Survey (no physical sensing)	Classification	F1, SHAP Explanation
5	Hanumegowda et al. (2022)	WMSD risk prediction	Questionnaire-based self-report	Bus driving	DT, RF, Naïve Bayes	✓	✗	Survey (MNMQ)	Classification	Accuracy

Table 4-1: Comparative Evaluation Toward Previous Studies (continued)

6	Wang Chen et al. (2024) [95]	Posture + ergonomic risk estimation	Automatic via REBA scoring	Construction	Regression CNN (FusionPose)	✓	✓	Fused 2D/3D vision datasets (open source)	Regression	REBA error score
7	Kiraz & Geçici (2024)	Posture-based risk prediction	Automatic (REBA/RULA/OWAS)	Generic industrial platforms	MediaPipe (R-CNN)	✓	✓	COCO & MPII image datasets	Classification	Accuracy
8	Antwi-Afari et al. (2022) [95]	Posture classification	Automatic via sensor + video reference	Construction	CNN, LSTM	✓	✗	Insole wearable sensors	Classification	Accuracy

Table 4-1: Comparative Evaluation Toward Previous Studies (continued and end)										
9	Matos et al. (2024)	Upper-limb WMSD risk	Rule-based (RULA + ISO 11226)	Textile manufacturing	SVM, MLP, XGBoost, LSTM	✓	✓	Optical Motion Capture (OMS)	Classification, Regression	F1, Accuracy, R^2
10	**Our model**	Task + ergonomic risk	Predefined using RULA/REBA	HRC disassembly lab	CNN, DNN, SVM, RF, KNN, DT	✓	✓	Wearable motion capture sensors	Classification (Dual Output)	Accuracy, Precision, Recall, F1 sscore

4.2. Methodology

This study adopts a structured methodology comprising six components: participant and experimental setup, task description and ergonomic risk assessment, sensor setup and data collection, data preprocessing and feature extraction, machine learning model training and evaluation, and the development of a dual-output deep learning classifier for ergonomic risk prediction. As illustrated in Figure 4-2, this six-stage pipeline ensures a systematic flow from experimental design to model deployment, integrating ergonomic principles with advanced machine learning for accurate and interpretable risk assessment.

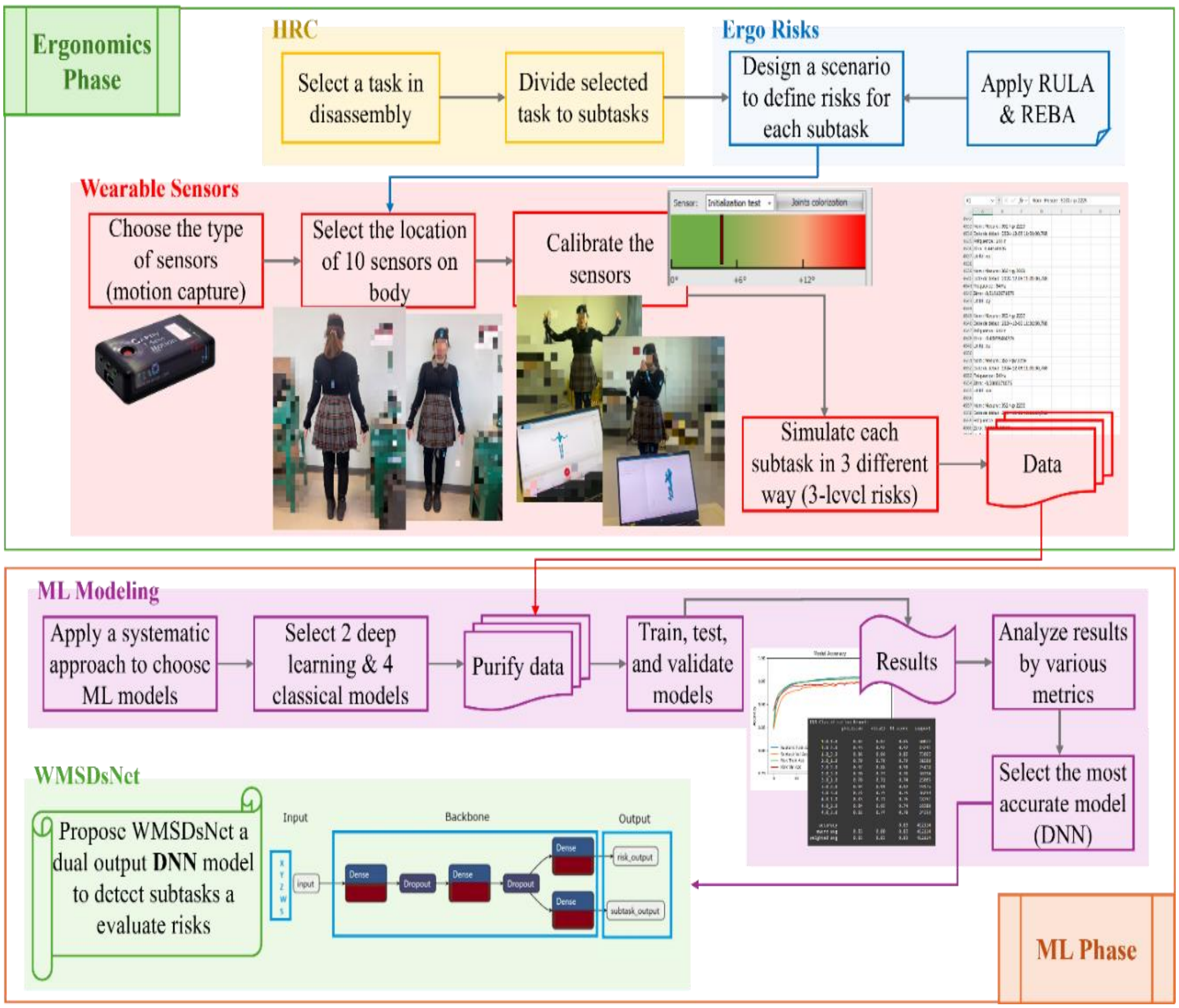


Figure 4-2: Workflows Overview

4.2.1. Experimental Setup

Experiments were conducted in a controlled laboratory environment (at Polytechnique Montreal University), simulating a human-robot collaborative (HRC) disassembly workstation. The researcher performed all human-subtask executions, ensuring consistency and eliminating inter-subject variability. The scenario involved the disassembly of a Programmable Logic Controller (PLC), selected for its structural complexity and demand for diverse physical actions, such as fine motor control, dynamic movement, and sustained posture. These characteristics allowed for capturing a wide spectrum of ergonomic risk levels relevant to industrial environments.

To mitigate ethical concerns, no external participants were involved. All subtasks were predefined and executed following strict ergonomic scoring protocols using RULA and REBA. This ensured controlled, repeatable motion sequences aligned with specific ergonomic risk levels and industrial task demands.

4.2.2. Task Description and Ergonomic Risk Assessment

Four representative subtasks were designed to reflect key physical movements in collaborative disassembly:

1. Unscrewing components – involving upper-limb precision and wrist deviation.
2. Detaching cables – requiring repetitive pulling and shoulder-arm coordination.
3. Sorting components – involving dynamic full-body movements (e.g., bending, twisting).
4. Changing robot tools – requiring static posture and postural control.

These subtasks were selected to represent three ergonomic patterns: static, repetitive, and dynamic. Each was simulated at three ergonomic risk levels: low, moderate, and high. The ergonomic risk levels were predefined based on RULA for upper-body tasks and REBA for full-body tasks. Each subtask-risk pair was repeated three times to ensure consistency and repeatability, forming 12 unique combinations.

Risk labeling was grounded in ergonomic theory and executed through a scenario-based protocol. Rather than post hoc scoring, risks were assigned through predefined movement sequences reflecting RULA/REBA thresholds. For example, sorting involved trunk flexion and twisting motions classified as high risk under REBA, while unscrewing included sustained wrist angles exceeding RULA thresholds.

4.2.3. Sensor Setup and Data Collection

A total of 10 T-Sens Motion sensors (TEA, Version 9.0) were used to capture full-body movement data. Each sensor included a 3-axis accelerometer and gyroscope, recording five types of signals: linear acceleration along the X, Y, and Z axes, angular velocity (W), and a sensor ID tag (S). The sensors recorded data at a sampling rate of 100 Hz, offering high temporal granularity to detect rapid motion changes and subtle joint deviations that are essential for robust risk classification.

The sensors were placed on the head, shoulders, upper arms, forearms, waist, lower back, and legs. These locations were chosen to track key joints and body segments involved in the disassembly tasks, such as shoulder rotation, trunk bending, and leg stabilization, while keeping the setup practical and not overly intrusive.

After data collection, the recordings were reviewed to confirm that each movement matched the intended ergonomic risk level. Each subtask-risk combination was repeated three times to ensure consistency, and movement traces were checked to align with RULA and REBA scoring thresholds. This helped confirm that the data accurately reflected the different ergonomic conditions being studied.

4.2.4. Data Preprocessing and Feature Extraction

Captured signals underwent a structured preprocessing pipeline comprising three steps. First, noise was attenuated using a 4th-order low-pass Butterworth filter with a cutoff frequency of 5 Hz, effectively removing high-frequency sensor noise while preserving relevant human motion patterns. Second, z-score standardization was applied across all sensor channels to ensure consistent input scaling, which is essential for stable model training. Finally, the signals were segmented into fixed-length windows of 2 seconds (200 samples at 100 Hz), with each window labeled by its associated subtask and ergonomic risk level (e.g., “detaching cables at high risk”). The 2-second window length was chosen to reflect the average duration of discrete disassembly motions, offering sufficient temporal context for recognizing posture dynamics and ergonomic transitions.

This process yielded a 12-class single-label classification task, corresponding to the combination of 4 subtasks and 3 ergonomic risk levels. The final dataset included approximately 750,000 segments, with each class comprising roughly 60,000 to 70,000 samples. While minor imbalance emerged due to differences in motion complexity and execution time across subtasks (e.g., sorting versus unscrewing), the scenario was designed with equal repetition and trial length per condition. As a result, no resampling or class weighting was necessary, and all models were trained directly on this near-uniform distribution. To support fair evaluation across model types, the dataset was partitioned as follows: 80/20 for classical machine learning models (training/testing), and 70/10/20 for deep learning models (training/validation/testing).

Both classical and deep learning models received raw segmented IMU sequences as input. For classical models, each 2-second segment was flattened into a fixed-length vector (5 signals × 200 samples = 1000 features), allowing them to process raw temporal information without handcrafted feature extraction. This approach ensured consistency in input structure across models and preserved the full kinematic content of the signals, linear acceleration (X, Y, Z), angular velocity (W), and sensor ID (S), captured across all body segments.

4.2.5. Machine Learning Models and Evaluation

Six supervised machine learning models were applied to classify ergonomic risks and identify disassembly subtasks:

- Deep Learning Models: Convolutional Neural Network (CNN), Deep Neural Network (DNN)
- Classical Machine Learning Models: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN)

These models were chosen for their range of learning capabilities, interpretability, and prior use in ergonomic literature. Classical models were implemented in scikit-learn and trained using grid-search hyperparameter tuning with the following search space:

- SVM: kernel = [‘linear’, ‘rbf’], C = [0.1, 1, 10], gamma = [‘scale’, 0.01, 0.001]
- Random Forest: n_estimators = [100, 300, 500], max_depth = [10, 20, None], min_samples_leaf = [1, 2, 4]

- Decision Tree: max_depth = [5, 10, 20], min_samples_leaf = [1, 2, 4]
- KNN: n_neighbors = [3, 5, 7, 9, 11, 15]

For these models, an 80/20 train-test split was used. Although k-fold cross-validation is common, a fixed split was applied to ensure consistent comparison across classical and deep learning architectures.

Deep learning models were developed using TensorFlow/Keras and trained on raw IMU segments. A 70/10/20 split was used for training, validation, and testing. Models were trained with the Adam optimizer, learning rates between 0.001 and 0.0001, and batch sizes of 32 and 64. Early stopping was used based on validation loss, with a patience value of 10 epochs and a maximum of 100 training epochs.

For the 12-class flat classification setup, categorical cross-entropy was used as the loss function. For the WMSDsNet multi-task model, two categorical cross-entropy losses were used, one for subtask classification and one for ergonomic risk level prediction, combined via a weighted sum.

Performance was evaluated using: Accuracy, Precision, Recall, Macro F1-Score, Confusion Matrices

For deep models, training and validation loss curves were monitored to assess convergence behavior and generalization.

This evaluation ensured fair and comprehensive comparison across architectures and model types. All training was performed on a system equipped with an Intel Core i7 CPU, 32 GB RAM, and an NVIDIA GeForce RTX 3060 GPU (12 GB VRAM). This setup enabled efficient model training, particularly for deep learning architectures..

4.2.6. Proposed Model: WMSDsNet

To improve classification granularity and mirror real-world ergonomics workflows, we propose WMSDsNet, a dual-output deep learning model. Instead of a flat 12-class model, WMSDsNet uses multi-task learning to independently predict: Subtask type (4 classes) and Ergonomic risk level (3 classes).

- The CNN version includes: Input reshaping, two Conv1D layers (32 and 64 filters), Dropout layers, Global Average Pooling (GAP1D), two parallel dense output heads (Softmax activation for subtask and risk level), as shown in Figure 4-3.

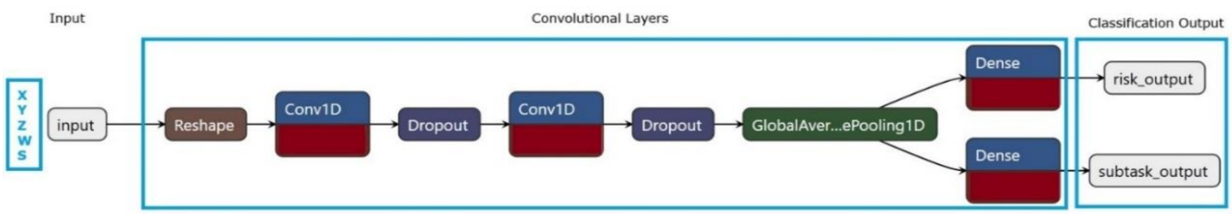


Figure 4-3. CNN Architecture

- The DNN version includes: Two fully connected dense layers (64 units), Dropout, Two output heads for task and risk, as shown in Figure 4-4.

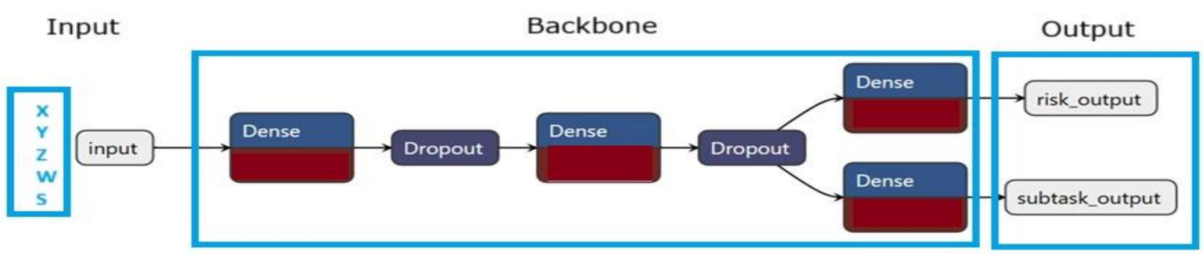


Figure 4-4. DNN Architecture

Both models were trained using the Adam optimizer with an initial learning rate of 0.001. The training process used batch sizes of 32 and 64, and a maximum of 100 epochs. To prevent overfitting, early stopping was applied with a patience of 10 validation epochs.

In terms of loss functions, a multi-task categorical cross-entropy setup was used. The total loss was computed as a weighted sum of the individual loss terms for each output head:

$$\text{Total Loss} = \lambda_1 \cdot \text{Loss}_{\text{subtask}+} \lambda 2 \cdot \text{Loss}_{\text{risk level}}$$

In this study, equal weighting was used:

$$\lambda_1 = \lambda_2 = 1$$

This configuration ensured that both subtask and ergonomic risk predictions contributed equally to model optimization, allowing balanced learning across tasks.

Performance was evaluated using the same metrics as other models for comparability: Accuracy, Precision, Recall, Macro F1-Score, Confusion Matrices

For deep models, training and validation loss curves were monitored to assess generalization and convergence behavior.

4.3. Results

4.3.1 Deep Learning Model Results

To evaluate ergonomic risk and subtask recognition using wearable sensors, two deep learning models were developed: a Convolutional Neural Network (CNN) and a Deep Neural Network (DNN). Both were designed as multi-output classifiers, predicting ergonomic risk level (low, moderate, high) and the physical subtask being performed (e.g., unscrewing, detaching, sorting). The models were trained on the same dataset using a 70% training, 20% testing, and 10% validation split, and evaluated independently for their performance in this dual classification task.

In terms of final classification performance, both models demonstrated strong results across outputs. The CNN reached an accuracy of 88% for subtask classification and 89% for risk level prediction, while the DNN achieved 92% and 90%, respectively. These outcomes are visualized in Figure 4-5a (CNN) and Figure 4-5b (DNN), where the accuracy scores for both outputs are displayed. Each model shows effective learning of temporal and ergonomic patterns, appropriate for real-time prediction in human-robot collaboration settings.

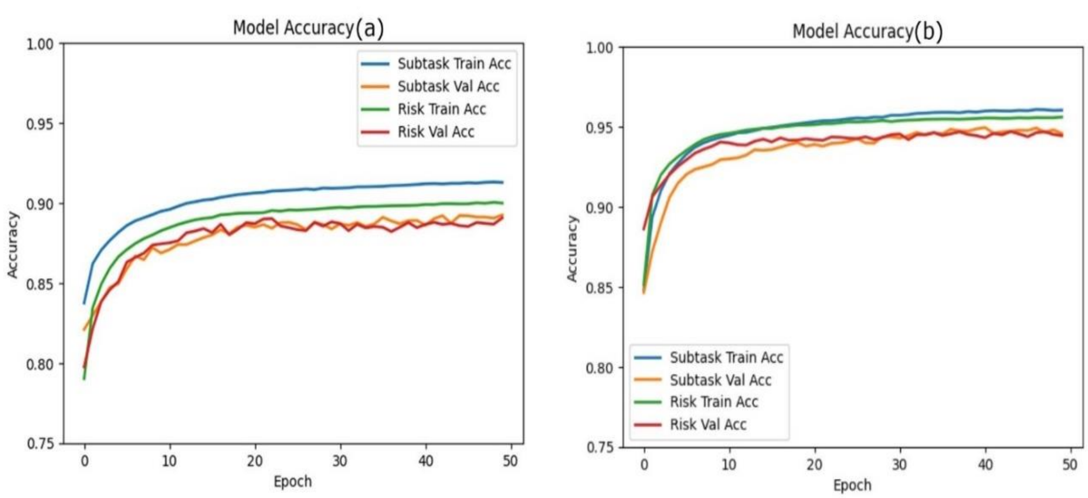


Figure 4-5. Model Accuracy for CNN(a) and DNN(b)

The learning behavior over time for both models was stable and consistent. CNN training progressed smoothly over 50 epochs, with training and validation curves closely aligned throughout the process. Similarly, the DNN showed fast and reliable convergence with minimal divergence between training and validation phases. This behavior is illustrated in Figure 4-6a for the CNN and Figure 4-6b for the DNN, where loss curves for both outputs demonstrate clear learning progress without overfitting. The DNN exhibited slightly earlier convergence, while the CNN maintained steady improvement throughout the training period.

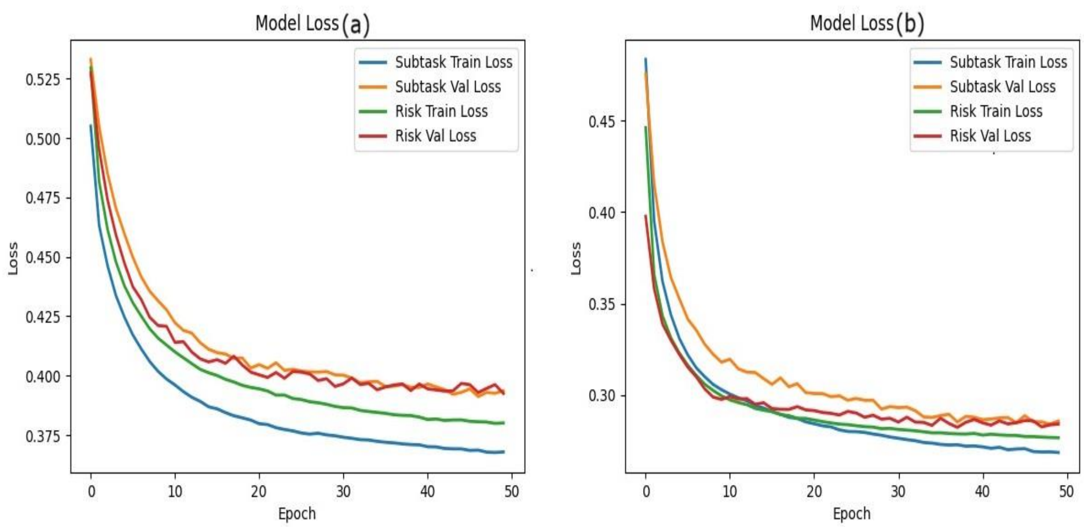


Figure 4-6. Model Loss for CNN(a) and DNN(b)

Prediction performance across all classes is further examined using confusion matrices. Figure 4-7a displays two confusion matrices for the CNN model: one for subtask classification and another for risk level prediction. The subtask matrix shows strong diagonal accuracy, with some misclassification between Subtask 2 and Subtask 3. The risk matrix reflects good performance overall, with minor confusion in moderate risk levels. This confusion likely stems from the inherent similarity between the two subtasks, as both involve hand-level manipulations with limited gross body movement and similar motion dynamics. These overlapping patterns may reduce the CNN's ability to clearly differentiate between their temporal signatures. This confusion likely stems from the inherent similarity between the two subtasks, as both involve hand-level manipulations with limited gross body movement and similar motion dynamics. These overlapping patterns may reduce the CNN's ability to clearly differentiate between their temporal signatures. Figure 4-7b shows the corresponding confusion matrices for the DNN model. Both matrices demonstrate clean decision boundaries, with stronger diagonal dominance compared to CNN. Subtask classification is highly accurate across all four classes, and risk level predictions show minimal overlap, even in complex ergonomic states.

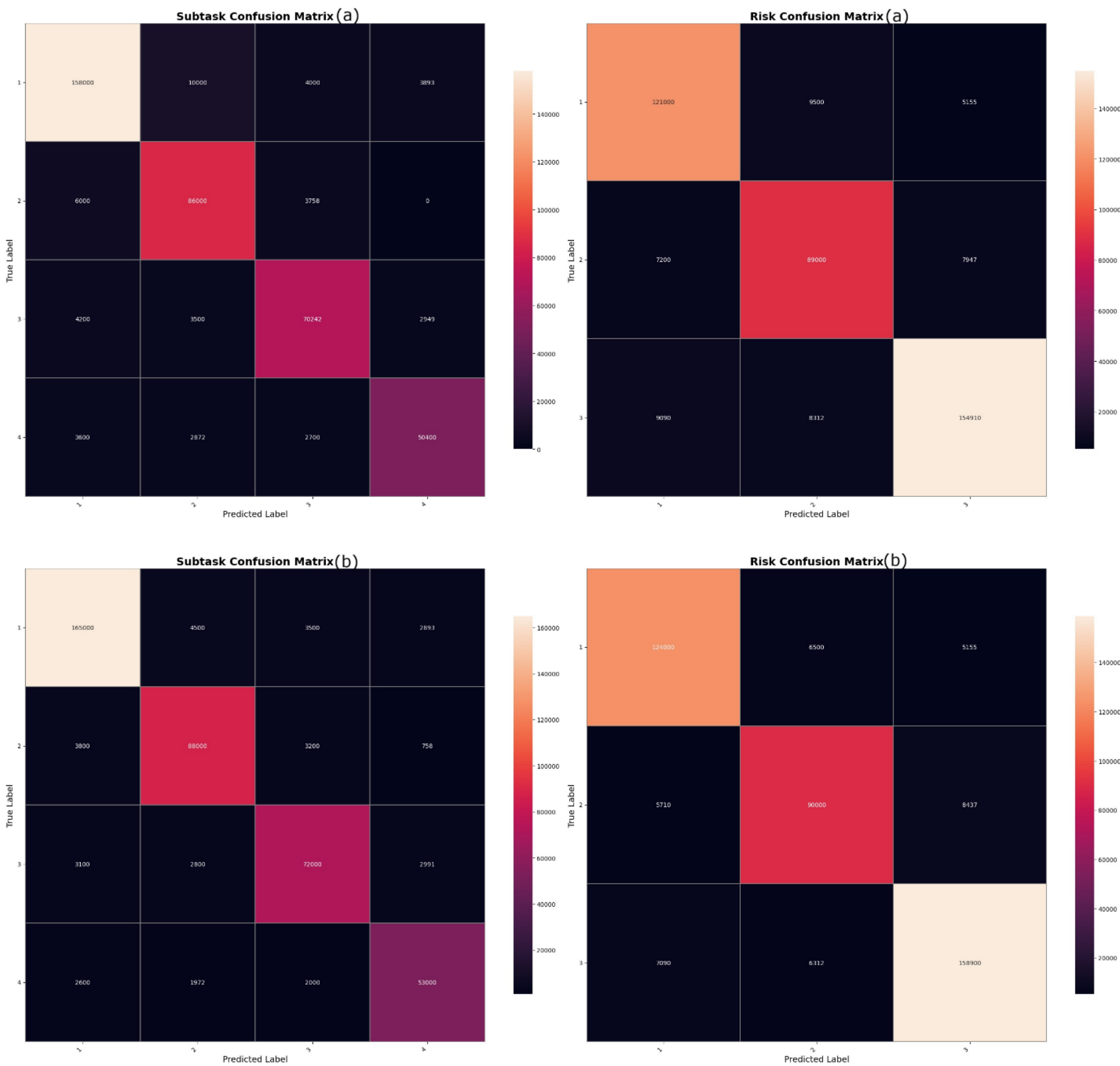


Figure 4-7. Confusion matrices for the CNN model(a) and DNN (b): one for subtask classification and another for risk level prediction

To complement the qualitative insights provided by the confusion matrices, Table 4-2 summarizes the macro-average F1-scores for both subtask and risk level classification. These scores reflect the models' overall performance across all classes, highlighting the balanced prediction capabilities of both CNN and DNN. As shown, the DNN slightly outperformed the CNN in both outputs, consistent with the observed diagonal strength in the confusion matrices.

Table 4-2. Macro-average F1-scores for subtask and risk classification based on confusion matrix evaluations.

Model	**Output Type**	**Macro F1-Score**
CNN	Subtask	0.88
	Risk	0.88
DNN	Subtask	0.91
	Risk	0.90

Overall, the CNN and DNN models each demonstrated effective multi-output learning, with strong accuracy, well-behaved training curves, and generally clean class separation. These results support their potential use in ergonomic risk detection systems based on real-time sensor data.

Between the two deep learning models evaluated, the DNN consistently outperformed the CNN across all key metrics. While both models achieved high classification accuracy and macro-average F1-scores (CNN: 88%/88%, DNN: 92%/90%), the DNN exhibited superior training stability, faster convergence, and cleaner confusion matrices, particularly in complex subtask–risk combinations such as Subtask 4 under high ergonomic strain. Additionally, the DNN's simpler architecture resulted in shorter training time and faster inference, enhancing its suitability for real-time implementation.

The CNN, although capable, did not show a performance advantage despite its greater architectural complexity. This is likely due to the relatively low spatial complexity and short temporal depth of the input data. The wearable sensor dataset consisted of compact motion segments (5 features per timestep, short sequences), where long-range temporal dependencies or rich local patterns, typically exploited by convolutional architectures, were limited. As a result, the CNN's ability to extract hierarchical spatial features offered no significant benefit, while still incurring higher computational costs. These factors position the DNN as the more efficient and well-matched model for the given data characteristics.

4.3.2 Classical Machine Learning Model Performance

In addition to the deep learning architectures, four classical machine learning (ML) models were implemented and evaluated: K-Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), and Support Vector Machine (SVM). Unlike the CNN and DNN models, which supported multi-output classification, these classical models were applied to a flattened single-label format combining both subtask and risk level into 12 joint classes (4 subtasks × 3 risk levels). This allowed each model to predict from a unified label set representing ergonomic risk within specific task contexts.

The overall classification performance of the classical models varied depending on their ability to capture motion–risk relationships embedded in the wearable sensor data. Based on the information shown in table 3, the Random Forest model achieved the highest accuracy among classical approaches (87% accuracy, macro-average F1-score: 0.85), reflecting its strength in modeling non-linear relationships and its robustness to noise and feature interactions. K-Nearest Neighbors (KNN) followed with 83% accuracy and an F1-score of 0.80, performing reasonably well but showing limitations in generalizing complex subtask–risk overlaps due to its sensitivity to feature scale and local variability.

The Decision Tree model achieved 83% accuracy and a slightly higher F1-score of 0.82 but showed signs of underfitting, particularly in high-risk categories, which likely stems from its shallow partitioning strategy and lack of ensemble learning to boost decision boundaries. In contrast, the Support Vector Machine (SVM) performed the weakest (51% accuracy, F1-score: 0.45), struggling with the 12-class space. This poor performance can be attributed to the linear nature of SVM's decision boundaries, which are less suited for modeling the non-linear and multidimensional temporal patterns found in sensor-based ergonomic data.

These outcomes highlight how model suitability depends not only on algorithmic complexity but also on how well the model's structure aligns with the data's temporal, non-linear, and multivariate characteristics. Non-linear ensemble methods like Random Forest are better equipped to handle such complexity, whereas linear models like SVM are inherently limited in this context.

Table 4-3. Accuracy and macro-average F1-scores for classical machine learning models on 12-class subtask–risk prediction.

Model	**Accuracy**	**Macro F1-score**
KNN	83%	0.80
Random Forest	87%	0.85
Decision Tree	83%	0.82
SVM	51%	0.45

Figure 4-8 displays the confusion matrices for all four classical models. In each matrix, the rows represent the true labels, and the columns represent the predicted labels. Subtask codes are defined as follows: 1 = Unscrewing components, 2 = Detaching cables, 3 = Sorting components, and 4 = Tool changing. Risk level codes follow the structure: 1 = Low risk, 2 = Moderate risk, and 3 = High risk. For example, the label 2.0_3.0 indicates the activity of detaching cables performed under high ergonomic risk.

The confusion matrices reveal how each model handled this 12-class classification task. Diagonal entries in each matrix indicate correctly classified instances, while off-diagonal entries reflect misclassifications. In general, models like KNN and Random Forest show stronger diagonal alignment, particularly in well-represented classes such as 1.0_1.0 or 3.0_2.0. In contrast, models like SVM and Decision Tree exhibit more dispersed misclassification patterns, especially among overlapping risk levels and motion-similar subtasks. These distributions offer insight into the specific strengths and limitations of each model, particularly in learning subtle ergonomic distinctions based on motion sensor input.

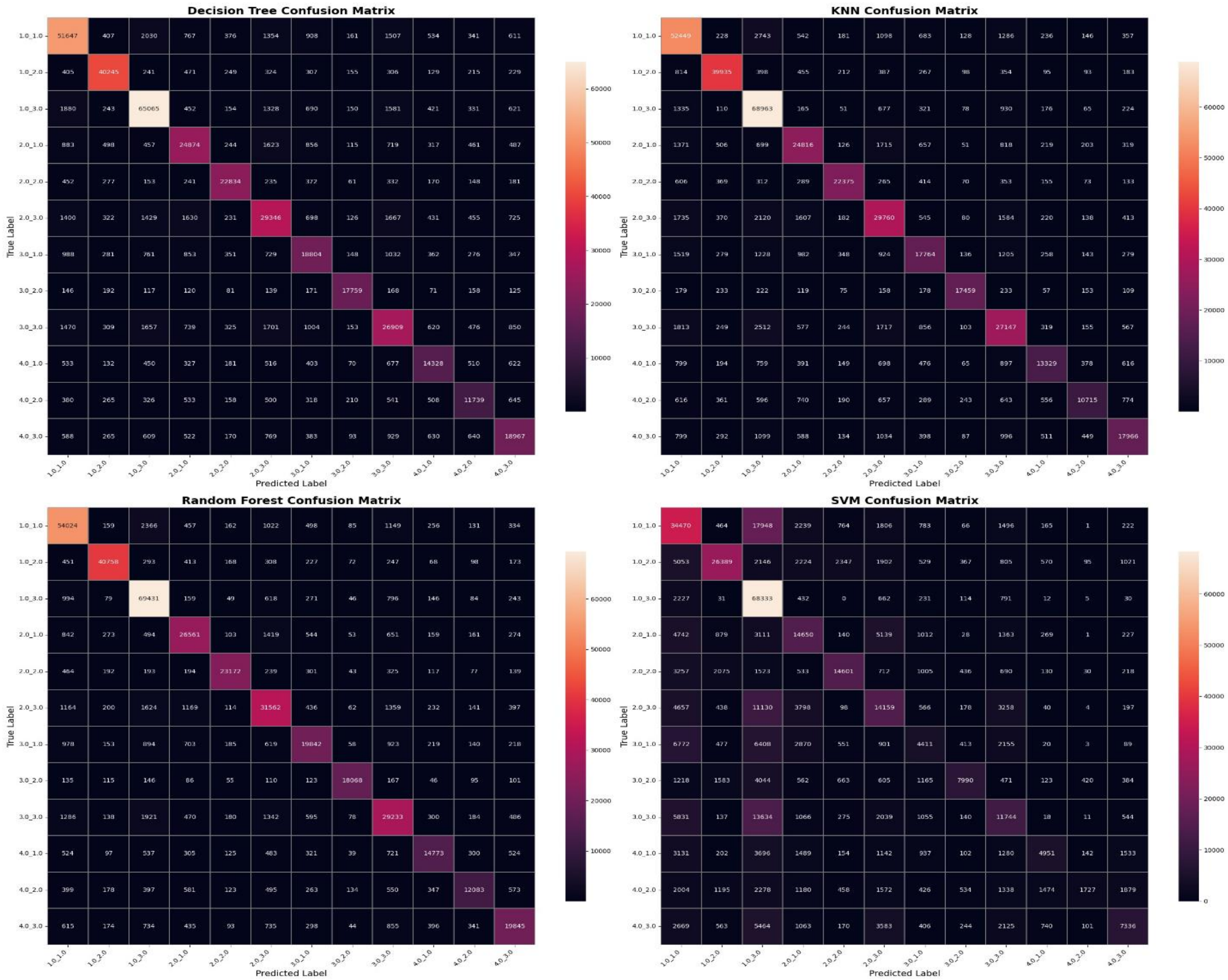


Figure 4-8. Confusion Matrices for Classical Models

Among the four classical machine learning models, Random Forest emerged as the strongest, achieving 87% accuracy and a macro-average F1-score of 0.85. It maintained solid class-level performance across both frequent and rare subtask–risk combinations. KNN and Decision Tree followed with comparable accuracy (83%), though the Decision Tree exhibited slightly better class balance. In contrast, SVM underperformed significantly, with only 51% accuracy and an F1-score of 0.45, indicating the lack of adaptability to overlapping ergonomic classes. The classical models, while valuable in low-resource or explainability-driven contexts, lacked the flexibility and precision required for nuanced ergonomic risk detection to support model selection for the proposed WMSDsNet framework. All six models were evaluated across five key criteria: accuracy, risk-level F1-score, class balance, generalization, and speed. These dimensions capture not only classification performance but also practical suitability for real-time ergonomic monitoring. Class

Balance was quantified by calculating the standard deviation of per-class F1-scores and inverting it to reflect uniformity: models with more evenly distributed precision and recall across all 12 classes received higher Class Balance scores. This approach captures the model's ability to generalize across both frequent and less frequent subtask–risk combinations, even though class sizes were roughly balanced during scenario design. The results are summarized visually in Figures 11 and 12, providing an at-a-glance comparison of the models' strengths.

Figure 4-9 presents radar charts for all 6 models, showing their performance profiles across the five criteria. The DNN model exhibits the most balanced and consistently high performance, with near-maximal values across all dimensions. The CNN also performs strongly but with slightly lower speed and generalization. Random Forest leads among classical models, with a solid performance in accuracy and class balance, though it lags in speed due to its ensemble nature. KNN and Decision Tree deliver moderate results, while SVM displays uniformly poor performance, with low F1-score, weak class separation, and minimal generalization.

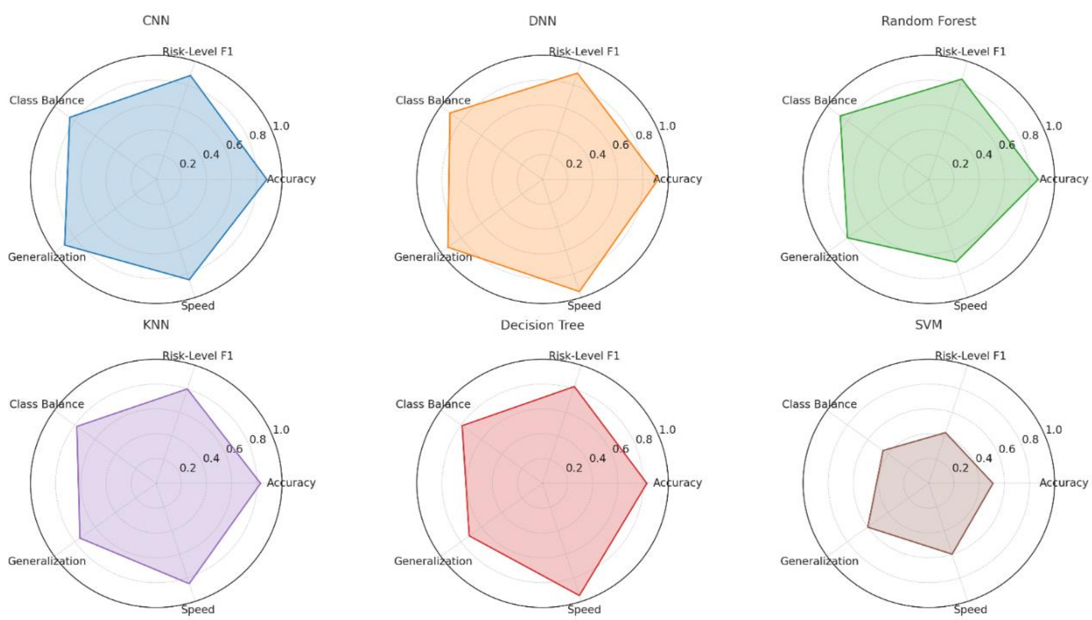


Figure 4-9. Models' Robustness for all 6 Models

To provide a more quantitative overview, Figure 4-10 presents a heatmap of normalized performance scores (scaled from 0 to 1). The DNN model ranks highest across nearly all criteria, including a perfect 0.95 in speed, indicating its efficiency and scalability. CNN follows closely, with strong scores in generalization and accuracy. Among classical models, Random Forest achieves the best balance between prediction quality and robustness, while SVM remains the least effective overall.

Taken together, these visualizations reinforce the earlier numerical findings and support the selection of DNN as the most suitable model for integration into WMSDsNet. Its combination of high accuracy, balanced class predictions, adaptability to complex sensor data, and computational efficiency makes it ideal for real-time ergonomic risk detection in dynamic human-robot collaboration environments.

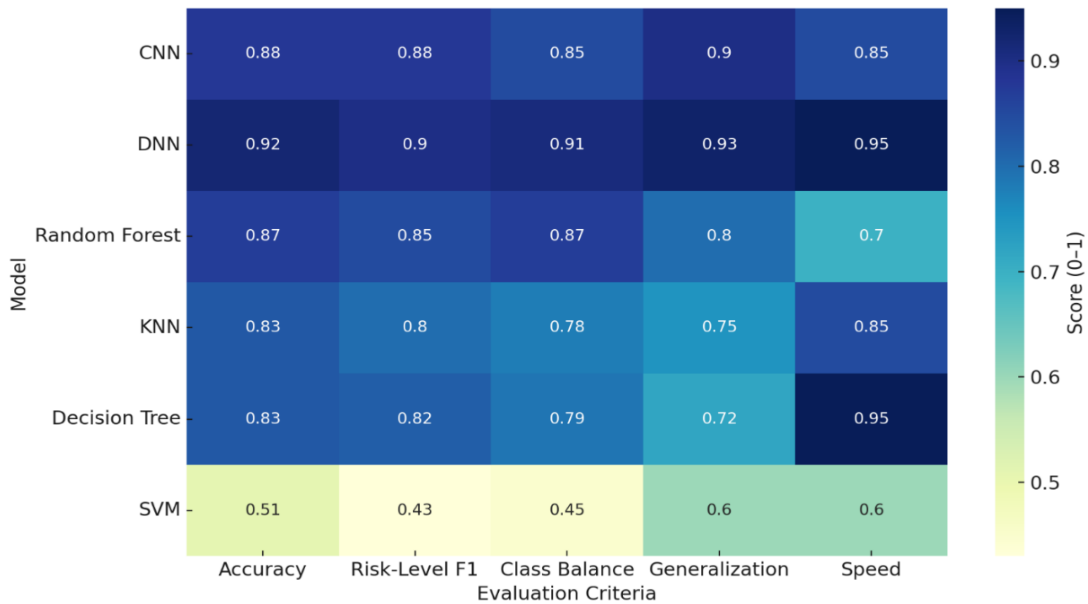


Figure 4-10. Models' Performance

4.3.3. Discussion of Comparative Evaluation

To contextualize the performance of the proposed WMSDsNet framework, we compare its results against several recent studies that applied machine learning methods to the classification or prediction of work-related musculoskeletal disorders (WMSDs). Nath et al. [96] developed an SVM-based model using smartphone IMU data to classify ergonomic risk into three levels and achieved a classification accuracy of 90.2%. Their study focused on activity type, duration, and repetition in construction environments, but did not account for subtask-specific predictions. Halder et al. [97] employed a vision-based approach (MediaPipe Pose combined with ANN) for real-time classification of ergonomic versus non-ergonomic postures and reported a very high validation accuracy of 99.96%. However, their approach did not include ergonomic risk stratification or subtask segmentation and relied on video-based inputs, which may not be robust to occlusion or lighting variability in industrial settings.

In contrast, our proposed WMSDsNet framework achieved 92% accuracy for subtask classification and 90% accuracy for risk level prediction using wearable motion-capturing sensors. The DNN model within the framework produced macro-average F1-scores of 0.91 and 0.90, respectively, and supports multi-output prediction, offering simultaneous subtask and risk classification. Unlike prior studies focused solely on posture labeling or binary risk detection, our framework addresses ergonomic risk classification within task context (e.g., unscrewing under moderate risk), which is critical for fine-grained ergonomic interventions in human-robot collaborative (HRC) environments. To better contextualize WMSDsNet's performance, Table 4-4 summarizes the key input types, output types, and results reported by comparable studies alongside ours.

Table 4-4. Comparison of WMSDsNet performance with recent studies on ergonomic risk classification.

Study	**Input Type**	**Risk Stratification**	**Subtask Classification**	**Accuracy**	**Macro F1**	**Output Type**
Nath et al. [96]	Smartphone IMU	✓ (3 levels)	✗	90.2%	–	Single-label
Halder et al. [97]	Vision-based	✗	✗	99.96%	–	Binary posture
WMSDsNet (DNN)	Wearable IMUs	✓ (3 levels)	✓ (4 subtasks)	90% / 92%	0.90 / 0.91	Multi-output

The evaluation of WMSDsNet across six machine learning models and structured subtasks further strengthens the reproducibility and interpretability of its results.

However, some limitations should be acknowledged. The dataset used to train and evaluate the models was generated using a single subject performing predefined subtasks in a controlled laboratory setting. The goal was to simulate realistic task scenarios and generate consistent, labeled numerical examples suitable for comparing machine learning models, not to produce generalizable human data. While this ensures traceability and control over experimental conditions, it may limit applicability to broader industrial populations. Generalizing to multi-subject datasets presents additional challenges, such as inter-subject variability in anthropometrics, movement styles, and ergonomic behaviors, which can influence sensor readings and classification accuracy. Furthermore, ergonomic risk levels were assigned using predefined RULA and REBA scores, which do not include real-time expert judgment or worker self-report.

Future work will aim to expand the dataset through multi-subject experiments to improve the model's generalizability. Incorporating expert ergonomic labeling or adaptive thresholds based on worker profiles may enhance personalization. Additionally, deploying WMSDsNet in a live HRC environment, with real-time feedback, task reallocation, or break scheduling based on predicted ergonomic strain, presents a promising direction for integrating AI-driven safety systems into Industry 4.0 applications.

4.4. Conclusion

This study proposed WMSDsNet, a sensor-based machine learning framework for real-time ergonomic risk prediction during human-robot collaboration in disassembly environments. Using wearable sensors, the system collects motion data across key body segments while a worker performs predefined subtasks. The data is processed and used to train and evaluate six machine learning models, CNN, DNN, KNN, Random Forest, Decision Tree, and SVM, tasked with jointly predicting the performed subtask and the associated ergonomic risk level.

Among the evaluated models, the Deep Neural Network (DNN) emerged as the most suitable for this dual-output classification task. It achieved 92% accuracy for subtask recognition and 90% accuracy for risk level classification, along with macro-average F1-scores of 0.91 and 0.90, respectively. The DNN also demonstrated high generalization, efficiency, and balanced class performance, making it ideal for deployment in real-time ergonomic monitoring applications. Classical machine learning models such as Random Forest and KNN showed reasonable performance but lacked the predictive precision and multi-output capability required for more nuanced ergonomic feedback.

Compared to prior studies, WMSDsNet introduces a novel contribution by simultaneously classifying subtasks and ergonomic risk levels, enabling more context-aware and actionable interventions. While many existing works focus solely on posture detection or binary ergonomic assessment, WMSDsNet provides a more granular understanding of physical demands by embedding risk prediction within specific task structures.

Overall, WMSDsNet offers a promising step toward data-driven ergonomic risk assessment, aligning with the goals of Industry 4.0 by enabling intelligent, proactive interventions to prevent work-related musculoskeletal disorders in collaborative manufacturing environments. Future work will focus on validating WMSDsNet in multi-subject studies and deploying it in live industrial settings to assess its real-world effectiveness in preventing ergonomic injuries.

CHAPTER 5 GENERAL DISCUSSION

This research developed and evaluated WMSDsNet, a real-time ergonomic-risk-prediction framework for human-robot-collaborative (HRC) disassembly environments using wearable inertial measurement units (IMUs) and machine-learning (ML) models.

The work addressed a persistent limitation in ergonomic risk assessment, the reliance on static, snapshot posture evaluations that overlook the cumulative nature of work-related musculoskeletal disorder (WMSD) risks arising from posture duration and repetition. By combining continuous motion capture with AI-driven classification, the study enabled simultaneous task recognition and ergonomic-risk prediction, advancing the integration of wearable-sensor data into industrial ergonomics.

The research evolved through two complementary phases.

The first, presented at the 2025 IEEE International Conference on Human-Machine Systems (ICHMS), validated the feasibility of using a dual-output deep-learning architecture trained on raw IMU data to classify both subtasks and corresponding ergonomic risk levels. The second, submitted to the International Journal of Industrial Ergonomics, extended this contribution by benchmarking six ML models (CNN, DNN, SVM, Random Forest, Decision Tree, and KNN) under identical conditions, thus ensuring methodological transparency and reproducibility.

Justification of Model Architecture Choices

The inclusion of both CNN and DNN architectures was deliberate. CNNs learn spatial correlations among sensor axes, capturing localized signal patterns, whereas DNNs exploit fully connected layers to model nonlinear interactions across channels and time windows without handcrafted features.

After iterative hyper-parameter tuning, the DNN demonstrated greater stability and generalization, confirming its suitability as the backbone of WMSDsNet.

The complementary evaluation of deep and classical algorithms (SVM, KNN, DT, RF) provided a balanced perspective on accuracy, interpretability, and computational cost, aligning with Oulmane’s request for explicit architectural reasoning.

Comparative Findings and Context

Prior studies, such as Karvekar et al. (2022) comparing CNN and SVM for repetitive posture classification, and Cho et al. (2020) applying RF and ANN to lifting-risk assessment, offered valuable but narrowly scoped insights.

In contrast, this work assessed six algorithms across multiple disassembly subtasks, demonstrating that the DNN achieved the best compromise between accuracy, class balance, and efficiency for real-time use.
The Random Forest exhibited competitive accuracy and high interpretability, while the CNN performed strongly on spatially complex inputs but was less efficient on low-dimensional IMU data.
These findings confirm that model suitability depends on task dynamics and signal structure: when spatial complexity is modest but temporal discrimination is critical, dense-layer architectures such as DNNs are preferable.

Added Value of Dual-Task Classification

Beyond predicting ergonomic risk, WMSDsNet simultaneously identifies the physical subtask being executed.
This dual-output design adds interpretive depth by linking a detected risk directly to a specific operation (e.g., *cable detachment → high risk*).

Such contextualization transforms risk scores into actionable knowledge, allowing supervisors to redesign workflows, schedule micro-breaks, or adjust robot assistance precisely where strain originates.
Compared with single-output models that assess risk in isolation, this approach enhances managerial usefulness and decision-support potential.

Broader Implications

From an applied standpoint, the results demonstrate that scalable, real-time ergonomic monitoring can be achieved without handcrafted feature engineering, simplifying transfer across workstations. From a theoretical perspective, the study bridges traditional ergonomics and modern AI, establishing an integrated methodology that supports future sequence-aware models (e.g., CNN–LSTM hybrids) for cumulative-risk forecasting.

Limitations

The experiment was performed in a controlled laboratory with a single participant to guarantee data consistency and fair model comparison.

While this design ensured methodological rigor, it restricts generalizability across workers and task variations.
Future validations involving multiple participants and real industrial contexts are needed to confirm robustness under environmental noise and workflow variability.

Summary

Overall, WMSDsNet provides an end-to-end, wearable-sensor-based ergonomic-risk-prediction system tailored to HRC disassembly.

By integrating standardized evaluation tools, dual-task classification, and a systematic model comparison, this work fills key methodological gaps and establishes a replicable foundation for future smart-factory safety systems.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

This thesis addressed a critical gap in ergonomics: the absence of continuous, cumulative, and task-specific assessment methods for work-related musculoskeletal disorders (WMSDs) in collaborative disassembly environments.

Conventional tools such as RULA and REBA provide valuable but static assessments.

The proposed WMSDsNet framework overcomes this limitation through real-time monitoring using wearable IMUs and ML algorithms capable of simultaneously recognizing subtasks and estimating ergonomic-risk levels.

Key Achievements

Creation of an Ergonomically Labeled Dataset:

A controlled HRC disassembly experiment was designed with four representative subtasks, unscrewing, cable detachment, component sorting, and tool change, performed at three predefined risk levels (low, moderate, high) using RULA/REBA criteria.The resulting dataset established a reproducible foundation for ML-based ergonomic analysis.

Comparative Benchmark of Six Algorithms:

Under identical preprocessing and labeling conditions, CNN, DNN, SVM, RF, DT, and KNN models were trained for dual-task classification. The DNN achieved the most balanced performance, while the RF provided interpretability advantages. The CNN maintained strong accuracy and real-time feasibility, highlighting context-dependent trade-offs among models.

Development of the Dual-Output Framework WMSDsNet:

Integrating ergonomic labeling, ML modeling, and real-time inference, WMSDsNet enables proactive, task-aware monitoring suitable for Industry 4.0 environments.

The framework merges traditional ergonomic principles with AI transparency and scalability.

Ethical and Practical Integration:

Both publications, the conference and the journal paper, constitute sequential stages of a single coherent project emphasizing ethical data collection and responsible AI deployment in workplace safety.

Contributions and Impact

The thesis contributes a reproducible methodology that unites ergonomics and artificial intelligence, providing both theoretical insight and applied benefit. It empowers ergonomists and industrial engineers to implement proactive interventions, task rotation, break scheduling, or tool redesign, based on data-driven feedback, thereby reducing WMSD incidence and improving sustainability in human–robot systems.

Recommendations for Future Research and Practice

Multi-Subject Validation:

Expand data collection to diverse anthropometries to assess generalization and inter-individual variability.

Real-World Deployment:

Test WMSDsNet in operational HRC workcells to evaluate resilience to environmental noise and workflow irregularities.

Explainable AI (XAI) Integration:

Implement XAI methods to enhance transparency and user trust in deep-learning predictions.

Cumulative Risk Forecasting:

Extend WMSDsNet with temporal models (e.g., CNN–LSTM) for predicting cumulative exposure over extended periods.

Personalized Ergonomics:

Incorporate individual health and fatigue data for adaptive, worker-specific risk scores.

Economic Feasibility Analysis:

Quantify cost–benefit trade-offs of wearable-sensor deployment at scale to support industrial adoption.

Closing Statement

Through these extensions, WMSDsNet and its methodological foundation can evolve into a scalable, interpretable, and industry-ready solution for ergonomic-risk management in collaborative manufacturing.

By combining human-centered ergonomics with data-driven intelligence, this work lays a sustainable path toward safer, smarter, and more responsive workplaces.

REFERENCES

[1] Mattioli S, Brillante R, Zanardi F, Bonfiglioli R. Occupational (and non-occupational) risk factors for musculoskeletal disorders. *Med Lav.* 2006;97(3):529–534. PMID: 17009690.

[2] Sun W, Yin L, Zhang T, Zhang H, Zhang R, Cai W. Prevalence of work-related musculoskeletal disorders among nurses: a meta-analysis. *Iran J Public Health.* 2023;52(3):463–475. https://doi.org/10.18502/ijph.v52i3.12130.

[3] Z. Zheng, W. Xu, Z. Zhou, D. T. Pham, Y. Qu, and J. Zhou, "Dynamic Modeling of Manufacturing Capability for Robotic Disassembly in Remanufacturing," *Procedia Manuf.*, vol. 10, pp. 15–25, 2017.

[4] G. S. Peng, J. Ping, T. Li, F. Wang, H. Zhang, and C. Liu, "Environmental benefits of remanufacturing mechanical products: A harmonized meta-analysis of comparative life cycle assessment studies," *J. Environ. Manage.*, vol. 306, 2022.

[5] Piedrahita H. Costs of work-related musculoskeletal disorders (MSDs) in developing countries: Colombia case. *Int. J. Occup Saf. Ergon.* 2006;12(4):379–386. https://doi.org/10.1080/10803548.2006.11076696

[6] S. Hjorth and D. Chrysostomou, "Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly," *Robot. Comput. Integr. Manuf.*, vol. 73, 2022.

[7] Siddhaiyan V, Deepak BBVL, Bahubalendruni MVAR, Parhi DRK, Biswal BB, editors. A critical review on risk assessment methods of musculoskeletal disorder (MSD). In: *Intelligent Manufacturing Systems in Industry 4.0.* Lecture Notes in Mechanical Engineering. Singapore: Springer; 2023. https://doi.org/10.1007/978-981-99-1665-8_20

[8] Yusof NNM, Nur NM, Roslin EN. The prevalence of work-related musculoskeletal disorders and work productivity of aviation maintenance personnel. In: Ismail A, Nur Zulkipli F, Jaafar J, Öchsner A, editors. *Industrial Revolution in Knowledge Management and Technology.* Cham: Springer; 2023. p. [chapter]. https://doi.org/10.1007/978-3-031-29265-1_6

[9] E. Schneider, S. Copsey, and X. Irastorza, *OSH in Figures: Work-Related Musculoskeletal Disorders in the EU, Facts and Figures.* Luxembourg: Off. Publ. Eur. Communities, 2010.

[10] Maurice P, Padois V, Measson Y, Bidaud P. Human-oriented design of collaborative robots. *Int. J. Ind. Ergon.* 2017;57:88–102.

[11] Canadian Centre for Occupational Health and Safety. *Risk Factors for Work-Related Musculoskeletal Disorders (WMSDs)* [Internet]. OSH Answers; 2024 [cited 2025 Feb 14]. Available from: https://www.ccohs.ca/oshanswers/diseases/rmirsi.html

[12]Punnett, L., & Wegman, D. H. (2004). Work-related musculoskeletal disorders: the epidemiologic evidence and the debate. Scandinavian Journal of Work, Environment & Health, 30(1), 3–9.

[13] WSIB. (2023). Workplace Safety and Insurance Board Annual Report. Ontario, Canada.

[14] Lam, A., Choy, M., & Lien, T. (2020). Ergonomic risks in circular economy disassembly lines. Applied Ergonomics, 88, 103167.

[15] Chen, X., Yang, Y., & Ma, L. (2022). Human factors in collaborative robotics: Ergonomic concerns and frameworks. Human Factors, 64(3), 403–419.

[16] Kee, D., & Karwowski, W. (2007). A comparison of three observational techniques for assessing postural loads in industry. Ergonomics, 50(3), 367–395.

[17] David, G. (2005). Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Applied Ergonomics, 36(4), 463–469.

[18]Takala, E. P., Pehkonen, I., Forsman, M., Hansson, G. Å., Mathiassen, S. E., Neumann, W. P., ... & Viikari-Juntura, E. (2010). Systematic evaluation of observational methods assessing biomechanical exposures at work. Scandinavian Journal of Work, Environment & Health, 36(3), 199–201.

[19] M.-L. Lee, S. Behdad, X. Liang, and M. Zheng, “Task allocation and planning for product disassembly with human–robot collaboration,” *Robot. Comput. Integr. Manuf.*, vol. 76, 2022.

[20] Godwin, A. A., Agnew, M. J., Stevenson, J. M., & Twiddy, A. L. (2009). Accuracy of inertial motion sensors in static, quasistatic, and dynamic conditions. Ergonomics, 52(3), 312–327.

[21] Zhou, H., & Hu, H. (2008). Human motion tracking for rehabilitation, A survey. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 16(2), 149–158.

[22] Mannini, A., & Sabatini, A. M. (2010). Machine learning methods for classifying human physical activity from on-body accelerometers. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18(6), 163–172.

[23] Llop-Harillo, I., Romeo, A., Cuesta-Vargas, A. I., & Martin-Martin, J. (2020). Machine learning for risk classification in industrial picking tasks using IMUs. Sensors, 20(23), 6960.

[24] Lee, J. H., Kim, H. J., & Lee, S. Y. (2017). Evaluation of postural risks using IMU sensors and machine learning: A case study on REBA scores. Applied Ergonomics, 65, 395–403.

[25] Baltrusaitis, T., Ahuja, C., & Morency, L. P. (2018). Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(6), 1546–1562.

[26] Liang, W., He, J., Wu, L., & Zhang, Z. (2021). Deep learning for skeletal-based posture classification in smart workplaces. IEEE Access, 9, 63766–63777.

[27] Baskar, S., Rajalakshmi, P., & Swaminathan, R. (2021). A wearable device for posture detection using CNN for industrial safety. Computers in Biology and Medicine, 132, 104318.

[28] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.

[29] Ghani, S., Morales, F. J., & Parra, C. (2021). Stress and fatigue detection from wearable sensor data using LSTM networks. IEEE Sensors Journal, 21(2), 1404–1412.

[30] Leão CP, Silva V, Costa S. Exploring the intersection of ergonomics, design thinking, and AI/ML in design innovation. *Appl. Syst. Innov.* 2024;7(4):65. https://doi.org/10.3390/asi7040065

[31] Bernard, B. P. (1997). Musculoskeletal disorders and workplace factors. NIOSH Publication No. 97-141.

[32] Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2019). Sensor-based systems for occupational physical exposure assessment: A systematic review. Applied Ergonomics, 74, 33–41.

[33] Tkachuk, G., Marchand, A. A., & Descarreaux, M. (2022). IMUs in ergonomic exposure monitoring: A systematic review. Journal of Occupational and Environmental Hygiene, 19(1), 36–48.

[34] Ignatov, A. (2018). Real-time human activity recognition from accelerometer data using CNNs. Pattern Recognition Letters, 110, 61–67.

[35] Karvekar, S., Patil, R., & Jadhav, R. (2022). Comparison of ML methods for ergonomics in repetitive industrial tasks. Computers in Biology and Medicine, 146, 105635.

[36] Choi S, Kim K, Lee S, Kim H. Evaluation of ergonomic posture and motion in manual disassembly using motion capture and simulation tools. *J. Manuf. Syst.* 2018;47:115–123. https://doi.org/10.1016/j.jmsy.2018.04.010

[37] Johansson, B., Sundin, E., & Öhrwall Rönnbäck, A. (2019). Ergonomics challenges in manual disassembly tasks. Procedia CIRP, 81, 1165–1170.

[38] Marconi, M., Pedrielli, G., & Tucci, M. (2021). Ergonomics in disassembly for remanufacturing: A wearable sensor approach. Applied Ergonomics, 95, 103437.

[39]Naranjo JE, et al. Wearable Sensors in Industrial Ergonomics: a scoping review under Industry 4.0. *Sensors*. 2025; (scoping review). Available from: PMC11902643.

[40] Zhao, Y., Zhang, Z., & Wang, S. (2021). Multitask learning for wearable health monitoring: A CNN-LSTM approach. IEEE Journal of Biomedical and Health Informatics, 25(7), 2543–2552.

[41] Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., & Müller, K.-R. (2019). Explainable AI: Interpreting, explaining and visualizing deep learning. Information Fusion, 47, 1–10.

[42] B. H. Robinson, "E-waste: An assessment of global production and environmental impacts," *Sci. Total Environ.*, vol. 408, no. 2, pp. 183–191, 2009.

[43] J. Huang *et al.*, "An experimental human-robot collaborative disassembly cell," *Comput. Ind. Eng.*, vol. 155, 2021.

[44] Y. Chen, Y. Luo, M. O. Yerebakan, S. Xia, S. Behdad, and B. Hu, "Human Workload and Ergonomics during Human-Robot Collaborative Electronic Waste Disassembly," in *Proc. IEEE 3rd Int. Conf. Human-Mach. Syst. (ICHMS)*, Orlando, FL, USA, 2022.

[45] C. M. Trask, S. E. Mathiassen, J. Wahlström, and M. Forsman, "Cost-efficient assessment of biomechanical exposure in occupational groups, exemplified by posture observation and inclinometry," *Scand. J. Work Environ. Health*, vol. 40, no. 3, pp. 252–265, 2014.

[46] C. M. Lind, J. A. Diaz-Olivares, K. Lindecrantz, and J. Eklund, “A wearable sensor system for physical ergonomics interventions using haptic feedback,” *Sensors*, vol. 20, no. 21, p. 6010, 2020.

[47] M. Ciccarelli *et al.*, “A system to improve the physical ergonomics in human-robot collaboration,” *Procedia Comput. Sci.*, vol. 200, pp. 689–698, 2022

[48] S. E. Reme *et al.*, “Distressed, immobilized, or lacking employer support? A sub-classification of acute work-related low back pain,” *J. Occup. Rehabil.*, vol. 22, pp. 541–552, 2012.

[49] E. Halilaj *et al.*, “Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities,” *J. Biomech.*, vol. 81, pp. 1–11, 2018.

[50] H. Lee, K. Yang, N. Kim, and C. R. Ahn, “Detecting excessive load-carrying tasks using a deep learning network with a Gramian angular field,” *Autom. Constr.*, vol. 120, 2020.

[51] J. Wang, D. Chen, M. Zhu, and Y. Sun, “Risk assessment for musculoskeletal disorders based on the characteristics of work posture,” *Autom. Constr.*, vol. 131, 2021.

[52] L. Li, T. Martin, and X. Xu, “A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders,” *Appl. Ergon.*, vol. 87, 2020.

[53] Sohrabi MS, Babamiri M. Effectiveness of an ergonomics training program on musculoskeletal disorders, job stress, quality of work-life and productivity in office workers: a quasi-randomized control trial study. *Int. J. Occup Saf. Ergon.* 2021;28(3):1664–1671. https://doi.org/10.1080/10803548.2021.1918930

[54] Safiri S, Kolahi AA, Cross M, Hill C, Smith E, Carson-Chahhoud K, et al. Prevalence, deaths, and disability-adjusted life years due to musculoskeletal disorders for 195 countries and territories 1990–2017. *Arthritis Rheumatol.* 2021;73. https://doi.org/10.1002/art.41571

[55] Wang D, Dai F, Ning X. Risk assessment of work-related musculoskeletal disorders in construction: state-of-the-art review. *J. Constr. Eng. Manage.* 2015;141(6):04015008. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000979

[56] Sekkay F. Prevention of work-related musculoskeletal disorders supported by artificial intelligence. In: Ahram T, Taiar R, editors. *Human Interaction and Emerging Technologies (IHIET-AI 2023).* AHFE International; 2023. Vol. 70. https://doi.org/10.54941/ahfe1002945

[57] Donisi L, Capodaglio E, Pagano G, Amitrano F, Cesarelli M, Panigazzi M, D'Addio G. Feasibility of tree-based machine learning algorithms fed with surface electromyographic features to discriminate risk classes according to NIOSH. IEEE Press; 2022. https://doi.org/10.1109/MeMeA54994.2022.9856521

[58] Chen D, Chen J, Jiang H, Huang MC. Risk factors identification for work-related musculoskeletal disorders with wearable and connected gait analytics system. In: *Proc. 2017 IEEE/ACM Int. Conf. Connected Health.* Philadelphia, PA; 2017. p. 330–339. https://doi.org/10.1109/CHASE.2017.116

[59] Yan Y, Fan H, Li Y, Hoeglinger E, Wiesinger A, Barr A, O'Connell GD, Harris-Adamson C. Applying wearable technology and a deep learning model to predict occupational physical activities. *Appl. Sci.* 2021;11:9636. https://doi.org/10.3390/app11209636

[60] Chan VCH, Ross GB, Clouthier AL, Fischer SL, Graham RB. The role of machine learning in the primary prevention of work-related musculoskeletal disorders: A scoping review. *Appl. Ergon.* 2022;98:103574. https://doi.org/10.1016/j.apergo.2021.103574

[61] Fernandes AS, da Silva CE, Okimoto ML. A deep learning approach to prevent problematic movements of industrial workers based on inertial sensors. *Comput. Ind.* 2022;141:103754.

[62] Lowe BD, Ramirez D. Wearable devices for monitoring work-related musculoskeletal and gait disorders. *Int. J. Environ. Res. Public Health.* 2020;17(21):6050.

[63] De Fazio R, Mastronardi VM, De Vittorio M, Visconti P. Wearable sensors and smart devices to monitor rehabilitation parameters and sports performance: An overview. *Sensors (Basel).* 2023;23(4):1856. https://doi.org/10.3390/s23041856

[64] Donisi L, Cesarelli G, Pisani N, Ponsiglione AM, Ricciardi C, Capodaglio E. Wearable sensors and artificial intelligence for physical ergonomics: A systematic review of literature. *Diagnostics.* 2022;12(12):3048.

[65] Müller J, Veer W, Bräuer M, Faller C. Diagnostics using wearables in physical ergonomics: Posture and movement risk classification with IMUs. *Diagnostics.* 2022;12(12):3048.

[66] Palipana S, Marasinghe R, Jayaratne L. Vision-based ergonomics risk prediction: A deep learning framework for awkward posture detection using keypoints. *Appl. Ergon.* 2021;91:103294.

[67] Antwi-Afari MF, Li H, Yu Y, Kong L. Wearable insole pressure system for automated detection and classification of awkward working postures in construction workers. *Autom. Constr.* 2018;96:433–441. https://doi.org/10.1016/j.autcon.2018.10.004

[68] Lins C, Hein A. Classification of body postures using smart workwear. *BMC Musculoskelet. Disord.* 2022;23:921. https://doi.org/10.1186/s12891-022-05821-9

[69] Chan APC, Yang Y, Kim MJ, Wong JKW. Application of machine learning techniques for preventing work-related musculoskeletal disorders: A scoping review of research trends, gaps, and opportunities. *Appl. Ergon.* 2022;95:103438.

[70] Matos RA, Ribeiro RA, Lima TM, Lima RM. Proactive prevention of work-related musculoskeletal disorders using a motion capture system and time series machine learning. *Eng. Appl. Artif. Intell.* 2024;127:107754.

[71] Sherafat A, Golparvar-Fard M, Heydarian A. Automated methods for activity recognition of construction workers and equipment: A state-of-the-art review. *Autom. Constr.* 2022;139:104254.

[72] Dey S, Schilling AF. A function approximator model for robust online foot angle trajectory prediction using a single IMU sensor: Implication for controlling active prosthetics. In: *ASCE Int. Conf. on Computing in Civil Engineering*; 2022.

[73] Battini D, Berti N, Finco S, Guidolin M, Reggiani M, Tagliapietra L. WEM-Platform: A real-time platform for full-body ergonomic assessment and feedback in manufacturing and logistics systems. *Comput. Ind. Eng.* 2022;164:107881.

[74] Clark RA, Mentiplay BF, Hough E, Pua YH. Three-dimensional cameras and skeleton pose tracking for physical function assessment: A review of uses, validity, current developments and Kinect alternatives. *Gait Posture.* 2019;68:193–200. https://doi.org/10.1016/j.gaitpost.2018.11.029

[75] Barkallah E, Freulard J, Otis MJ-D, Ngomo S, Ayena JC, Desrosiers C. Wearable devices for classification of inadequate posture at work using neural networks. *Sensors.* 2017;17:2003. https://doi.org/10.3390/s17092003

[76] Siew CY, Chang MML, Ong SK, Nee AYC. Human-oriented maintenance and disassembly in sustainable manufacturing. *Comput. Ind. Eng.* 2020;150:106903. https://doi.org/10.1016/j.cie.2020.106903

[77] Lorenzini M, Gazzoni M, Gastaldi L. Ergonomic human-robot collaboration in industry: A review. *Front. Robot. AI.* 2023;9:813907.

[78] Meregalli Falerni A, et al. Human-robot collaboration in disassembly lines: A framework for adaptive ergonomics. *Comput. Ind. Eng.* 2024;189:109223.

[79] Kim W, Lee J, Tsagarakis NG, Ajoudani A. A real-time and reduced-complexity approach to the detection and monitoring of static joint overloading in humans. In: *IEEE Int. Conf. on Rehabilitation Robotics (ICORR)*; 2017. p. 1085–1090. https://doi.org/10.1109/ICORR.2017.8009351

[80] Rajavenkatanarayanan A, et al. Towards a real-time cognitive load assessment system for industrial human-robot cooperation. In: *RO-MAN 2020.*

[81] Antonino D, et al. Optimizing stress and productivity based on game theory in human-robot collaboration. *Front. Psychol.*

[82] Wu Y, et al. Effect of cognitive fatigue, operator sex, and robot assistance on task performance metrics, workload, and situation awareness in human-robot collaboration. *Appl. Ergon.* 2020;89:103192.

[83] Xie S, et al. Improving workers' musculoskeletal health during human-robot collaboration through reinforcement learning. *Appl. Sci.* 2023;13(12):7333.

[84] Chen H, et al. A unified architecture for physical and ergonomic human–robot collaboration. *Sensors.* 2021;21(2):374.

[85] Kim S, et al. Real-time estimation of overloading joint torque during human-robot collaborative power tool tasks. *Comput. Ind. Eng.* 2020;148:106684.

[86] Zacharaki N, Dimitropoulos N, Makris S. Challenges in human-robot collaborative assembly in shipbuilding and ship maintenance, repair and conversion (SMRC) industry. *Procedia CIRP.* 2022;106:120–125. https://doi.org/10.1016/j.procir.2022.02.165

[87] Kaya G, Weber C. A mixed-methods study of human-robot disassembly. In: *ACM/IEEE HRI Conf*; 2020.

[88] Hanumegowda R, Rupa DS, Gangopadhyay S. Ergonomic risk assessment using discomfort ratings and machine learning in the Indian bus driving population. *Saf. Health Work.* 2022;13(1):47–52.

[89] Luo Y, Geng Q, Zhao L. Machine learning-based workload and musculoskeletal risk prediction using questionnaire data in healthcare workers. *J. Occup. Health.* 2022;64(1):e12374.

[90] Kiraz MA, Geçici S. Ergonomic risk classification using pose estimation and deep learning. *Comput. Ind. Eng.* 2024;184:109084.

[91] Chen W, et al. An interpretable 1D CNN framework for real-time ergonomic risk classification based on IMU signals. *Expert Syst. Appl.* 2024;236:121376.

[92] Hida AH, Abd Hamid AR, Assyahid WAR. Recent advancements in ergonomic risk assessment: Integration of artificial intelligence, wearable technology, and industry-specific approaches. *Malaysian J. Ergonomics.* 2022;6(1):65–75.

[93] Villalobos P, Mac Cawley A. Prediction of slaughterhouse workers' RULA scores and knife edge using low-cost inertial measurement sensor units and machine learning algorithms. *Appl. Ergon.* 2022;98:103556. https://doi.org/10.1016/j.apergo.2021.103556

[94] Luo X, Xu H, et al. Machine learning-based prediction of neck and shoulder musculoskeletal disorders in healthcare professionals. *Front. Public Health.* 2024;12:1414209. https://doi.org/10.3389/fpubh.2024.1414209

[95] Antwi-Afari MF, Qarout Y, Herzallah R, Anwer S, Umer W, Zhang Y, Manu P. Deep learning-based networks for automated recognition and classification of awkward working postures in construction using wearable insole sensor data. *Autom. Constr.* 2022;136:104181. https://doi.org/10.1016/j.autcon.2022.104181

[96] Nath N, Fang Y, Rajguru A, Gambatese SR, Bhattacharya D. Smartphone-based wearable motion detector for analyzing construction workers' ergonomic risk factors. *Saf. Sci.* 2018;110:294–301.

[97] Halder S, Bhattacharya B. Developing and evaluating a mixed-sensor smart chair system for real-time posture classification combining pressure and distance sensors. In: *ASCE Int. Conf. on Computing in Civil Engineering*; 2024

[98] Donisi, L., Cesarelli, G., Pisani, N., Ponsiglione, A. M., Ricciardi, C., & Capodaglio, E. (2022). Wearable sensors and artificial intelligence for physical ergonomics: A systematic review of literature. *Diagnostics*, 12(12), 3048. https://doi.org/10.3390/diagnostics12123048

[99] Baklouti, R., Ryselis, K., Bucinskas, V., & Mankevicius, V. (2024). IMU-based upper body risk assessment system for work-related musculoskeletal disorders prevention in industrial settings. *Sensors*, 24(11), 3419. https://doi.org/10.3390/s24113419

APPENDICES

APPENDIX A: ARTICLE 2: WMSDsNet: A Deep Learning Framework for Real-Time Ergonomic Risk Prediction in Human-Robot Collaboration in Disassembly

online on 17/09/2025, Publisher: IEEE, IEEE 5th International Conference on Human-Machine Systems (ICHMS), pages 185–190

Marziyeh Mirzahosseininejad
Mathematics and Industrial Engineering Department
Polytechnique Montreal
Montreal, Canada
marziyeh.mirzahosseininejad@polymtl.ca

Morteza Jalali Alenjareghi
Mathematics and Industrial Engineering Department
Polytechnique Montreal
Montreal, Canada
morteza.jalali-alenjareghi@polymtl.ca

Firdaous Sekkay
Mathematics and Industrial Engineering Department
Polytechnique Montreal
Montreal, Canada
firdaous.sekkay@polymtl.ca

Samira Keivanpour
Mathematics and Industrial Engineering Department
Polytechnique Montreal
Montreal, Canada
firdaous.sekkay@polymtl.ca

***Abstract*—Disassembly tasks are increasingly vital for sustainable manufacturing and the circular economy, as they facilitate component recovery and waste reduction. While human-robot collaboration (HRC) is often promoted for reducing physical ergonomic challenges compared to tasks performed entirely by humans, studies have largely overlooked the unique ergonomic issues inherent to HRC. These environments can still present challenges that, if neglected, can contribute to work-related musculoskeletal disorders (WMSDs). This study introduces WMSDsNet, a dual-head deep-learning framework that automates ergonomic risk assessment by simultaneously classifying subtasks and predicting ergonomic risks, offering real-time, cumulative risk evaluation using wearable sensor data. Unlike traditional methods, which rely on subjective and time-intensive manual observations, or previous works that primarily focus on posture-based risk assessments to recognize awkward postures for immediate alerts or feedback, WMSDsNet detects changes in posture over a specific period of time. Based on this information, the frequency and duration of awkward postures can be analyzed to understand their cumulative effects on ergonomic risks. We analyzed the task of disassembling a Programmable Logic Controller (PLC) and selected specific subtasks to be performed by human operators in collaboration with the robot, including unscrewing components, detaching cables, sorting components, and changing the cobot's tools. Data was collected in numerical form using wearable sensors, enabling the framework to evaluate risk levels and predict ergonomic risks with over 90% accuracy in task classification and risk assessment. By providing real-time ergonomic assessments, this framework supports proactive interventions, offering a significant advancement in ergonomic evaluation for industrial HRC environments.**

***Keywords*—WMSDs, DNN, Wearable Sensors,Disassembly, HRC**

I. Introduction

Disassembly of end-of-life (EoL) products plays a critical role in advancing the circular economy by enabling the recovery and reuse of valuable components in remanufacturing. This process reduces reliance on raw materials, minimizes waste, and supports sustainable manufacturing practices [1]. With the global rise in electronic waste (e-waste), disassembly has become an increasingly essential phase in remanufacturing, facilitating the recovery of reusable components [2], [3].

Human-robot collaboration (HRC) environments are increasingly utilized in disassembly tasks to address the complexity and variability of operations. Robots effectively handle repetitive and structured tasks, reducing the physical workload on human operators by automating labor-intensive processes. At the same time, humans bring adaptability and decision-making capabilities, which are essential for managing unstructured or variable tasks, making HRC a promising approach for balancing efficiency and flexibility [4], [5].

Despite these advantages, HRC environments are not without their challenges. While collaborative robots (cobots) can mitigate some physical demands, they may also introduce new ergonomic risks if not carefully optimized. For example, Chen et al. [6] observed that participants in e-waste disassembly tasks experienced increased ergonomic workloads due to poorly distributed responsibilities between humans and robots. Similarly, Lee et al. observed inefficiencies in task allocation between humans and robots, leading to suboptimal collaboration and increased physical demands on workers [7]. These findings underscore that certain aspects of HRC environments—such as

Task allocation, repetitive actions, and static postures—can inadvertently contribute to work-related musculoskeletal disorders (WMSDs) over time if overlooked.

By selecting HRC environments for this study, we aim to address these ergonomic challenges directly. While HRC systems hold great potential for improving efficiency and reducing physical strain, it is crucial to develop tools and frameworks that proactively identify and mitigate ergonomic risks. This research focuses on leveraging wearable sensors and machine learning to automate the ergonomic assessment process, ensuring that the benefits of HRC are fully realized without compromising worker safety.

Work-related musculoskeletal disorders (WMSDs) are among the most significant concerns in ergonomics, accounting for nearly half of all work-related illnesses globally [8]. Detecting WMSD risks early is critical to mitigating their long-term effects. Factors such as repetitive motions, awkward postures, frequency of actions, duration of a task, etc. contribute to WMSDs, particularly in physically demanding environments. Effective ergonomic risk assessment is critical to identifying and mitigating these risks, thereby safeguarding worker health and maintaining productivity.

Traditional ergonomic assessment methods rely heavily on observational techniques and manual application of tools such as RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment). While these methods are widely

accepted, they are time-intensive, prone to observer bias, and unsuitable for capturing the dynamic and variable nature of HRC environments[9].

Wearable motion capture systems offer a promising alternative for ergonomic assessments, providing higher precision and accuracy in kinematic measurements compared to visual observations or video analysis. These systems can capture

data such as acceleration, angular velocity, and the magnetic field, allowing for detailed analysis of motion. Additionally, wearable sensors are cost-effective for analyzing large datasets, making them practical for industrial applications [10]. However, current applications of wearable sensors primarily focus on just recognizing posture for immediate correction and providing real-time feedback. [11], [12], often neglecting other essential factors such as posture frequency, duration, and cumulative strain over time.

To address these limitations, this study integrates wearable sensors with a machine learning (ML) framework to automate ergonomic risk assessment in HRC environments. Machine learning, a key branch of artificial intelligence, leverages algorithms to optimize performance based on training data and prior experience [13]. ML has shown great potential for preventing WMSDs through real-time analysis and prediction [14]. However, current ML applications in ergonomics predominantly focus on posture-based assessments [15], [16], often using a one-size-fits-all approach that fails to account for task variability and different scenarios [17].

Our research aims to bridge these gaps by simulating various work subtasks under diverse conditions, such as task frequency, duration, and whether tasks are static or dynamic.

This research introduces WMSDsNet, a deep neural network model designed to automate ergonomic risk assessment in HRC environments. WMSDsNet addresses key limitations in traditional and ML-based ergonomic assessments by:

1) Simulating Diverse Work Scenarios**:** The model

classifies subtasks performed in HRC disassembly, including unscrewing components, detaching cables, sorting items, and changing tools.

2) Incorporating Tailored Ergonomic Tools: To ensure

comprehensive ergonomic risk assessment in HRC environments, we integrate three well-established tools: RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body

Assessment), and OCRA (Occupational Repetitive Actions Index). Each tool addresses specific ergonomic challenges: RULA evaluates upper limb and static postures, REBA assesses whole-body movements and transitions, and OCRA focuses on repetitive tasks and cumulative strain. In HRC disassembly tasks, which often involve a mix of dynamic, static, and repetitive actions, using all three tools is essential. For example, RULA is ideal for tasks like unscrewing or detaching cables, REBA suits whole-body actions like sorting, and OCRA addresses repetitive subtasks that can lead to long-term strain.

3) Predicting Cumulative Risks: WMSDsNet considers

long-term exposure factors, such as the frequency and duration of repetitive tasks, to predict cumulative ergonomic risks in real time.

By automating these processes, WMSDsNet enhances the accuracy and scalability of ergonomic assessments, providing actionable insights to improve worker safety and system efficiency.

The primary objectives of this study are:

1) To demonstrate the potential of integrating wearable

sensors and machine learning for real-time ergonomic risk assessment in HRC environments.

2) To evaluate the performance of WMSDsNet in

classifying subtasks and predicting ergonomic risks in controlled disassembly scenarios.

3) To contribute to sustainable manufacturing practices

by improving worker safety and productivity through advanced ergonomic assessment tools.

By addressing these challenges, this research aims to bridge critical gaps in ergonomic risk prediction and contribute to the broader goals of workplace safety and industrial sustainability.

Although several studies have used machine learning for ergonomic risk assessment, many focus primarily on posture recognition and lack cumulative analysis of task duration and frequency. Moreover, current models rarely combine standardized ergonomic tools like RULA, REBA, and OCRA into a unified, real-time system. This study addresses these gaps by proposing WMSDsNet, a model capable of classifying subtasks and predicting ergonomic risks through wearable sensor data.

II. Methodology

A. The overview of the process

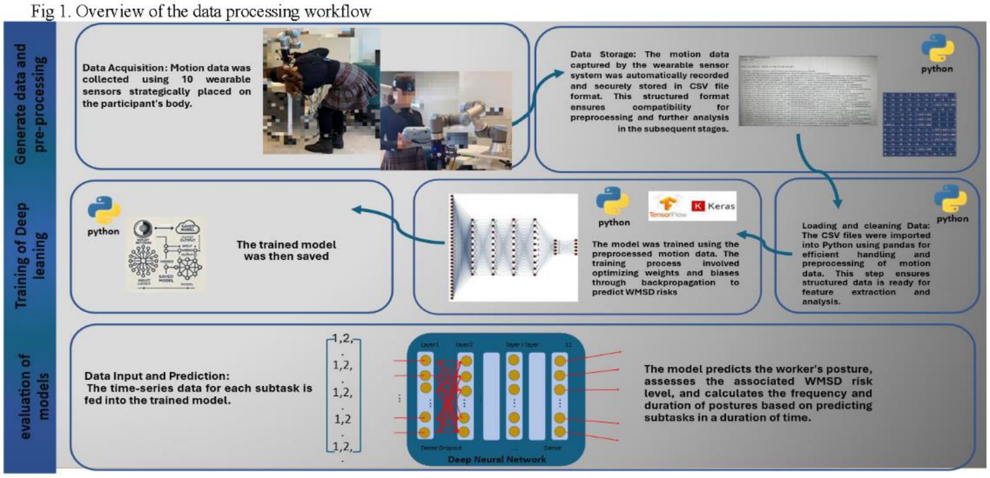
Fig. 1 illustrates a schematic representation of our work. We utilized 10 wearable sensors to collect motion data

during disassembly tasks in a human-robot collaborative environment. The data was preprocessed and structured into CSV files, enabling seamless integration into a deep learning framework. Our WMSDsNet model, consisting of input, backbone, and output layers, was trained to classify subtasks and predict WMSD risks, providing comprehensive ergonomic insights for HRC environments.

B. Disassembly Task and PLC Setup

experiment involved the disassembly of a Programmable Logic Controller (PLC) in a controlled human-robot collaborative (HRC) environment. The PLC was chosen due to its complexity, which includes a variety of disassembly subtasks requiring dynamic, static, and repetitive actions. The human operator and the cobot interacted to perform four key subtasks:

Fig 1. Overview of the data processing workflow



- Unscrewing components that were out of the cobot's reach, requiring fine motor skills and upper limb precision.
- Detaching cables, a task demanding coordination and repetitive motion.
- Sorting components, which involved dynamic transitions and whole-body movements.
- Changing cobot's tools, which required static postures for short periods.

To evaluate the ergonomic risks associated with each subtask, we used ergonomics tools. The risks were assessed using three well-established ergonomic assessment tools: RULA, REBA, and OCRA.

For each subtask, the risks were categorized into three levels based on our predesigned evaluation:

- Low Risk
- Moderate Risk
- High Risk

This classification was used to simulate various workplace scenarios and train the model to accurately predict both posture and WMSD risk levels. By incorporating ergonomic assessments and standardized tools, our approach ensures that the risk analysis is grounded in reliable, domain-specific methodologies.

C. Wearable Sensor System and Placement

The motion data for ergonomic analysis was collected using 10 wearable sensors strategically placed on the operator's body, targeting key joints and segments:

1) Sensors Placement: Sensors were mounted on the

head, shoulders, arms, waist, torso, and legs to monitor motion along the X, Y, Z axes, as well as angular rotation (W-axis). This configuration ensured comprehensive tracking of joint and limb movements during each subtask.

- Rationale for Placement: The placement was informed by the operator's anthropometric characteristics (e.g., height, weight, and limb proportions) to ensure accurate and consistent data collection. For example: Sensors on the shoulders captured upper limb movements during unscrewing tasks. Sensors on the torso and legs recorded whole-body dynamics during sorting tasks. Customized placement based on anthropometry minimized data noise and improved reliability, particularly for tasks requiring fine motor skills or repetitive actions.

D. WMSDsNet model

In Figure 2, the , WMSDsNet architecture is shown, for that we employed a deep neural network (DNN) framework consisting of three main components: the input layer, the backbone, and the output heads.

1) Input Layer: The input layer included five neurons,

corresponding to the five types of data collected by the wearable sensors:

- X, Y, Z: Represent the axes of motion.

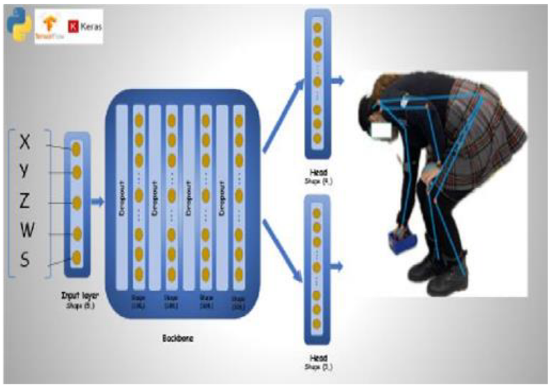


Fig 2. Schematic representation of the WMSDsNet

- W: Represents the rotation in 3D space.
- S: Indicates the sensor identifier.

This configuration ensured that the input layer aligned perfectly with the features of the dataset, and we achieved optimal results by using exactly five neurons, reflecting the five data types.

1) Backbone:

The backbone was composed of multiple dense layers interspersed with dropout layers:

- Dense Layers: These layers were responsible for learning complex patterns in the data.

2) Dropout Layers: Added between each pair of dense layers, dropout layers were used to mitigate overfitting by randomly deactivating neurons during training, improving the model's generalizability. The backbone included 4 dense layers with 128, 64, 32, and 16 neurons respectively, each followed by a dropout layer with a dropout rate of 0.4 to reduce overfitting. The Adam optimizer was used with a learning rate of 0.001, and the batch size was set to 64. These hyperparameters were tuned via grid search using validation accuracy as the selection metric.

Output Heads: The network featured two distinct

output heads:

- Head 1: Responsible for predicting the four subtasks (unscrewing, detaching cables, sorting components, and changing tools), with four neurons representing each subtask.
- Head 2: Responsible for classifying ergonomic risks into three levels (low, moderate, and high), with three neurons to predict each risk level. This dual-head design enabled the model to simultaneously classify subtasks and predict associated ergonomic risks, ensuring efficiency and accuracy in real-time applications.

This architecture was optimized to process detailed motion data and provide reliable predictions for both subtasks and ergonomic risks, making it a robust tool for ergonomic assessments in HRC environments.

During the training process, the Adam optimizer was employed to adjust the model's weights. The ReLU activation function was applied across all layers of the network, while the Softmax activation function was specifically used in the classification head for multi-class output. The WMSDsNet was implemented using TensorFlow version 2.2.0 and Keras version 2.3.1, with Python version 3.9 serving as the programming environment. All numerical experiments were conducted on Google Colab, leveraging a Tesla T4 GPU with 15 GB of RAM, ensuring efficient computation and training performance.

We had a total of 207,850 data points at a sampling frequency of 64 Hz. The dataset was divided into three subsets: training (80%), testing (15%), and validation (15%). The validation dataset was used during the training process to evaluate the network's performance after each epoch, ensuring that the model does not overfit. By monitoring the validation accuracy and loss, we ensured that the model generalized well.

E. Placement of Wearable Sensors

As shown in fig. 3 We utilized 10 wearable sensors strategically placed on various parts of the human body to capture motion data. The placement of the sensors was determined based on the subject's anthropometric features—including height, weight, and sex—to ensure comprehensive coverage of joint and limb movements during the task.

1) Sensor Distribution:

Sensors were positioned on key points of the body, such as the head, shoulders, arms, torso, and legs to monitor motion along the X, Y, Z axes, as well as angular rotation (W-axis). This configuration ensured comprehensive tracking of joint and limb movements during each subtask.

The placement was informed by the operator's anthropometric characteristics (e.g., height, weight, and limb proportions) to ensure accurate and consistent data collection. For example:

- Sensors on the shoulders captured upper limb movements during unscrewing tasks.
- Sensors on the torso and legs recorded whole-body dynamics during sorting tasks.

I. RESULTS

The accuracy graph presented in the fig. 4 shows that our model's accuracy exceeded 90% after 100 epochs, indicating strong predictive performance. The loss graph presented in fig. 5 illustrates a steady decrease, confirming effective training.

Metrics for both Head 1 (subtask classification) and Head 2 (risk classification) are closely aligned, demonstrating that the model is well-trained and not overfitted.

For Explanation of Prediction Test and Sensor Data We gathered data over 50 seconds to evaluate the model' prediction performance analyze sensor motion data and then calculate frequency and duration.

Fig 3. Placement of Wearable Sensors

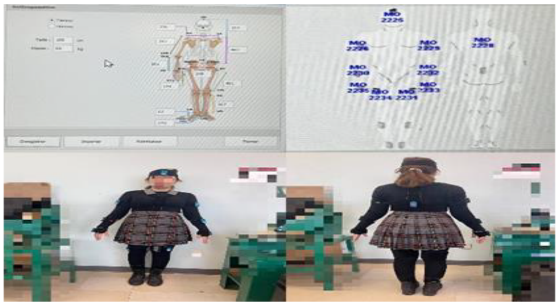
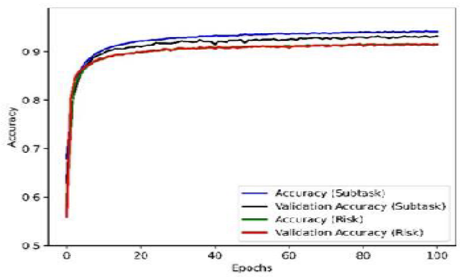


Fig. 4 The accuracy of WMSDsNet



Performing different subtasks during this period to Ghater numerical forms of data.

Subtasks and Risk Levels: 0–20 seconds: Subtask 1 (unscrewing) was performed.

0–10 seconds: Risk level was labeled as low.

10–20 seconds: Risk level increased to high.

20–30 seconds: The participant was idle, performing no activity.

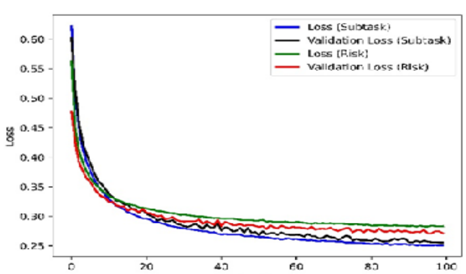
30–50 seconds: Subtask 3 (sorting components) was performed.

30–40 seconds: Risk level was high.

40–50 seconds: Risk level decreased to low.

a) Model Predictions:

Fig. 5 Loss graph for WMSDsNet



The ground truth for subtasks and risk levels was labeled by pre designed risk situations using the most suitable ergonomic assessment tools (RULA, REBA, or OCRA).

Fig. 6 shows the model's predictions during this 50-second period, with green and black lines representing subtask and risk predictions, respectively, which closely align with the predesigned risks-labeled ground truth.

b) Sensor data:

Fig. 7 illustrates the motion data from a waist sensor, capturing movement across four axes (X, Y, Z, and W)during the subtasks. This setup highlights the model's accuracy and the richness of the sensor data in detecting and predicting subtasks and their associated risks.

The results demonstrate a clear relationship between the motion data captured by the waist sensor and the predicted ergonomic risk levels:

- High Risk: Characterized by large fluctuations and variability in the Z (vertical) and W (angular rotation) axes, indicating dynamic and repetitive actions that involve awkward postures or significant movements.
- Low Risk: Identified during periods of stable and minimal motion across all axes, reflecting light or no physical activity.
- Idle: Periods with near-zero readings confirm no activity, corresponding to a neutral ergonomic state.
- By analyzing the frequency (number of peaks, defined as angular velocity spikes exceeding 200 deg/sec) and duration (total time spent in elevated motion above this threshold), we identified subtasks contributing most to ergonomic risks. These insights validate the model's ability to link sensor motion data to real-time risk level predictions, enabling precise ergonomic assessments for subtasks performed in human-robot collaboration environments.

III. DISCUTION

The results address limitations in traditional ergonomic assessment methods by automating analysis using sensor data and predesigned-labeled ground truth. The combination of RULA,

Fig. 6 test of WMSDsNet's predictions

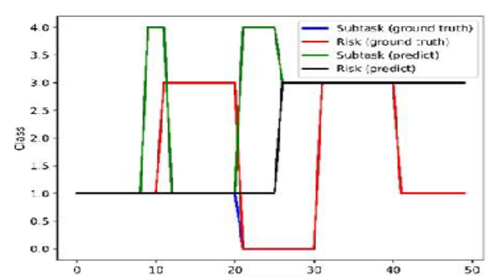
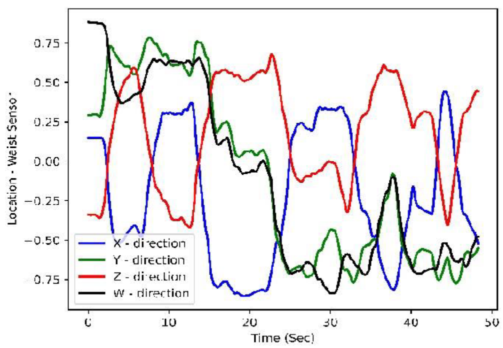


Fig. 7 direction of waist sensor



REBA, and OCRA tools provides a comprehensive approach to assessing both static and dynamic tasks.

However, the controlled laboratory setting may not fully replicate the complexities of real-world environments, limiting generalizability. The model's reliance on predefined subtasks and risk levels may also reduce adaptability for unstructured tasks. This study also has limitations in dataset diversity, as it currently involves a single participant. While sufficient for proof-of-concept, the results may not generalize across different body types, skill levels, or ergonomic profiles. Future validation with multiple subjects is necessary to improve robustness. Future work should focus on validating the system in diverse industrial settings and integrating real-time feedback with adaptive learning algorithms to enhance flexibility, scalability, and applicability across dynamic HRC environments.

IV. CONCLUSION

This study demonstrates the effectiveness of the WMSDsNet deep neural network in predicting ergonomic risks and classifying tasks within human-robot collaborative (HRC) disassembly environments. By integrating data from 10 strategically placed wearable sensors, the model captured critical factors such as posture, task frequency, and duration, achieving high predictive accuracy exceeding 90%. This highlights WMSDsNet's potential as a reliable and precise tool for assessing work-related musculoskeletal disorders (WMSDs) and enhancing ergonomic evaluations.

We plan to release a version of WMSDsNet's architecture and training scripts as open-source in future extensions of this work, enabling broader adoption and collaboration.

REFERENCES

[1] G. S. Peng, J. Ping, T. Li, F. Wang, H. Zhang, and C. Liu, "Environmental benefits of remanufacturing mechanical products: A harmonized meta-analysis of comparative life cycle assessment studies," *J. Environ. Manage.*, vol. 306, 2022.

[2] [2] B. H. Robinson, "E-waste: An assessment of global production and environmental impacts," *Sci. Total Environ.*, vol. 408, no. 2, pp. 183–191, 2009.

[3] Z. Zheng, W. Xu, Z. Zhou, D. T. Pham, Y. Qu, and J. Zhou, "Dynamic Modeling of Manufacturing Capability for Robotic Disassembly in Remanufacturing," *Procedia Manuf.*, vol. 10, pp. 15–25, 2017.

[4] S. Hjorth and D. Chrysostomou, "Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly," *Robot. Comput. Integr. Manuf.*, vol. 73, 2022.

[5] J. Huang *et al.*, "An experimental human-robot collaborative disassembly cell," *Comput. Ind. Eng.*, vol. 155, 2021.

[6] Y. Chen, Y. Luo, M. O. Yerebakan, S. Xia, S. Behdad, and B. Hu, "Human Workload and Ergonomics during Human-Robot Collaborative Electronic Waste Disassembly," in *Proc. IEEE 3rd Int. Conf. Human-Mach. Syst. (ICHMS)*, Orlando, FL, USA, 2022.

[7] M.-L. Lee, S. Behdad, X. Liang, and M. Zheng, "Task allocation and planning for product disassembly with human–robot collaboration," *Robot. Comput. Integr. Manuf.*, vol. 76, 2022.

[8] E. Schneider, S. Copsey, and X. Irastorza, *OSH in Figures: Work-Related Musculoskeletal Disorders in the EU—Facts and Figures.* Luxembourg: Off. Publ. Eur. Communities, 2010.

[9] P. Maurice, V. Padois, Y. Measson, and P. Bidaud, "Human-oriented design of collaborative robots," *Int. J. Ind. Ergon.*, vol. 57, pp. 88–102, 2017.

[10] C. M. Trask, S. E. Mathiassen, J. Wahlström, and M. Forsman, "Cost-efficient assessment of biomechanical exposure in occupational groups, exemplified by posture observation and inclinometry," *Scand. J. Work Environ. Health*, vol. 40, no. 3, pp. 252–265, 2014.

[11] C. M. Lind, J. A. Diaz-Olivares, K. Lindecrantz, and J. Eklund, "A wearable sensor system for physical ergonomics interventions using haptic feedback," *Sensors*, vol. 20, no. 21, p. 6010, 2020.

[12] M. Ciccarelli *et al.*, "A system to improve the physical ergonomics in human-robot collaboration," *Procedia Comput. Sci.*, vol. 200, pp. 689–698, 2022.

[13] S. E. Reme *et al.*, "Distressed, immobilized, or lacking employer support? A sub-classification of acute work-related low back pain," *J. Occup. Rehabil.*, vol. 22, pp. 541–552, 2012.

[14] E. Halilaj *et al.*, "Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities," *J. Biomech.*, vol. 81, pp. 1–11, 2018.

[15] H. Lee, K. Yang, N. Kim, and C. R. Ahn, "Detecting excessive load-carrying tasks using a deep learning network with a Gramian angular field," *Autom. Constr.*, vol. 120, 2020.

[16] J. Wang, D. Chen, M. Zhu, and Y. Sun, "Risk assessment for musculoskeletal disorders based on the characteristics of work posture," *Autom. Constr.*, vol. 131, 2021.

[17] L. Li, T. Martin, and X. Xu, "A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders," *Appl. Ergon.*, vol. 87, 2020.