Revista Pădurilor 138(3) (2023) 001-044

Revista Pădurilor

disponibil online la: www.revistapadurilor.com

Revistă tehnico-ştiinţifică editată de Societatea „Progresul Silvic"

ISSN: 1583-7890
ISSN (Varianta online): 2067-1962

Indexare în baze de date:

CABI
DOAJ
Google Academic
SCIPIO

CUPRINS

Revista Pădurilor 138(3) (2023) 001-044

Revista Pădurilor

available online at: www.revistapadurilor.com

Journal edited by the "Progresul Silvic" Society

ISSN: 1583-7890
ISSN (ONLINE): 2067-1962

Indexed by:

CABI
DOAJ
Google Academic
SCIPIO

CONTENTS

Revista Pădurilor 138(3) (2023) 001-044

Revista Pădurilor

available online at: www.revistapadurilor.com

A SYSTEMATIC SURVEY OF CONVENTIONAL AND NEW POSTURAL ASSESSMENT METHODS

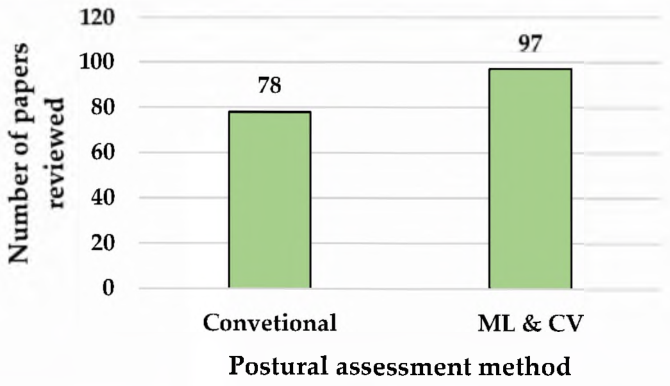
Gabriel Osei Forkuo[a,*]

[a]Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, Faculty of Silviculture and Forest Engineering, Transilvania University of Braşov, Şirul Beethoven 1, Braşov 500123, Romania, gabriel.forkuo@unitbv.ro (G.O.F.).

HIGHLIGHTS

- Postural assessment is crucial in evaluating the ergonomic condition in forest activities.
- A range of traditional and modern methods are used for postural assessment.
- Machine Learning (ML) algorithms and Computer Vision (CV) are emerging techniques for postural assessment that allow for analysis of data from sensors and digital images/videos.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Manuscript received: 22 September 2023
Received in revised form: 25 September 2023
Accepted: 25 September 2023
Page count: 34 pages.

Article type: Review

Editor: Stelian Alexandru Borz

Keywords:
Postural assessment
Traditional methods
Machine learning
Algorithms
Computer vision

ABSTRACT

Postural assessment is essential for evaluating the ergonomic condition of work systems, especially in forest activities. Traditional and state-of-the-art methods such as self-reports, observational techniques, motion capture systems, electromyography, and force plates are used. Machine Learning (ML) algorithms can analyse data from sensors to find trends or abnormalities in posture, whereas Computer Vision (CV) extracts information from digital images and videos. This systematic review identifies studies that have used ML and CV for postural assessment, appraises their quality, and synthesizes available evidence on the accuracy and reliability of different techniques. The review also documents the potential benefits and limitations of ML and CV in postural assessment. The review highlights the importance of large and diverse datasets, ethical considerations, and the interpretability of ML models. Gaps and the need for further research are also identified.

* Corresponding author.
E-mail address: gabriel.forkuo@unitbv.ro

1. INTRODUCTION

Postural assessment is the process of observing and evaluating a person's posture, or the alignment and orientation of the body segments in relation to each other and the environment [1]. Postural assessment is an important element in identifying the implications of working postures for health and safety, and it can assist in the implementation of ergonomic interventions aimed at reducing work-related injuries in forest operations [2,3]. Thus, a thorough postural assessment can help identify high-risk postures and inform the development of ergonomic interventions. Additionally, postural assessment can provide valuable information about the health, function, and performance of the musculoskeletal system, as well as the potential risk factors for injury, pain, or discomfort [1,3]. Postural assessment is an essential aspect of diagnosing and treating musculoskeletal and neurological disorders, as well as monitoring the progress of rehabilitation programs [4-6].

A variety of methods, both conventional and new, are used in postural assessment [7-9]. Conventional methods include direct observation, APM, and RULA [8,10]. However, new methods include the use of wearable sensors and motion capture technologies [8,11,10]. Both conventional and new methods have their advantages and disadvantages, but they can be effective in improving ergonomic conditions [3]. For instance, direct observation is a low-cost method that can provide detailed information on worker postures and movements [8], while motion capture technologies can provide accurate and objective data [10]. Besides, postural assessment can be performed in various settings, such as clinical, sports, occupational, or educational environments, and can involve different methods and tools, such as visual inspection, palpation, goniometry, photography, video recording, or specialized software [3,12]. However, these methods and tools have some limitations, such as subjectivity, variability, low accuracy, high cost, or low accessibility [3,8]. Traditional methods of postural assessment, such as manual goniometry, REBA, RULA and OWAS are subjective and can be unreliable and time-consuming [3].

Machine learning (ML) and computer vision (CV) are two branches of artificial intelligence (AI) that deal with the analysis and interpretation of data using algorithms that can learn from data and make predictions or decisions [13,14]. ML is a subset of AI that analyses and learns from data [15,16], whereas CV focuses on the processing, analysis, and understanding of digital images or videos [17,18]. ML and CV have been applied to various domains and tasks, such as face recognition, object detection, natural language processing, medical diagnosis, or self-driving cars. Recent advancements in computing, ML and CV have also led to the development of more objective and innovative methods for postural assessment [5,6,12] using ML and CV. ML and CV have numerous applications in postural assessment, including the assessment of gait patterns, balance measures, and postural deviations [5,6,12]. These techniques can be used to develop automated systems for postural assessment, which can provide more accurate and efficient assessments compared to manual assessments [19,20]. For example, one common application of ML in postural assessment is the use of sensors, such as accelerometers and gyroscopes, to monitor subjects' postures and movements in real-time [11,21]. These sensors collect large amounts of data, which can be processed with algorithms to detect abnormalities in posture and movement patterns [11]. Similarly, CV techniques can be used to analyze video recordings of subjects' postures, which can provide highly accurate measurements of joint angles and other postural variables [19,20].

In recent years, the application of ML and CV to postural assessment has offered new possibilities and advantages for the detection, measurement, classification, and correction of postural deviations [12,19,20]. Some of the benefits of using ML and CV for postural assessment are higher objectivity and reliability, higher accuracy and precision, higher speed and efficiency, lower cost and complexity, higher accessibility and convenience and higher scalability and flexibility [8,19,20]. Despite the growing interest and ongoing research in this area [12], few systematic reviews have been conducted to assess the applications of ML and CV in postural assessment. After considering the nature and scope of this study, a systematic review was considered the most appropriate methodological approach [22,23]. In particular, a systematic review provides a comprehensive and rigorous approach to summarizing the available evidence on a specific research question through a predefined and reproducible selection process [23]. It involves a thorough and exhaustive search of the literature, comprehensive screening and data collection, quality appraisal, data synthesis, and reporting procedures [22,23]. This approach ensures that all eligible studies relevant to the research question are identified and evaluated in a standardized manner [24]. The outcomes of a systematic review are valid, reliable, and evidence-based, which is why it is considered the gold standard method for evidence synthesis [23-25]. On the other hand, a scoping review is a methodology used to identify gaps in the literature and to map the existing literature of a topic or a research field [23]. While scoping reviews provide an overview of a research field, they do not conduct quality appraisal or assess the impact of different variables on the findings [23]. Hence, they may be less useful when providing specific recommendations for clinicians and policymakers and may not be useful for answering specific research questions in healthcare [23].

The aim of this systematic review is to provide a comprehensive overview of the current state-of-the-art of ML and CV applications in postural assessment. Specifically, this review addresses the following research questions: (i) What are the traditional methods used for postural assessment? (ii) What are the main types of ML and CV methods/techniques and algorithms used in postural assessment? (iii) What are the data sources for training ML and CV algorithms? (iv) What are the main types of outcomes (e.g., accuracy scores) obtained by ML and CV techniques for postural assessment? (v) What are the main challenges and limitations of ML and CV techniques for postural assessment? and (vi) What are the main future directions and opportunities for machine learning and computer vision techniques for postural assessment?

This review follows a systematic methodology based on the PRISMA guidelines [24,25] to identify, select, appraise, synthesize, and report relevant studies from various databases. The review also provides a critical analysis of the quality, validity, and applicability of the studies included. The review would contribute to the advancement of knowledge and practice in the field of postural assessment by providing a comprehensive summary of the current evidence and highlighting the gaps and needs for further research. The objectives of this study are to comprehensively search the scientific literature to identify studies that have used ML and CV algorithms in postural assessment; critically appraise the quality of the identified studies using established frameworks and tools; synthesize the available evidence on the accuracy and reliability of different ML and CV techniques in postural assessment; and document the potential benefits and limitations of ML and CV techniques in postural assessment.

2. MATERIALS AND METHODS

The purpose of this review was to explore the existing research on machine learning and computer vision applications in postural assessment. To achieve this, the following steps in the methodology were implemented in line with the methods adopted in previous studies: scoping the literature review; adopting a search strategy and identifying information sources; selection and screening of literature; data extraction and analysis; and synthesis and reporting [24-26]. The literature selection process, study characteristics, results and findings were reported following the PRISMA reporting guidelines [24-26].

A protocol was developed that outlined the objectives, scope, and methodology of the review before it was started [24]. This would help to guide the review process and maintain clarity and focus [26]. Information on the research question, inclusion and exclusion criteria, and the search strategy for identifying relevant studies were included in the protocol. Then the research questions or objectives that guided the literature review were defined. The scope and boundaries were identified within the field of postural assessment and specific domains and subdomains relevant to the research question were determined. Factors such as time frame, geographical location, and specific populations or industries were considered to focus the literature search.

Appropriate academic databases, registers and reference lists (e.g., PubMed, Scopus, ScienceDirect, Google scholar, Elsevier, Web of Science, IEEE Xplore, Springer Link) were chosen, and a comprehensive list of keywords and synonyms related to the research topic methods of postural assessment, and ML and CV in postural assessment were developed [24,25]. Citation chaining and reviewing gray literature sources, such as reports, theses, dissertations, and conference papers that are relevant to postural assessment methods were also taken into consideration. The search was conducted by executing the search strategy in the selected databases and registers using the identified keywords and search terms such as *musculoskeletal disorders*, *OWAS*, *RULA*, *REBA*, *machine learning*, *deep learning*, *computer vision*, *postural assessment*, *gait analysis* and *balance assessment*. The search was limited to articles published in English without any year range.

A total of 182 articles were selected for inclusion in this review, based on their relevance to the topic and methodological quality. The search results were downloaded and stored, and duplicates were identified and removed [24-26]. After identifying relevant studies, inclusion and exclusion criteria were specified based on the scope and research questions [27]. During literature selection and screening, specific criteria for the selection of articles were developed, including publication date, study design, relevance to the research question on postural assessment, and quality of methodology. Titles and abstracts were initially screened to identify potentially relevant articles, and the full texts of the selected articles were subsequently reviewed to determine their suitability for inclusion in the literature review on postural assessment. Inclusion criteria considered studies that were published on postural assessment at any time, including research conducted with humans, related to ML and CV applications in postural assessment, and were available in English. Exclusion criteria included studies that focused on animals, studies that were not peer-reviewed, and studies that were not relevant to ML and CV applications in postural assessment. To extract and analyze relevant information, a data collection framework was created [24] to systematically document key information from selected articles, such as study objectives, methodology, findings, limitations, and gaps identified by the authors relevant to postural assessment. A structured framework, such as a table or thematic matrix, was further developed to facilitate the comparison and analysis of the extracted information within the context of postural assessment. In analyzing the data, common themes, patterns, and trends within the literature on ML and CV applications in postural assessment were identified. Findings, methodologies, theories, and gaps in knowledge identified by different authors were compared and contrasted to determine if significant gaps, limitations, or inconsistencies existed within the existing body of knowledge [24]. Discrepancies, unanswered research questions, contradicting findings, or emerging areas with limited study were sought in relation to postural assessment.

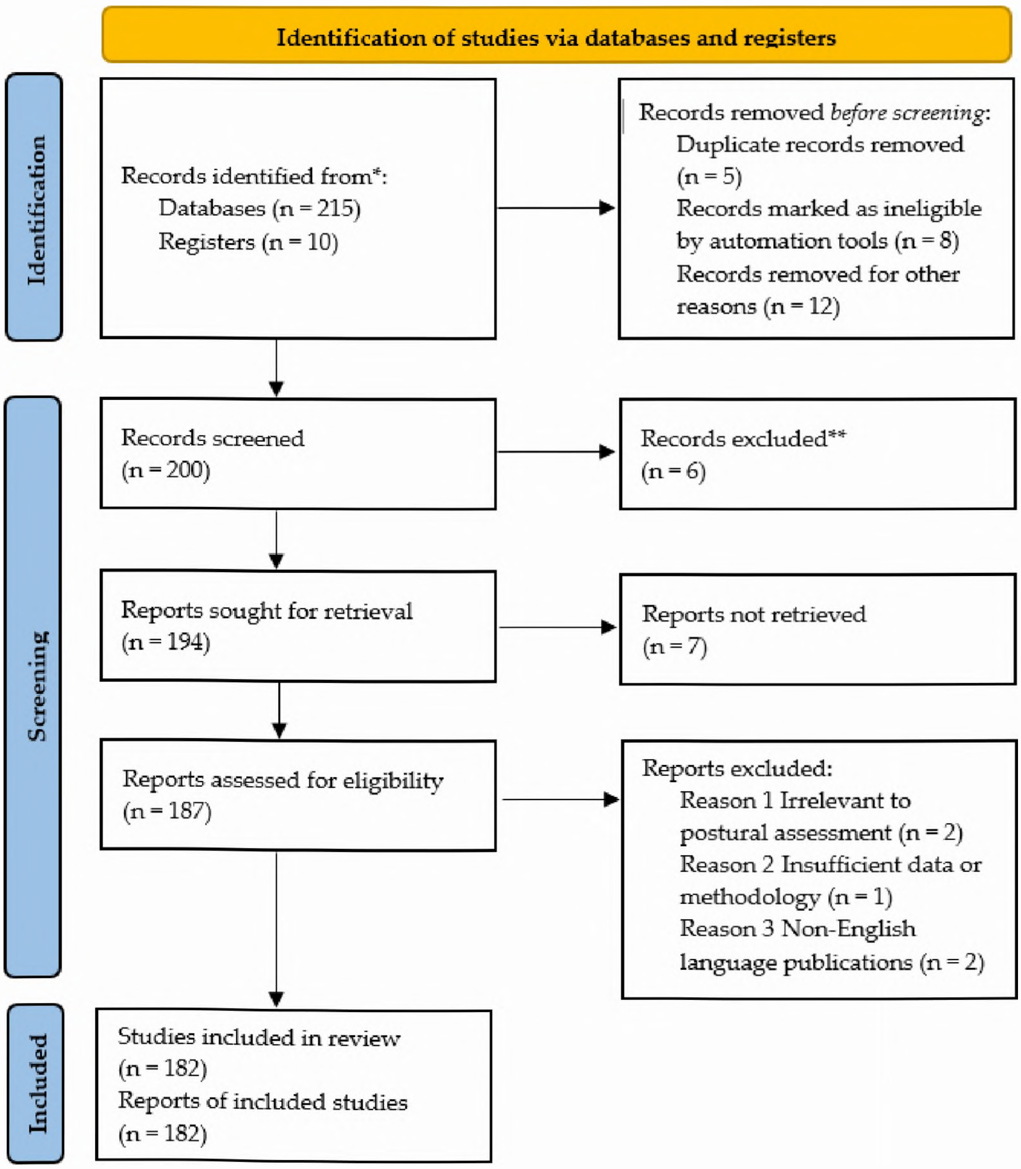


Figure 1. The PRISMA flow diagram of the methodological phases of the literature review for this study.

Finally, the findings of the literature review were synthesized by summarizing the main themes, knowledge gaps, and current research trends that emerged from the literature review within the context of postural assessment. The PRISMA guidelines were followed to ensure transparent and comprehensive reporting of the review methodology [24]. Strengths and weaknesses in the existing literature, including any biases, limitations, or areas requiring further investigation, were also identified [23-25]. A comprehensive literature review document, annotated bibliographies, or thematic summaries were used to present the results of the literature review in a clear and organized manner. The existing knowledge gaps within the research field of machine learning and computer vision in postural assessment were identified and analyzed, providing a solid foundation for further developing research and contributing to the advancement of the scholarly discourse in the specific domain of postural assessment. The risk of bias and quality of the studies were assessed using appropriate tools [23]. **Figure 1** is a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram [28,26] that illustrates the methodological phases of the literature review on ML and CV applications in postural assessment.

3. RESULTS AND DISCUSSION

3.1. Conventional methods used in postural assessment

A wide variety of methodologies used in postural assessment have been identified and grouped into three categories that have typically been utilized by past reviewers [8,29]. Studies of [3] and [29] categorized postural evaluation methods into three groups based on their level of accuracy and invasiveness towards the workers being assessed. In descending order of accuracy and invasiveness [29], they are direct measurements, observational approaches, and self-reports [3,8,30-33]. Worker self-reports can serve as a valuable postural evaluation technique for gathering information on their exposure to work-related physical and psychological health hazards [3,29]. Various methods can be used, including worker diaries, interviews, and questionnaires. Recent innovations can also be used, such as the self-evaluation of video films of job [34] or the use of web-based surveys [35,36]. Employees document their postures and motions during the workday for worker diaries. For the use of interviews, experts or supervisors conduct interviews with workers to gather information on physical and psychosocial factors related to postural risks. Regarding questionnaires, workers complete questionnaires to provide information on their work tasks, physical demands, and psychosocial factors [3,8,32]. Some examples of studies that have used self-reports as a method of postural assessment in forestry and office work were presented in the studies of [35-39]. The ease of use, adaptability to various work situations, and cost-effectiveness of these strategies for surveying a large sample size are just a few of its advantages, according to [3] and [29]. Moreover, they enable the estimation of exposure for more extended periods than what can be observed at work [3]. Despite the usefulness of self-reports in postural assessment, it has been found that worker perceptions of exposure can be vague and unreliable, posing challenges to self-reporting. For example, workers experiencing significant low back or neck pain have been found to report longer or more frequent periods of physical activity compared to pain-free workers, although the findings of such studies may vary [38]. Additionally, differences in worker literacy, comprehension, or question interpretation can impact the reliability of self-reports [39]. Although self-reports have drawbacks, [3] and [29] both point out that they can be useful in identifying occupational groups that are more at risk. Study of [29] reports that self-reports can be utilized to collect information regarding demographic characteristics, reported symptoms such as pain and postural discomfort, and levels of perceived exertion. Large sample sizes are frequently needed to guarantee that the data collected is representative of the occupational groups under study, and the right skills are needed to properly evaluate the results [3,29]. As a result, using employee self-reports as a tool for postural evaluation can help gather information on how exposed employees are to physical and psychosocial problems at work. While they have limitations in terms of their reliability and validity, they can still be used to identify occupational groups at higher risk for further analysis using other methods. In order to acquire a more complete picture of workplace exposure to risk factors for work-related musculoskeletal disorders (WRMSDs), it is crucial to consider the limits of self-reports when utilizing them as a technique of postural evaluation and to combine them with additional approaches [3,29]. More research is required to increase the accuracy and dependability of self-reports and to find the most effective applications for them in the diagnosis and avoidance WRMSDs.

Observational methods of postural assessment are crucial in assessing the external exposure of workers [3,8]. There are two types of observation methods: subjective and systematic [8]. Subjective methods ask workers directly about their workload, discomfort, and stress using body maps, rating scales, checklists, or interviews [3,8]. In contrast, systematic observations involve recording and tracking the workers' postures and movements [8]. Study of [3] reported that systematic observational methods can be categorized into simpler and advanced methods. Simpler methods involve using pro-forma sheets to systematically record workplace exposure, which helps prioritize intervention strategies. Simpler observational techniques include OWAS method [40], REBA method [41], Corlett method [42], Vira method [43,44], PATH method [45], NIOSH equation [46,47], Snook and Ciriello tables [48], KIM method [49], MAC method [50], Liberty Mutual tables [51], RULA method [52], "Job Strain Index" method [53], PRRI [54], IBV method [55], OCRA method [56], PLIBEL method [57], Posturegram [58], HAMA [59], QEC [31], checklists [60], FIOH Risk Factor Checklist [61], ACGIH TLVs [62] and Upper Limb Disorder Guidance, HSG60 [63]. Some methods, such as those used by [31] and [63], exclusively evaluate the posture of various body parts. Conversely, other methods, as discussed by [47], gather subjective data from workers as part of the assessment of physical or psychosocial demands. For a variety of workplaces where other observation techniques can be disruptive, these methods are practicable and affordable [3,29]. They are best suited for evaluating static or repetitive jobs, although they may vary slightly when it comes to selecting between various exposure level groups [64]. Besides, various techniques, such as those described by [8] and [31], allow for the calculation of overall scores for combinations of exposure factors. These scores can then be used to determine acceptable exposure limits or the order of priority for intervention. According to [8] and [29], the data used to create these scoring systems is sparse, particularly when it comes to figuring out how much weight to give to particular traits or characterizing the connections between components. Study of [3] pointed out that ergonomic approaches can be utilized to evaluate exposure to factors that increase the risk of developing musculoskeletal problems at work. In contrast, study of [32] highlights the importance of considering multiple aspects and recommends more complex techniques for MSD risk assessment. Methods such as those described by [8], [31], and [47] allow for overall indices or scores to be determined. The ratings obtained from scoring systems are essential in determining acceptable exposure limits for workers and selecting the most critical activities for interventions. However, as noted by [3] and [29], these scoring systems are based on limited epidemiological data, with a particular lack of information on how to weigh or quantify interactions between different parameters. It is important to note that these scoring systems are speculative and may not provide an accurate representation of the numerous physical exposure issues that employees face. To prevent WRMSDs and other health issues, it is essential to consider a variety of variables and continuously evaluate and improve the assessment methods [3,8,29,31].

Traditionally, postural assessment in the forestry industry has been conducted using a range of methods, strategies, and equipment [65]. For example, [65] utilized four different assessment methods, including OWAS, Revised NIOSH Lifting Equation (RNLE), OCRA, and REBA to evaluate the index of exposure to WMSDs and assess the risks of injuries in workplace activities. In another study, [66] systematically compared three observational methods, OWAS, RULA, and REBA, for assessing musculoskeletal loadings and their connection to musculoskeletal disorders (MSDs). The finding was that RULA is the most commonly used technique among the three, although it has a significant constraint of only having two categories for leg positions. According to [67] and [68], all pen-and-paper techniques for postural evaluation require trained experts and are time-consuming. Therefore, attempts have been made to automate some of these techniques to perform online evaluations. For instance, [69] and [70] employed human motion data in both simulated and real-world settings to integrate RULA with REBA. Nevertheless, observational approaches still have limits because they only take task dynamics, such as constant contact forces, into restricted consideration [71]. Nonetheless, traditional methods have been shown to be feasible due to the availability of specific software and the ease of evaluations required [65,72]. Nevertheless, there is still a need for improving the current methods for postural assessment since there has not been much research done in this area [65]. Furthermore, there are not many studies examining postural risks in forest operations in terms of human-machine interaction [73].

In order to create and improve postural evaluation techniques that can efficiently identify and reduce the hazards of WRMSDs in the forestry industry, more study is therefore needed. Therefore, recent research has focused on developing advanced methods that can better capture the dynamic nature of work tasks. One potential area for improvement is the use of wearable sensors and motion capture technology to provide more accurate and objective measurements of postural positions and movements [73]. For example, wearable sensors have been used to monitor workers' postures and movements at the actual time during which the event occurs [74]. Virtual reality simulations have also been used to evaluate ergonomic risk factors in a controlled and repeatable environment [8,74]. These technologies can also provide workers with immediate feedback, allowing them to correct their posture and prevent the progression of musculoskeletal problems. By incorporating ergonomic design principles into the development of forestry instruments and equipment, workplace ergonomics can be improved, reducing the risk of musculoskeletal disorders [72]. Postural variation during dynamic activities is measured using sophisticated observational techniques, and data is captured on videotape or processed using specialist software [3,8]. To provide a more accurate and thorough evaluation of ergonomic risk factors, these methods involve computerized data collecting and analysis. Using computerized time sampling, ROTA [75] and TRAC [64] approaches, for instance, record and evaluate activity and posture while allowing for the assessment of both dynamic and static tasks. To calculate internal exposures during task execution, the Biomechanical models method [76] links segments of the human body together. Other techniques make use of video-based techniques, like the Simi Motion technique [31]. Overall, these advanced observational methods are used to provide a more objective and comprehensive assessment of postural risk factors in the workplace, allowing for the development of effective interventions to prevent work-related injuries and improve worker health and safety.

Postural evaluation techniques vary in their assessment of exposure factors, with some considering physical and psychosocial aspects in addition to postural alterations, while others focus solely on postural changes [71]. Some techniques use video-based observational methods and specialized software to objectively record and analyze data, while others rely on subjective data collected from employees [53,77]. Advanced methods may quantify intersegmental moments and forces using biomechanical models as well as a variety of movement dimensions, such as distance, angular shifts, velocities, and accelerations [78]. Study of [71] emphasize that when evaluating workplace activities, it is important to consider factors beyond movement characteristics, such as load, repetition, movement duration, and vibration. A lack of epidemiological data limits the usefulness of the many indices and scoring systems that have been established to determine acceptable exposure limits for employees or to prioritize interventions [71]. Although some methods are more exhaustive, they lack precision and reliability and are subject to discrepancies between different observers and within the same observer [71]. The EAWS and CERA methods were created in order to give a thorough ergonomic study [79,80]. The Key Indication Method (KIM) was created to assess manual handling tasks such as lifting, carrying, holding, pushing, and tugging, as described by [81] and [82]. The EAWS, CERA, and KIM approaches provide a thorough ergonomic study; nevertheless, additional research is needed to determine their validity and usefulness in practical contexts [8]. In addition, these techniques may not always capture the nuances of individual tasks and may require customization for specific industries and work environments. Therefore, continuous improvement and development of postural assessment methods and techniques are necessary to ensure the prevention of MSDs resulting from work and to enhance workers' general well-being and security. According to [3] and [29], the use of advanced observational methods for assessing postures can be costly and requires extensive technical support from highly trained staff. Although these methods are relatively inexpensive and can be used in various work situations, they have limitations in terms of reliability and validity, particularly for subjective judgement methods. As a result, it is crucial to combine several methods, including objective measures and self-reporting, to ensure comprehensive and accurate postural assessment in forest operations. While some methods may be more exhaustive, they can lead to inconsistencies between different observers and within the same observer, which can be time-consuming. Recent technological advancements have led to the development of more objective and dynamic assessment methods, but further research is needed to establish their validity and reliability in real-world settings [8]. Despite their drawbacks, advanced observational techniques have been found to be better suited for capturing and assessing simulated tasks than for conducting actual workplace assessments. This is due to the fact that their utilization might be time-consuming in practice and necessitate intensive technical support. But using these techniques at work is crucial to preventing musculoskeletal conditions brought on by improper posture.

Direct measurement of exposure variables can be achieved by attaching sensors to the subject's workspace [3,8,29]. Data can be collected both on-site at the workplace, and during laboratory simulations [8]. Direct methods, including hand-held instruments that measure joint mobility and electronic goniometers that continuously record joint movement during task performance were reported and used in the studies of [31,86-93]. Specialized lightweight devices can be attached directly across articulating joints to measure finger, wrist, and forearm angles, as well as forearm rotation, with corresponding systems available for computerized data analysis [3,29]. Techniques for observing one's posture are additional direct methods for evaluating physical workload. With these techniques, certain anatomical sites on the worker are marked with optical, acoustic, or electromagnetic markers, which are subsequently tracked by related scanning equipment to keep track of different body components' angles of movement and positions. All body markers' three-dimensional coordinates can be recorded by sophisticated computing equipment immediately. However, according to [3] and [29], these systems are more appropriate for task simulations than industrial setting investigations. Studies of [3] and [8] have pointed out that Electromyography (EMG) is another direct method for measuring muscle tension that involves recording and analyzing myoelectrical activity using a computer. EMG activity can be translated into muscle tension using empirical models, although the relationship may not be linear and needs careful interpretation. By examining changes in the spectrum properties of the myoelectric signal, EMG can also evaluate local muscle exhaustion, however interpretation can be difficult. In order to drive simulations of musculoskeletal models for the upper and lower extremities, EMG-based approaches have been utilized to monitor physical exposure and cumulative compression in the low back [3,29,94]. Additionally, the direct method involves the use of inclinometers which measure the angle of the spine or other body segments to determine the degree of bending or twisting, and force plates which measure the ground reaction forces during work tasks to determine the level of physical demand [3,8,29]. While direct sensor attachment to the subject can make the subject uncomfortable and change their working habits, direct measurement techniques provide very accurate data on a variety of exposure characteristics. These systems produce a large amount of data, however because to the time needed for data analysis and interpretation, practitioners may find it unworkable. Additionally, in order to ensure effective functioning, direct measurement systems need a sizeable initial expenditure to pay for the equipment, cover maintenance expenses, and hire highly qualified technical employees [3]. A flexible model was created by [95] to investigate compressive strain on the human spine. The goal of this model is to reduce complexity while preserving accuracy for more intricate body parts. Moreover, a stochastic methodology for ergonomic evaluation was introduced by [96] by simultaneously evaluating human whole-body kinematics and dynamics. However, further research and development needs to be done on these techniques before they can be completely applied in scenarios connected to forests [3,8]. In order to quantify exposure factors at work, direct approaches for postural assessment entail directly attaching sensors to the individual. These methods provide large quantities of highly accurate data but require considerable investment and technical expertise for effective operation [8]. Recent innovative approaches aim to account for workers' internal exposure and address the limitations of traditional ergonomic tools and laboratory-based methods. While these approaches show promise, they still need further development and validation before being widely adopted in forest industry settings. Recent advancements in sensor technologies have enabled the automation of many methods belonging to the observational and direct measurement categories [3,8]. To better understand the physical internal exposure of humans, researchers use sensor systems to collect direct measurements on human subjects [8]. These measurements are then integrated with complex models of the human body to estimate muscle tensions and joint loads [3,8]. OpenSim is a freely available application that can create interactive simulations of movement utilizing models of the neuromusculoskeletal system. It incorporates a commonly used algorithm, while Anybody, another software, views the human musculoskeletal system as a rigid-body system. Both programs consider the muscle recruitment patterns and geometry in their models. By utilizing techniques such as inverse kinematics and inverse dynamics, the motion of these models can be analyzed [97,98]. However, their utilization is not strictly obligatory, as ergonomics assessments can still be approximated by incorporating them into ad-hoc models or directly retrieved from acquired data [8]. Overall, the classification/categorization of the various methods used in postural assessment in forest operations provides a systematic and comprehensive overview of the different approaches available. This categorization enables a better knowledge of the advantages and disadvantages of each approach, which can aid researchers and practitioners in choosing the approach that is best suitable for their individual needs. By using a combination of these methods, it is possible to obtain a comprehensive assessment of postural risks in forest operations, which can ultimately lead to the development of effective interventions to prevent MDSs and injuries resulting from work. Generally, these methods can be used individually or in combination to assess postural risks in forest operations, and each method has its advantages and limitations depending on the specific needs of the study or intervention.

The selection of postural assessment methods should be based on the particular research subject and the environment where the evaluation is taking place. Other relevant considerations include the level of detail required, available resources and time, and the target group being evaluated. The selected method should allow for accurate and reliable data collection, while also being practical and feasible for the research context. For example, simpler methods may be more appropriate for assessing postural risks in low-risk work environments, while more advanced techniques may be necessary for high-risk work environments with complex postural demands. In addition, the use of multiple methods can provide a more comprehensive assessment of postural risks and can help to validate the findings of each individual method. Overall, a multi-method approach can help to identify postural risk factors and develop effective interventions to prevent and manage musculoskeletal disorders. Combining several approaches makes it feasible to get a more comprehensive picture of the postural demands of daily tasks and to pinpoint areas that can benefit from treatments in order to lower the risk of MSDs.

3.2. ML and CV algorithms and methods used for postural assessment

Algorithms form the core of ML and CV systems [12,19,20,99]. According to [100], *"informally, an algorithm is any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as output. An algorithm is thus a sequence of computational steps that transform the input into the output."* Consequently, various algorithms are employed for different CV applications, including image classification, object detection, segmentation, and more [12,19,20,99,101]. According to studies of [12,19,20,99], substantial research has been done on CV in the areas of pose estimation, activity recognition, pose or gesture recognition, and other topics. Postural assessment is an important component of human health monitoring and rehabilitation, as there is a direct correlation between poor posture and various musculoskeletal disorders [102]. Recent advances in ML and DL algorithms have enabled the development of efficient and accurate CV methods for assessing posture from visual cues, such as images and videos of individuals [12,99]. In this context, computer vision-based algorithms have been developed to obtain and assess posture parameters in order to be used as an assistance for physical therapists in their posture assessment and correction [99]. These algorithms have been used in a variety of fields, including healthcare, sports, and ergonomics, to analyze and improve posture in different settings [12,19,20,99,101]. They have shown promising results in assessing for instance sitting posture [101] and detecting postural deformity in the spine [103].

Some of the common traditional ML algorithms used in CV for postural assessment research include SIFT, HOG, SVM, GMM, DTW and HMM [12,104]. Other traditional ML classification algorithms that are utilized for postural assessment using CV include RF, DT, k-NN, the Bayesian classification algorithm, naive Bayes (NB), and linear discriminant analysis (LDA) among others. Besides, a large number of researchers utilize both DL algorithms and narrow neural networks in CV for postural assessment research [12]. In this regard, researchers have proposed several Convolutional Neural Network (CNN) algorithms and architectures, and *"improved CNN methods, such as stacked hourglass networks, multi-stage pose estimation networks, convolutional pose machines, and high-resolution nets"* [12]. Furthermore, researchers have explored the use of explainable deep neural networks, graph neural networks, transfer learning (TL), ensemble learning (EL), and other advanced neural network applications for posture identification [12].

Regarding the traditional ML algorithms used in CV applications, SIFT is a feature detection and extraction algorithm that captures all significant local features in an image [105,106]. It detects and describes local features within an image, which are invariant to scale, rotation, and affine transformations [105,106]. It has been used in posture analysis to detect key points of the humans. These key points can be extracted using SIFT to provide feature vectors that are used to classify posture [106]. Moreover, HOG is an algorithm used for detecting objects, particularly for detecting humans [107]. HOG is a feature descriptor that represents the presence of gradients in an image [107]. It calculates the distribution of gradient orientations within an image, which is then used to create feature vectors for classification [108]. It has been used for feature extraction in identifying human posture. HOG features can be extracted from a body part's image and trained with a classifier to recognize different postures [108]. According to [109], SVMs are commonly used classification algorithms for image classification in computer vision. In posture recognition, SVMs have been used to perform binary classification to determine whether a posture is correct or incorrect. Apart from posture classification, SVMs have also been widely applied in various CV applications like object detection and face recognition [110]. Similarly, GMM is a probabilistic model that has been used for multimodal posture modeling [111,112]. Gaussian components of the model represent different posture modes, and the model is trained with posture observations to estimate the probability of each component [111,112]. GMM can be used to identify the most probable posture mode for each observed posture [12]. DTW is a similarity measure that has been used to measure the similarity between sequence data [113,114]. DTW aligns two sequences and computes the distance between them according to the minimum warping path. DTW has been used for measuring the similarity between two postures and identifying any deviations between them [113,115]. Furthermore, the temporal dependencies between postures have been modeled using the Hidden Markov Model (HMM) statistical model [116,117]. The HMM consists of a set of states that represent various postures, and transitions between the states represent the likelihood of a posture change. In order to anticipate the sequence of postures based on the observed data, HMM has been employed in posture recognition [116,117]. The HMM algorithm is a statistical model used for time-series data that considers uncertainty in postural data analysis to provide more accurate results [118-121]. HMMs can be used in both supervised learning (SL) and unsupervised learning (UL) settings, with the model trained using labeled data for SL and unlabeled data for UL [119,121]. HMMs have been used in both supervised and unsupervised learning settings for postural assessment tasks, achieving high accuracy rates in various studies [118,122-124]. HMMs are a flexible ML algorithm that can model the temporal sequence of postural transitions and handle missing data and noisy sensor signals, making them suitable for wearable sensor-based postural assessment [119-121]. The utilization of HMMs for physical activity classification using on-body accelerometers has potential applications in healthcare and sports [119]. Additionally, HMMs have been applied to UL to examine temporal patterns among posture sequences to identify categories associated to a child's level of interest, with overall accurate results of 76.5 - 82.3% [120].

RF are ensemble learning algorithms that consist of multiple decision trees (DT), where each tree independently classifies an input image or extracts features [125]. It is utilized for tasks such as classification, regression, and others that generate a lot of DT during the training phase [125-128]. According to [125], RF are renowned for their dependability and capacity to handle high-dimensional data. Studies show that numerous DT are integrated in RF to improve the model categorization's accuracy [125,127-129]. By adding up each tree's individual decisions, the final choice is made. In postural assessment, RF which are supervised learning algorithms have been used to classify postures based on different features extracted from images or videos. For example, RF have been used in the context of postural assessment to classify different postures based on various motion capture data [5,12]. They have also been used to predict postural sway in individuals with Parkinson's disease [5]. They are particularly helpful for activities involving a lot of characteristics or variables. In the context of forest operations, RF could be used to classify different postures based on data collected from wearable sensors [128]. They are used in CV for tasks like object detection and image classification. Several studies report the use of RF in CV for postural assessment research [129-131]. DT are graphical models that split the data into branches based on some criteria, such as entropy or Gini index [132,133]. Each branch represents a possible outcome or a decision rule [132,133]. The leaf nodes at the end of the branches indicate the predicted class or value for the data. Studies of [132] and [133] have noted that DT are straightforward to interpret and can handle both categorical and numerical data. However, they are prone to overfitting and instability [132,133]. DT have been utilized in CV for postural assessment research [12,134-136]. For instance, [134] used DT to classify different postures of workers, such as standing, sitting, bending, etc. in a manufacturing environment. They achieved an accuracy of 94.4% on a dataset of 1200 images. Similarly, [135] used DT to classify the posture quality of office workers based on their head, neck, and trunk angles. They achieved an accuracy of 86.7% on a dataset of 300 images. Additionally, Singh and Garg (2016) used DT to classify the posture of drivers based on their steering wheel grip, head position, and seat belt usage. They achieved an accuracy of 88.9% on a dataset of 180 images. The K nearest neighbors (KNN) algorithm, which is based on distance, assigns a new data point to the category or value of its K nearest neighbors in the training data [17]. According to [137] and [138], KNN is another algorithm used for classification of a new data point in light of its closest neighbors' classes. The value of K is a hyperparameter that can be chosen based on the data distribution or cross-validation [17]. KNN is simple and flexible, but it can be slow and sensitive to noise and outliers [17]. Study of [139] implemented the KNN algorithm, in addition to SVM, DT, and RF, to classify the posture of elderly individuals in postural assessment research. Their study achieved high levels of detection accuracy (97.34%), precision (98.50%), recall (97.33%), and F1 score (97.91%). Moreover, [137] utilized many ML algorithms, such as k-nearest neighbor, to classify different activities and movements based on data from the activity monitor. The k-nearest neighbor algorithm demonstrated high accuracy in classifying different activities and movements. Likewise, [140] evaluated the identification of work posture and musculoskeletal disorder risk levels in workers in the fireworks industry. The authors employed machine learning algorithms, including K nearest neighbors to classify different work postures and evaluate musculoskeletal disorder risk levels. The study found that K nearest neighbors algorithm demonstrated high accuracy in classifying different work postures. The Bayesian classification algorithm is another probabilistic method that makes use of Bayes' theorem to establish the posterior probability of each class in light of the properties of the data [141]. Study of [141] asserts that given the class identification, it is presumed that the traits are conditionally independent. It can handle uncertainty and missing data, according to [141], although it can have problems with the zero-frequency problem and unrealistic independence assumption. In CV, the Bayesian classification algorithm has used for postural assessment research [12]. For example, study of [142] used Bayesian classification algorithm to classify the posture of patients with spinal cord injury based on their electromyographic signals. They achieved an accuracy of 83.3% on a dataset of 48 signals. A special instance of the Bayesian classification algorithm known as Naive Bayes (NB) operates under the presumption that, given the class label, all features are independent. By multiplying the class's prior probability and each feature's likelihood given the class, it determines each class's posterior probability. It is fast and simple, but it can be inaccurate if the features are correlated or have zero-frequency values. In the context of postural assessment, study of [143] used naive Bayes to classify the posture of workers in an assembly line based on their wrist angles and muscle activities. They achieved an accuracy of 91.7% on a dataset of 120 signals. Study of [134] used naive Bayes to classify different postures of workers in a manufacturing environment, such as standing, sitting, bending, etc. They achieved an accuracy of 92% on a dataset of 1200 images. According to [144], LDA is a method for classifying data and reducing its dimensionality that projects the data onto a lower-dimensional space, maximizing variation between classes and minimizing variance within classes. The data must have a multivariate normal distribution, and the classes must have equal covariance matrices, according to the LDA. Inaccuracy may result if the assumptions are broken, although it can minimize computational complexity and prevent overfitting. One example of using LDA for postural assessment research is that of [145] who used LDA to classify the posture of elderly people based on their body joint angles and center of mass. They achieved an accuracy of 93.8% on a dataset of 240 images. Moreover, the study of [146] used LDA to classify the posture of office workers based on their head, neck, and trunk angles. They achieved an accuracy of 87.5% on a dataset of 300 images.

However, the study of [12] suggest that traditional ML algorithms are not always effective in CV for postural assessment research. They argue that these algorithms have limited ability to represent complex and semantically rich information, which can hinder accurate recognition of features. Additionally, step-by-step recognition methods may not have robust real-time performance, posing further challenges for postural assessment. The study of [109] has argued that deep learning-based postural assessment approaches can improve the performance of postural assessment systems. They explain that using deep neural networks permits combining low-level features from the image with higher-level estimates, generating more accurate results. Compared to traditional ML algorithms, deep learning-based models can adapt better to new tasks and perform faster and more accurately in target detection. Consequently, the optimization of ML algorithms in postural assessment research mainly employs neural network models as parameter structures. The study of [12] cite CNN, DNN, RNN, LSTM, TL, and attention models as commonly used in postural assessment research using DL. These models are implemented as a complete learning approach, where feature extraction and model learning are automatically performed by the algorithm without manual operation. The study of [147] explains that by starting directly from the original input data, a hierarchical network extracts features and learns the model. DL has achieved impressive results in postural assessment research [12,148] and the study of [12] claims that DL-based identification posture can swiftly compare human posture data to sample labels to create a model that can assess posture. CNNs have demonstrated a great deal of success in postural assessment and identification, according to [12]. Convolutional layers, which extract useful features from the input images, are followed by pooling layers and fully connected layers for classification in CNNs. CNNs have achieved state-of-the-art performance on various CV tasks [149]. As observed by [150], CNNs have evolved over the years, leading to the emergence of various architectures and methods for a wide range of CV applications. As a result, various improved CNN methods, such as *"stacked hourglass networks, multi-stage pose estimation networks, convolutional pose machines, and high-resolution nets"*, YOLO, among others have been proposed and used for postural [12]. There are many examples of studies using DL on various datasets [152-162]. Stacked Hourglass Networks (SHN) is a popular CNN architecture used to estimate human posture [12,163]. SHN uses a multistage architecture to refine the prediction of human pose by regressing heatmaps of body joints. The network consists of several stacked hourglass structures, each with a series of encoding and decoding stages [163]. The network generates confidence maps for each joint's position and size in the image. According to research by [163], SHN performs at the cutting edge on baselines for posture estimation like MPII and COCO. Multi-Stage Pose Estimation Networks (MSPE) is another CNN-based method for human pose estimation [164]. MSPE divides the human body into several sub-regions and estimates the pose of each sub-region before aggregating the final position of the joints [164]. The network consists of multiple sub-networks, each focusing on a separate sub-region of the body. MSPE has been shown to improve the accuracy and robustness of pose estimation by providing more localized features [164]. Convolutional Pose Machines (CPM) is a CNN-based method for estimating multiple-person poses [165]. CPM processes the image using a series of convolutional layers and then applies a learning strategy that goes through several stages to improve the estimate of each joint's position [165]. The network incorporates features from lower layers into higher layers by using skip connections to pass information between the stages [165]. CPM has been shown to achieve modern performance on baselines for postural assessment of several people such as MPII and COCO [165]. High-Resolution Nets (HRN) is a CNN-based architecture designed for high-resolution image inputs, such as those encountered in human pose estimation applications [166]. HRN uses dilated convolutions to capture fine-grained details in the input image at different scales [166]. The network consists of a series of high-resolution feature maps that improve the accuracy of the final pose estimate. HRN has been shown to produce more accurate results than other CNN architectures on high-resolution pose estimation benchmarks such as the MPII dataset [166]. You Only Look Once (YOLO), according to [167], is an object identification algorithm that detects several items in an image in real-time and predicts their bounding boxes and class probabilities in a single pass. To anticipate object classes and bounding box coordinates, YOLO divides the input image into a grid and applies convolutional neural networks to each grid cell. The versions of YOLO include YOLOv7, PP-YOLOv2, and YOLOv8. It is well-known for being quick and effective at object detection tasks, making it appropriate for real-time uses like video surveillance. Although YOLO's high level of generalizability makes it less prone to failure when applied to new domains or unpredictable inputs, it may perform worse than state-of-the-art detection systems regarding accuracy, particularly in localizing smaller objects. The study of [168] has demonstrated the potential applicability of YOLO in human body posture recognition and tracking, achieving an average precision of 91.7% on a public dataset, and demonstrating the potential application of their framework in UAVs for surveillance and monitoring tasks. OpenPose is an open-source library that uses DL algorithms for multi-person 2D pose detection, tracking, and key point estimation from video feeds [19,20,169]. OpenPose features pre-trained models and can use a variety of input sources, including pre-recorded video files as well as real-time streams from webcams and other devices. Its ability to detect up to 135 keypoints across body, hands and feet makes it suitable for several applications like action recognition, augmented reality, and motion capture [169]. Backpropagation (BP) is a supervised learning algorithm which makes use of gradient descent and is commonly used for artificial neural networks. The process of training neural networks for various applications often involves calculating the gradient of the error function based on the weights of the network. This is frequently used in the field of ML [12]. Regression, classification, and picture recognition are just a few of the potential jobs here. Study of [170], for instance, classified six different human postures using the angular information along with SVM and BP. Moreover, the study of [171] created a posture recognition method that applies BP, SVM, and Naive Bayes without the need for feature extraction by using skeletal data as the classifier's input data.

Therefore, the use of advanced DL algorithms in CV applications for postural assessment has shown tremendous promise. The accuracy of posture assessment can be increased by using these algorithms, which can automatically extract complicated and abstract information from photos while using less computer power. However, they also have several drawbacks, including the need for a sizable dataset, vulnerability to adversarial assaults, and a propensity for overfitting parameters. In general, the application of sophisticated algorithms to postural assessment has the potential to increase its precision and effectiveness as well as aid in the more accurate identification and treatment of associated diseases. However, according to [12], CNN models' intricate design can impact postural assessment research and practice, leading to a deeper model with more parameters that demand greater computational power. Lightweight CNN models like Xception [172], Mobile Net [173], Shuffle Net [174], Shuffle Net V2 [175], and Squeeze Net [176] are becoming more popular due to the rise of IoT technology and resource-constrained platforms. Thus, the emergence of these lightweight convolutional neural network models has allowed for more efficient and effective postural assessment research on resource-constrained platforms [12]. These models have been shown to be effective for posture recognition and can help mitigate the issue of limited computing resources. Future research can explore the potential of these models in addressing the challenges of postural assessment in various contexts.

3.3. Challenges and advancements in ML and CV applications for postural assessment

The use of ML and CV software and tools provides several benefits for data analysis, including the analysis of large and complex datasets, task automation, and user-friendly interfaces [12,177]. ML and CV algorithms can be used in postural assessment to identify movement patterns, detect deviations from normal alignment, and predict the risk of falls [12,177]. However, there are some drawbacks, including the computational demands of ML and CV methods, the importance of data quality and quantity, and the cost of some ML and CV tools and software [129,178]. However, there are new trends and technologies that could transform ML and CV as they continue to develop.

Deep learning, which involves training algorithms using big data sets and neural networks, is one of these new trends [12,179]. The creation of new algorithms that are more effective and efficient in processing vast amounts of data is another trend [12,180,181]. These new trends and technologies have the potential to have an impact on a number of industries, including ergonomics, healthcare, finance, and transportation [182].

According to [179], recent advancements in CV algorithms have been facilitated by DL techniques, particularly CNNs, which have integrated various architectures to revolutionize tasks including semantic segmentation, object detection, and picture categorization. These algorithms can learn complex visual patterns and features, making visual analysis more accurate and robust. However, CV algorithms still face several challenges, as noted by [154]. These challenges include occlusion, variations in lighting conditions, scalability, and processing time, especially in applications that require immediate responses such as autonomous vehicles or surveillance systems. Additionally, the study of [173] highlights that adapting to different lighting conditions is important for reliable CV systems, and the efficient processing and analysis of large-scale datasets requires efficient algorithms, distributed computing frameworks, and parallel processing techniques.

According to [167], achieving real-time performance while maintaining accuracy and robustness is complex and requires optimization of algorithms and hardware resources. The study of [150] notes that challenges related to data limitations and quality, generalization to new scenarios, interpretability and transparency, and adversarial attacks are of significant concern. Furthermore, computational requirements pose a serious challenge to CV since DL models often require massive amounts of computational resources for training and inference. Ethical and societal implications of CV technologies also arise, required to be addressed by researchers. Moreover, the integration of CV with other domains, such as natural language processing and robotics, will lead to more advanced and intelligent systems that can understand and interact with the world in a more human-like manner [18,162]. According to [181], CV algorithms can be harnessed to develop more advanced and intelligent systems that can better understand and interact with the world.

Future research in ML and CV applications in postural assessment aims to explore and develop new network types and architectures beyond current deep learning models, as noted by [150]. Furthermore, researchers aim to refine and adapt ML and CV techniques for more specialized scenarios, cross-domain collaboration between CV and other domains of ML is gaining attention. Enhancing the interpretability of ML and CV models is crucial for better understanding their decisions, and further research is dedicated to developing techniques that facilitate model, visualization, and interpretability, ensuring transparency and trust in ML and CV systems. Finally, researchers aim to address challenges related to training and deploying large-scale ML and CV models, including efficient optimization methods, distributed computing, and hardware acceleration.

4. CONCLUSIONS

Postural assessment is a key component of ergonomics that can help identify high-risk postures and inform the development of interventions. Moreover, a postural assessment can provide valuable information on worker postures and movements, as well as on the effectiveness of ergonomic interventions. Both conventional and new methods can be used in postural assessment and can be effective in improving ergonomic conditions. Therefore, it is important to continue to develop and refine methods for postural assessment to ensure that they are effective and practical for use in forest operations. ML algorithms are useful for a variety of applications because they can learn from their environment and adapt to changes. With the ability to automatically identify postures from photos or videos, ML has emerged as a key technique for postural recognition. CV is a rapidly evolving field that encompasses algorithms and techniques for analyzing and interpreting visual data. By leveraging diverse data sources, advanced algorithms, and efficient data processing, CV applications can achieve accurate and reliable results. The availability of different software platforms provides flexibility and convenience in developing and deploying CV applications across various environments. As ML and CV continue to advance, they hold immense potential to transform numerous industries and enhance human-computer interaction. Moreover, ML and CV algorithms have made significant advancements, particularly with the integration of DL and CNNs. Despite challenges like occlusion, lighting conditions, scalability, and real-time processing, ML and CV continue to evolve and find applications in various fields. The future of ML and CV holds promise with emerging technologies and interdisciplinary integration. ML and CV algorithms are poised to play a pivotal role in fields such as postural assessment and recognition, and healthcare. Though these algorithms have the potential to revolutionize industries, improve efficiency, and enhance human experiences, the prevailing challenges still need to be addressed. The future of ML and CV looks promising with the emergence of technologies like 3D vision and AR, as well as collaborations with other domains.

SUPPLEMENTARY MATERIALS

Not the case.

FUNDING

This work received no external funding.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

EXTENDED ABSTRACT – REZUMAT EXTINS

Titlu în română: *O sinteză a metodelor tradiționale și moderne folosite în evaluarea ergonomic-posturală*

Introducere: *Evaluarea posturilor adoptate în muncă este importantă pentru caracterizarea condițiilor ergonomice de desfășurare a muncii, mai ales în sectorul forestier. În ultimul timp, pentru evaluarea posturilor de muncă s-au folosit metode tradiționale cum ar fi evaluarea pe bază de auto-raport, prin metode observaționale, sisteme de detectare a mișcării și electromiografie. Dezvoltarea tehnologică a condus, în ultima perioadă, la apariția unor metode noi care au la bază învățarea și viziunea computerizată. Aceste metode oferă posibilitatea analizării datelor colectate cu senzori și/sau sub formă de imagini sau fișiere video, permițând evaluarea non-invazivă, caracterizată de costuri reduse.*

Materiale și metode: *Lucrarea de față utilizează metodologia PRISMA pentru a colecta și sintetiza informații cu privire la precizia și fiabilitatea diferitelor metode utilizate în evaluarea ergonomic-posturală, incluzând aici metodele bazate pe învățare și viziune computerizată, cu scopul de a identifica beneficiile și limitările metodelor respective. În plus, studiul evaluează importanța mărimii seturilor de date, aspectele de natură etică și interpretabilitatea modelelor de învățare automată, ca aspecte esențiale ale evaluării ergonomic-posturale.*

Rezultate și discuții: *Algoritmii specifici învățării și viziunii computerizate identifică posturile care pot cauza probleme de natură musculoscheletală fiind utili în dezvoltarea de acțiuni preventive prin educație specializată, evaluare ergonomică și planificare. Mărimea și diversitatea seturilor de date sunt elemente care prezintă o importanță mare în ceea ce privește performanța modelelor utilizate. Studiul evidențiază beneficiile metodelor ce au la bază învățarea și viziunea computerizată în identificarea de trenduri și anomalii posturale care sunt mai greu de detectat prin folosirea de metode tradiționale. De asemenea, metodele moderne implică costuri reduse, sunt non-invazive și pot opera cu seturi mari de date. Cu toate acestea, precizia și fiabilitatea acestor metode relativ noi sunt încă discutabile iar considerentele etice ce caracterizează protecția datelor reprezintă o prioritate. Operarea cu astfel de metode necesită transparență și responsabilitate în etapele de dezvoltare a modelelor.*

Concluzii: *Metodele are au la bază învățarea și viziunea computerizată sunt caracterizate de o serie de avantaje. Lucrarea de față caracterizează potențialul acestor metode de a îmbunătăți precizia și fiabilitatea evaluărilor posturale. Principalele probleme care trebuie avute în vedere atunci când se utilizează aceste metode sunt cele legate de protecția datelor, etică și interpretabilitatea modelelor.*

Cuvinte cheie: *evaluare posturală, metode tradiționale, învățare și viziune computerizată, algoritmi.*

REFERENCES

1. Physiopedia, 2023: Posture. Available online at: https://www.physio-pedia.com/Posture#cite_note-1 (Accessed May 15, 2023).

2. EU-OSHA, 2023: Occupational safety and health in Europe: state and trends 2023. Available online at: https://osha.europa.eu/en/publications/occupational-safety-and-health-europe-state-and-trends-2023 (Accessed May 26, 2023).

3. David G.C., 2005: Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occupational medicine, 55(3), 190-199. https://doi.org/10.1093/occmed/kqi082

4. Dang Q., Yin J., Wang B., Zheng W., 2019: Deep learning based 2d human pose estimation: A survey. Tsinghua Science and Technology, 24(6), 663-676. https://doi.org/10.26599/TST.2018.9010100

5. Zhang D., Wu Y., Guo M., Chen Y., 2021a: Deep learning methods for 3D human pose estimation under different supervision paradigms: a survey. Electronics, 10(18), 2267.

6. Zheng C., Wu W., Chen C., Yang T., Zhu S., Shen J., Kehtarnavaz N., Shah M., 2020: Deep learning-based human pose estimation: A survey. ACM Computing Surveys. https://doi.org/10.1145/3603618

7. Joshi M., Deshpande V., 2019: A systematic review of comparative studies on ergonomic assessment techniques. International Journal of Industrial Ergonomics, 74, 102865. https://doi.org/10.1016/j.ergon.2019.102865

8. Lorenzini M., Lagomarsino M., Fortini L., Gholami S., Ajoudani A., 2023: Ergonomic human-robot collaboration in industry: a review. Frontiers in Robotics and AI, 9, 262. https://doi.org/10.3389/frobt.2022.813907

9. Moreira R., Fialho R., Teles A.S., Bordalo V., Vasconcelos S.S., de Morais Gouveia G.P., Bastos V.H., Teixeira S, 2022: A computer vision-based mobile tool for assessing human posture: A validation study. Computer Methods and Programs in Biomedicine, 214, 106565. https://doi.org/10.1016/j.cmpb.2021.106565

10. Rybnikár F., Kačerová I., Hořejší P., Šimon M., 2022: Ergonomics evaluation using motion capture technology - literature review. Applied Sciences, 13(1), 162. https://doi.org/10.3390/app13010162

11. Liu S., Tang Z., Zhang B., Liang Y., Gu X., 2022: Ergonomic design of cab structure for wheeled combine harvester. Engenharia Agrícola, 42. https://doi.org/10.1590/1809-4430-Eng.Agric.v42n3e20220023/2022

12. Jiang X., Hu Z., Wang S., Zhang Y., 2023: A survey on artificial intelligence in posture recognition. Computer modeling in engineering & sciences: CMES, 137(1), 35. https://doi.org/10.32604/cmes.2023.027676

13. Alpaydin E., 2021: Machine learning (revised and updated edition). MIT Press. https://doi.org/10.7551/mitpress/13811.001.0001

14. Chollet F., 2021: Deep learning with Python. Simon and Schuster. Available online at: http://silverio.net.br/heitor/disciplinas/eeica/papers/Livros/[Chollet]-Deep_Learning_with_Python.pdf (Accessed June 21, 2023).

15. Géron A., 2022: Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly Media, Inc. ISBN-10 1098125975

16. Goodfellow I., Bengio Y., Courville A., 2016: Deep learning. MIT press. Available online at: https://book.huihoo.com/deep-learning/front_matter.pdf. (Accessed June 14, 2023).

17. IBM, 2023: What is computer vision? Available online at: https://www.ibm.com/topics/computer-vision#:~:text=Computer (Accessed July 1, 2023).

18. Szeliski R., 2022: Computer vision: algorithms and applications 2nd ed. Springer Nature. Available online at: https://szeliski.org/Book/ (Accessed June 29, 2023).

19. Ma N., Wu Z., Cheung Y.M., Guo Y., Gao Y., Li J., Jiang B., 2022: A survey of human action recognition and posture prediction. Tsinghua Science and Technology, 27(6), 973-1001. https://doi.org/10.26599/TST.2021.9010068

20. Song L., Yu G., Yuan J., Liu Z., 2021: Human pose estimation and its application to action recognition: A survey. Journal of Visual Communication and Image Representation, 76, 103055. https://doi.org/10.1016/j.jvcir.2021.103055

21. Wang Z., Yang Y., Liu Z., Zheng Y., 2023: Deep neural networks in video human action recognition: a review. arXiv preprint arXiv:2305.15692. https://doi.org/10.48550/arXiv.2305.15692

22. Munn Z., Peters M.D., Stern C., Tufanaru C., McArthur A., Aromataris E., 2018: Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. BMC medical research methodology, 18, 1-7. https://doi.org/10.1186/s12874-018-0611-x

23. Higgins J.P., Altman D.G., Gøtzsche P.C., Jüni P., Moher D., Oxman A.D., Savović J., Schulz K.F., Weeks L., Sterne J.A., 2011: The Cochrane Collaboration's tool for assessing risk of bias in randomised trials. British Medical Journal, 343, d5928. https://doi.org/10.1136/bmj.d5928

24. Moher D., Shamseer L., Clarke M., Ghersi D., Liberati A., Petticrew M., Shekelle P., Stewart L.A., 2015: Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Systematic reviews, 4(1), 1-9. https://doi.org/10.1186/2046-4053-4-1

25. Page M.J., McKenzie J.E., Bossuyt P.M., Boutron I., Hoffmann T.C., Mulrow C.D., Shamseer L., Tetzlaff J.M., Akl E.A., Brennan S.E., Chou R., 2021: The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. International journal of surgery, 88, 105906. https://doi.org/10.1136/bmj.n71

26. Shamseer L., Moher D., Clarke M., Ghersi D., Liberati A., Petticrew M., Shekelle P., Stewart L.A., 2015: Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015: elaboration and explanation. British Medical Journal, 349, g7647. https://doi.org/10.1136/bmj.g7647

27. Tricco A.C., Lillie E., Zarin W., O'Brien K.K., Colquhoun H., Levac D., Moher D., Peters M.D., Horsley T., Weeks L., Hempel S., 2018: PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Annals of internal medicine, 169(7), 467-473. https://doi.org/10.7326/M18-0850

28. Liberati A., Altman D.G., Tetzlaff J., Mulrow C., Gøtzsche P.C., Ioannidis J.P., Clarke M., Devereaux P.J., Kleijnen J., Moher D., 2009: The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. Annals of internal medicine, 151(4), W-65. https://doi.org/10.7326/0003-4819-151-4-200908180-00136

29. Kolgiri S., Bansode S., Hiremath R., 2017: A literature review on work-related body part discomfort with respect of postures and movements. IAETSD Journal for Advanced Research in Applied Sciences, 4(5). Available online at: https://www.researchgate.net/publication/320465867 (Accessed August 25, 2023).

30. Gomez-Galan M., Perez-Alonso J., Callejón-Ferre Á.J., López-Martínez J., 2017: Musculoskeletal disorders: OWAS review. Industrial Health, 55(4), 314-337. https://doi.org/10.2486/indhealth.2016-0191

31. Li G., Buckle P., 1999: Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods. Ergonomics, 42(5), 674-695. https://doi.org/10.1080/001401399185388

32. Roman-Liu D., 2014: Comparison of concepts in easy-to-use methods for MSD risk assessment. Applied Ergonomics, 45(3), 420-427. https://doi.org/10.1016/j.apergo.2013.05.010

33. Takala E.P., Pehkonen I., Forsman M., Hansson G.Å., Mathiassen S.E., Neumann W.P., Sjøgaard G., Veiersted K.B., Westgaard R.H., Winkel J., 2010: Systematic evaluation of observational methods assessing biomechanical exposures at work. Scandinavian journal of work, environment & health, 3-24. Available online at: http://www.jstor.org/stable/40967825 (Accessed June 10, 2023).

34. Kadefors R., Forsman M., 2000: Ergonomic evaluation of complex work: a participative approach employing video–computer interaction, exemplified in a study of order picking. International Journal of Industrial Ergonomics, 25(4), 435-445. https://doi.org/10.1016/S0169-8141(99)00042-6

35. Dane D., Feuerstein M., Huang G.D., Dimberg L., Ali D., Lincoln A., 2002: Measurement properties of a self-report index of ergonomic exposures for use in an office work environment. Journal of Occupational and Environmental Medicine, 73-81. https://doi.org/10.1097/00043764-200201000-00012

36. Viikari-Juntura E., Rauas S., Martikainen R., Kuosma E., Riihimäki H., Takala E.P., Saarenmaa K., 1996: Validity of self-reported physical workload in epidemiologic studies on musculoskeletal disorders. Scandinavian journal of work, environment & health, 251-259. https://doi.org/10.5271/sjweh.139

37. Pope D.P., Silman A.J., Cherry N.M., Pritchard C., Macfarlane G.J., 1998: Validity of a self-completed questionnaire measuring the physical demands of work. Scandinavian journal of work, environment & health, 376-385. https://doi.org/10.5271/sjweh.358

38. Balogh I., Örbaek P., Ohlsson K., Nordander C., Unge J., Winkel J., Hansson G.Å., Malmö Shoulder/Neck Study Group, 2004: Self-assessed and directly measured occupational physical activities—influence of musculoskeletal complaints, age and gender. Applied ergonomics, 35(1), 49-56. https://doi.org/10.1016/j.apergo.2003.06.001

39. Spielholz P., Bao S., Howard N., 2001: A practical method for ergonomic and usability evaluation of hand tools: a comparison of three random orbital sander configurations. Applied occupational and environmental hygiene, 16(11), 1043-1048. https://doi.org/10.1080/104732201753214143

40. Karhu O., Kansi P., Kuorinka I., 1977: Correcting working postures in industry: A practical method for analysis. Applied Ergonomics, 8(4), 199-201. https://doi.org/10.1016/0003-6870(77)90164-8

41. Hignett S., McAtamney L., 2000: Rapid entire body assessment (REBA). Applied ergonomics, 31(2), 201-205. http://dx.doi.org/10.1016/S0003-6870(99)00039-3

42. Corlett E.N., Bishop R.P., Madely S.J., Maneniee I., 1979: Posture targeting: a technique for recording working postures. Ergonomics, 22, 357-366. https://doi.org/10.1080/00140137908924619

43. Kilbom A., Persson J., Jonsson B., 1986: Risk factors for work-related disorders of the neck and shoulder-with special emphasis on working postures and movements. The ergonomics of working postures, 1, 44-53. CRC Press, 11, eBook ISBN 9780429205620. Available online at: https://www.taylorfrancis.com/chapters/edit/10.1201/b12565-5/risk-factors-work-related-disorders-neck-shoulder%E2%80%94with-s (Accessed June 2, 2023).

44. INSHT, 1998: Guía técnica para la evaluación y preven-ción de los riesgos relativos a la manipulación manual de cargas. Guías técnicas. Madrid, España. Available online at: https://cpage.mpr.gob.es/producto/guia-tecnica-para-la-evaluacion-y-prevencion-de-los-riesgos-relativos-a-la-manipulacion-manual-de-cargas-4/ (Accessed June 3, 2023).

45. Buchholz B., Paquet V., Punnett L., Lee D., Moir S., 1996: PATH: A work sampling-based approach to ergonomic job analysis for construction and other non-repetitive work. Applied Ergonomics, 27(3), 177-187. https://doi.org/10.1016/0003-6870(95)00078-X

46. NIOSH, 1981: Work practices guide for manual lifting. 1-198. NIOSH Technical Report No. 81-122, Cincinnati, Ohio, USA. Available online at: https://www.cdc.gov/niosh/docs/81-122/default.html (Accessed August 12, 2023).

47. Waters T.R., Putz-Anderson V., Garg A., Fine L.J., 1993: Revised NIOSH equation for the design and evaluation of manual lifting tasks. Ergonomics, 36(7), 749-776. https://doi.org/10.1080/00140139308967940

48. Snook S.H., Ciriello V.M., 1991: The design of manual handling tasks: revised tables of maximum acceptable weights and forces. Ergonomics, 34(9), 1197-1213. http://dx.doi.org/10.1080/00140139108964855

49. Jürgens W.W., Mohr D., Pangert R., Pernack E., Schultz K., Steinberg U., 2001: Handlungsanleitung zur Beurteilung der Arbeitsbedingungen beim Heben und Tragen von Las-ten. LASI Veröffentlichung 9. Hrsg. Länderausschuss für Arbeitsschutz und Sicherheitstechnik. 4. Überarbeitete Auflage.

50. Monnington S.C., Quarrie C.J., Pinder A.D., Morris L.A., 2003: Development of manual handling assessment charts (mac) for health and safety inspectors. In: McCabe T, ed. Contemporary Ergonomics. London: Taylor & Francis; 3–8, ISBN 0-415-30994-8. Available online at: https://www.taylorfrancis.com/books/9780429071751/chapters/10.1201/b12800-2 (Accessed June 8, 2023).

51. Mutual L., 2007: Liberty Mutual Manual Materials Handling Tables. Retrieved September 21, 2007, from: http://libertymmhtables. libertymutual. com/CM_LM TablesWeb. Liberty-Mutual. Manual Materials Handling Tables 2011. Available online at: http://libertymmhtables.libertymutual.com/CM_LMTablesWeb/pdf/LibertyMutualTables.pdf (Accessed June 1, 2023).

52. McAtamney L., Corlett E.N., 1993: RULA: a survey method for the investigation of work-related upper limb disorders. Applied Ergonomics, 24(2), 91-99. https://doi.org/10.1016/0003-6870(93)90080-S

53. Steven Moore J., Garg A., 1995: The strain index: a proposed method to analyze jobs for risk of distal upper extremity disorders. American Industrial Hygiene Association Journal, 56(5), 443-458. http://dx.doi.org/10.1080/15428119591016863

54. James C.P., Harburn K.L., Kramer J.F., 1997: Cumulative trauma disorders in the upper extremities: reliability of the postural and repetitive risk-factors index. Archives of physical medicine and rehabilitation, 78(8), 860-866. http://dx.doi.org/10.1016/S0003-9993(97)90201-X

55. García C., Chirivella C., Page A., Moraga R., Jorquera J., 1997: Método ERGO IBV. Evaluación de riesgos laborales asociados a la carga física Instituto de Biomecánica de Valencia. Available online at: https://www.prevencionintegral.com/documentacion/publicaciones/metodo-ergo-ibv-evaluacion-riesgos-laborales-asociados-carga-fisica (Accessed June 12, 2023).

56. Colombini D., 1998: An observational method for classifying exposure to repetitive movements of the upper limbs. Ergonomics, 41(9), 1261-1289. http://dx.doi.org/10.1080/001401398186306

57. Kemmlert K., 1995: A method assigned for the identification of ergonomic hazards - PLIBEL. Applied Ergonomics, 26(3), 199-211. http://dx.doi.org/10.1016/0003-6870(95)00022-5

58. Priel V.Z., 1974: A numerical definition of posture. Human Factors, 16(6), 576-584. https://doi.org/10.1177/001872087401600602

59. Christmansson M., 1994: The HAMA-method: a new method for analysis of upper limb movements and risk for work-related musculoskeletal disorders. In Proceedings of the 12th Triennial Congress of the International Ergonomics Association/Human Factors Association of Canada, August, Toronto (pp. 173-175).

60. Keyserling W.M., Brouwer M., Silverstein B.A., 1992: A checklist for evaluating ergonomic risk factors resulting from awkward postures of the legs, trunk and neck. International Journal of Industrial Ergonomics, 9(4), 283-301. https://doi.org/10.1016/0169-8141(92)90062-5

61. Ketola R., Toivonen I.V.R., Viikari-Juntura E., 2001: Interobserver repeatability and validity of an observation method to assess physical loads imposed on the upper extremities. Ergonomics, 44(2), 119-131. https://doi.org/10.1080/00140130118669

62. Hygienists A., 2002: Threshold limit values for chemical substances and physical agents, Cincinnati, Ohio. Documentation of the Threshold Limit Values & Biological Exposure Indices, TLVs and BEIs. Available online at: https://hero.epa.gov/hero/index.cfm/reference/details/reference_id/192015 (Accessed June 3, 2023).

63. Health and Safety Executive, 2002: Upper limb disorders in the workplace HSG60. Suffolk: HSE Books. Available online at: https://www.hse.gov.uk/pubns/books/hsg60.htm (Accessed May 28, 2023).

64. van der Beek A.J., van Gaalen L.C., Frings-Dresen M.H., 1992: Working postures and activities of lorry drivers: a reliability study of on-site observation and recording on a pocket computer. Applied Ergonomics, 23(5), 331-336. https://doi.org/10.1016/0003-6870(92)90294-6

65. Gallo R., Mazzetto F., 2013: Ergonomic analysis for the assessment of the risk of work-related musculoskeletal disorder in forestry operations. Journal of Agricultural Engineering, 44(s2), e147. https://doi.org/10.4081/jae.2013.389

66. Kee D., 2022: Systematic comparison of OWAS, RULA, and REBA based on a literature review. International Journal of Environmental Research and Public Health, 19(1), 595. https://doi.org/10.3390/ijerph19010595

67. Bortolini M., Gamberi M., Pilati F., Regattieri A., 2018: Automatic assessment of the ergonomic risk for manual manufacturing and assembly activities through optical motion capture technology. Procedia CIRP, 72, 81-86. https://doi.org/10.1016/j.procir.2018.03.198

68. Malaisé A., Maurice P., Colas F., Ivaldi S., 2019: Activity recognition for ergonomics assessment of industrial tasks with automatic feature selection. IEEE Robotics and Automation Letters, 4(2), 1132-1139. https://doi.org/10.1109/LRA.2019.2894389

69. Busch B., Maeda G., Mollard Y., Demangeat M., Lopes M., 2017: Postural optimization for an ergonomic human-robot interaction. In 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2778-2785. IEEE. https://doi.org/10.1109/IROS.2017.8206107

70. Van de Perre G., El Makrini I., Van Acker B., Saldien J., Vergara C., Pintelon L., Chemweno P., Weuts R., Moons K., Dewil R., Cattrysse D., 2018: Improving productivity and worker conditions in assembly: part 1: a collaborative architecture and task allocation. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Available online at: http://hdl.handle.net/1854/LU-8589348 (Accessed May 27, 2023).

71. Chaffin D.B., Andersson G.B., Martin B.J., 2006: Occupational biomechanics. John Wiley & sons. Available online at: https://www.wiley.com/en-us/Occupational+Biomechanics%2C+4th+Edition-p-9780471723431 (Accessed June 2, 2023).

72. Justavino F.C., Ramirez R.J., Perez N.M., Borz S.A., 2015: The use of OWAS in forest operations postural assessment: advantages and limitations. Bulletin of the Transilvania University of Brasov. Series II: Forestry, Wood Industry, Agricultural Food Engineering, 8(57)2, 7-16.

73. Micheletti Cremasco M., Giustetto A., Caffaro F., Colantoni A., Cavallo E., Grigolato S., 2019: Risk assessment for musculoskeletal disorders in forestry: A comparison between RULA and REBA in the manual feeding of a wood-chipper. International journal of environmental research and public health, 16(5), 793. https://doi.org/10.3390/ijerph16050793

74. Dianat I., Molenbroek J., Castellucci H.I., 2018: A review of the methodology and applications of anthropometry in ergonomics and product design. Ergonomics: an international journal of research and practice in human factors and ergonomics, 61(12), 1696-1720. https://doi.org/10.1080/00140139.2018.1502817

75. Ridd J. E., Nicholson A.S., Montan A.J., 1989: A portable microcomputer based system for "on site' activity and posture recording. Contemporary Ergonomics, 89, 366-71.

76. Chaffin D., Andersson G., Martin B., 1999: Occupational biomechanics, 3rd edn. New York: John Wiley. Available online at: https://www.amazon.com/Occupational-Biomechanics-Chaffin-Andersson-Hardcover/dp/B011DC0X6O (Accessed June 13, 2023).

77. Garg A., Moore J.S., Kapellusch J.M., 2017: The Revised Strain Index: an improved upper extremity exposure assessment model. Ergonomics, 60(7), 912-922. https://doi.org/10.1080/00140139.2016.1237678

78. Punnett L., 2014: Musculoskeletal disorders and occupational exposures: How should we judge the evidence concerning the causal association? Scandinavian journal of public health, 42(13_suppl), 49-58. https://doi.org/10.1177/1403494813517324

79. Schaub K., Caragnano G., Britzke B., Bruder R., 2013: The European assembly worksheet. Theoretical Issues in Ergonomics Science, 14(6), 616-639. https://doi.org/10.1080/1463922X.2012.678283

80. Szabò G., Dobò M., 2018: CERA, an integrated tool for ergonomic risk assessment. DEStech Transactions on Social Science Education and Human Science https://doi.org/10.12783/dtssehs/ise2018/33661

81. Klussmann A., Liebers F., Gebhardt H., Rieger M.A., Latza U., Steinberg U., 2017: Risk assessment of manual handling operations at work with the key indicator method (KIM-MHO) - Determination of criterion validity regarding the prevalence of musculoskeletal symptoms and clinical conditions within a cross-sectional study. BMC musculoskeletal disorders, 18(1), 1-13. https://doi.org/10.1186/s12891-017-1542-0

82. Steinberg U., 2012: New tools in Germany: development and appliance of the first two KIM ("lifting, holding and carrying" and "pulling and pushing") and practical use of these methods. Work, 41(Supplement 1), 3990-3996. https://doi.org/10.3233/WOR-2012-0698-3990.

83. Armstrong T.J., 1986: Upper-extremity posture: definition, measurement and control. The ergonomics of working postures, 59-73. CRC Press. eBook ISBN9780429205620

84. Wiktorin C., Mortimer M., Ekenvall L., Kilbom Å., Hjelm E.W., 1995: HARBO, a simple computer-aided observation method for recording work postures. Scandinavian journal of work, environment & health, 21, 440-449.

85. Fransson-Hall C., Gloria R., Kilbom Å., Winkel J., Karlqvist L., Wiktorin C., 1995: A portable ergonomic observation method (PEO) for computerized on-line recording of postures and manual handling. Applied Ergonomics, 26(2), 93-100. https://doi.org/10.1016/0003-6870(95)00003-U

86. Biometrics L., 1997: Goniometer and torsiometer operating manual. Gwent, UK: Blackwood Available online at: https://scholar.google.com/scholar?cluster=12967852851073641382&hl=en&inst=569367360547434339&oi=scholarr (Accessed August 17, 2023).

87. Radwin R.G., Lin M.L., 1993: An analytical method for characterizing repetitive motion and postural stress using spectral analysis. Ergonomics, 36(4), 379-389. https://doi.org/10.1080/00140139308967895

88. Bernmark E., Wiktorin C., 2002: A triaxial accelerometer for measuring arm movements. Applied ergonomics, 33(6), 541-547. https://doi.org/10.1016/S0003-6870(02)00072-8

89. Hasson G.-A., Asterland P., Holmer N.-G., Skerfving S., 2001: Validity, reliability and applications of an inclinometer based on accelerometers. In: Hagberg M, Knave B, Lillienberg L, Westberg H, eds. X2001—Exposure Assessment in Epidemiology and Practice. Stockholm, Sweden: National Institute for Working Life S-112 79, 405-407.

90. Johnson P.W., Hagberg M., Hjelm E.W., Rempel D., 2000: Measuring and characterizing force exposures during computer mouse use. Scandinavian Journal of Work, Environment & Health, 26(5), 398-405. https://doi.org/10.5271/sjweh.560

91. Marras W.S., Fathallah F.A., Miller R.J., Davis S.W., Mirka G.A., 1992: Accuracy of a three-dimensional lumbar motion monitor for recording dynamic trunk motion characteristics. International Journal of Industrial Ergonomics, 9(1), 75-87. https://doi.org/10.1016/0169-8141(92)90078-E

92. Wells R., Norman R., Neumann P., Andrews D., Frank J., Shannon H., Kerr M., 1997. Assessment of physical workload in epidemiologic studies: common measurement metrics for exposure assessment. Ergonomics, 40(1), 51-61. https://doi.org/10.1080/001401397188369

93. Freivalds A., Kong Y., You H., Park S., 2000: A comprehensive risk assessment model for work-related musculoskeletal disorders of the upper extremities. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 44, No. 31, pp. 5-728). Sage CA: Los Angeles, CA: SAGE Publications. https://doi.org/10.1177/154193120004403129

94. Mientjes M.I., Norman R.W., Wells R.P., McGill S.M., 1999: Assessment of an EMG-based method for continuous estimates of low back compression during asymmetrical occupational tasks. Ergonomics, 42(6), 868-879. https://doi.org/10.1080/001401399185342

95. Ventura L., Lorenzini M., Kim W., Ajoudani A., 2021: A flexible robotics-inspired computational model of compressive loading on the human spine. IEEE Robotics and Automation Letters, 6(4), 8229-8236. https://doi.org/10.1109/LRA.2021.3100936

96. Latella C., Traversaro S., Ferigo D., Tirupachuri Y., Rapetti L., Andrade Chavez F.J., Nori F., Pucci D., 2019: Simultaneous floating-base estimation of human kinematics and joint torques. Sensors, 19(12), 2794. https://doi.org/10.3390/s19122794

97. Damsgaard M., Rasmussen J., Christensen S.T., Surma E., De Zee M., 2006: Analysis of musculoskeletal systems in the AnyBody Modeling System. Simulation Modelling Practice and Theory, 14(8), 1100-1111. https://doi.org/10.1016/j.simpat.2006.09.001

98. Delp S.L., Anderson F.C., Arnold A.S., Loan P., Habib A., John C.T., Guendelman E., Thelen D.G., 2007: OpenSim: open-source software to create and analyze dynamic simulations of movement. IEEE transactions on biomedical engineering, 54(11), 1940-1950. https://doi.org/10.1109/TBME.2007.901024

99. Debnath B., O'Brien M., Yamaguchi M., Behera A., 2022: A review of computer vision-based approaches for physical rehabilitation and assessment. Multimedia Systems. https://doi.org/10.1007/s00530-021-00815-4

100. Cormen T.H., Leiserson C.E., Rivest R.L., Stein C., 2022: Introduction to algorithms. Fourth Edition. MIT Press. ISBN 9780262046305. Available online at: http://mitpress.mit.edu/algorithms/ (Accessed June 21, 2023).

101. Mallare J.C.T., Pineda D.F.G., Trinidad G.M., Serafica R.D., Villanueva J.B.K., Cruz A.R.D., Vicerra R.R.P., Serrano K.K.D., Roxas E.A., 2017: Sitting posture assessment using computer vision. In 2017IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 1-5. IEEE. https://doi.org/10.1109/HNICEM.2017.8269473

102. Byström P., Hanse J.J., Kjellberg A., 2004: Appraised psychological workload, musculoskeletal symptoms, and the mediating effect of fatigue: a structural equation modeling

approach. Scandinavian journal of psychology, 45(4), 331-341. https://doi.org/10.1111/j.1467-9450.2004.00413.x

103. Kim K.H., Sohn M.J., Park, C.G., 2022: Conformity assessment of a computer vision-based posture analysis system for the screening of postural deformation. BMC Musculoskeletal Disorders, 23(1), 799. https://doi.org/10.1186/s12891-022-05742-7

104. Ding W., Hu B., Liu H., Wang X., Huang X., 2020: Human posture recognition based on multiple features and rule learning. International Journal of Machine Learning and Cybernetics, 11, 2529-2540. https://doi.org/10.1007/s13042-020-01138-y

105. Giveki D., Soltanshahi M.A., Montazer G.A., 2017: A new image feature descriptor for content based image retrieval using scale invariant feature transform and local derivative pattern. Optik, 131, 242-254. https://doi.org/10.1016/j.ijleo.2016.11.046

106. Lowe D.G., 2004: Distinctive image features from scale-invariant keypoints. International journal of computer vision, 60, 91-110. https://doi.org/10.1023/B:VISI.0000029664.99615.94

107. Zhou J., Lin K.Y., Li H., Zheng W.S., 2021: Graph-based high-order relation modeling for long-term action recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 8984-8993. https://doi.org/10.1109/CVPR46437.2021.00887

108. Vashisth S., Saurav, S., 2018: Histogram of Oriented Gradients based reduced feature for traffic sign recognition. In 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2206-2212. IEEE. https://doi.org/10.1109/ICACCI.2018.8554624

109. Jiang X., Satapathy S.C., Yang L., Wang S.H., Zhang Y.D., 2020: A survey on artificial intelligence in Chinese sign language recognition. Arabian Journal for Science and Engineering, 45, 9859-9894. https://doi.org/10.1007/s13369-020-04758-2

110. Cortes C., Vapnik V., 1995: Support-Vector Networks. Machine Learning, 20, 273-297. https://doi.org/10.1007/BF00994018

111. Chen Q., Sang L., 2018: Face-mask recognition for fraud prevention using Gaussian mixture model. Journal of Visual Communication and Image Representation, 55, 795-801. https://doi.org/10.1016/j.jvcir.2018.08.016

112. Lee S., Rajan S., Jeon G., Chang J.H., Dajani H.R., Groza V.Z., 2017: Oscillometric blood pressure estimation by combining nonparametric bootstrap with Gaussian mixture model. Computers in biology and medicine, 85, 112-124. https://doi.org/10.1016/j.compbiomed.2015.11.008

113. Ghersi I., Ferrando M.H., Fliger C.G., Arenas C.F.C., Molina D.J.E., Miralles, M.T., 2020: Gait-cycle segmentation method based on lower-trunk acceleration signals and dynamic time warping. Medical Engineering & Physics, 82, 70-77. https://doi.org/10.1016/j.medengphy.2020.06.001

114. Ramezanpanah Z., Mallem M., Davesne, F., 2020: Human action recognition using laban movement analysis and dynamic time warping. Procedia Computer Science, 176, 390-399. https://doi.org/10.1016/j.procs.2020.08.040

115. Oszust M., Krupski J., 2021: Isolated sign language recognition with depth cameras. Procedia Computer Science, 192, 2085-2094. https://doi.org/10.1016/j.procs.2021.08.216

116. Huang C.L., Wu M.S., Jeng S.H., 2000: Gesture recognition using the multi-PDM method and hidden Markov model. Image and Vision Computing, 18(11), 865-879. https://doi.org/10.1016/S0262-8856(99)00042-6

117. Sánchez V.G., Lysaker O.M., Skeie N.O., 2020: Human behaviour modelling for welfare technology using hidden Markov models. Pattern Recognition Letters, 137, 71-79. https://doi.org/10.1016/j.patrec.2019.09.022

118. Eom H., Choi B., Noh J., 2014: Data-driven reconstruction of human locomotion using a single smartphone. In Computer Graphics Forum, 33(7), 11-19. https://doi.org/10.1111/cgf.12469

119. Mannini A., Sabatini A.M., 2010: Machine learning methods for classifying human physical activity from on-body accelerometers. Sensors, 10(2), 1154-1175. https://doi.org/10.3390/s100201154

120. Mota S., Picard R.W., 2003: Automated posture analysis for detecting learner's interest level. In 2003 Conference on computer vision and pattern recognition workshop, 5, 49-49. IEEE. https://doi.org/10.1109/CVPRW.2003.10047

121. Rabiner L.R., 1989: A tutorial on hidden Markov models and selected applications in speech recognition. Proc. IEEE. 77(2), 257-286. https://doi.org/10.1109/5.18626

122. Kale A., Rajagopalan A.N., Cuntoor N., Kruger V., 2002: Gait-based recognition of humans using continuous HMMs. In Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition, 336-341. IEEE. https://doi.org/10.1109/AFGR.2002.1004176

123. Panahandeh G., Mohammadiha N., Leijon A., Händel P., 2013: Continuous hidden Markov model for pedestrian activity classification and gait analysis. IEEE Transactions on Instrumentation and Measurement, 62(5), 1073-1083. https://doi.org/10.1109/TIM.2012.2236792

124. Taborri J., Rossi S., Palermo E., Patanè F., Cappa P., 2014: A novel HMM distributed classifier for the detection of gait phases by means of a wearable inertial sensor network. Sensors, 14(9), 16212-16234. https://doi.org/10.3390/s140916212

125. Breiman L., 2001: Random forests. Machine learning, 45, 5-32. https://doi.org/10.1023/A:1010933404324

126. Agnihotri N., 2023: Classification of machine learning algorithms. Available online at: https://www.engineersgarage.com/machine-learning-algorithms-classification/ (Accessed 17 June 2023).

127. Breiman L., 2017: Classification and regression trees. Routledge. https://doi.org/10.1201/9781315139470

128. Paul A., Mukherjee D.P., Das P., Gangopadhyay A., Chintha A.R., Kundu S., 2018: Improved random forest for classification. IEEE Transactions on Image Processing, 27(8), 4012-4024. https://doi.org/10.1109/TIP.2018.2834830

129. Imbeault-Nepton T., Maitre J., Bouchard K., Gaboury S., 2022: Filtering data bins of UWB radars for activity recognition with random forest. Procedia Computer Science, 201, 48-55. https://doi.org/10.1016/j.procs.2022.03.009

130. Nunes U.M., Faria D.R., Peixoto, P., 2017: A human activity recognition framework using max-min features and key poses with differential evolution random forests classifier. Pattern Recognition Letters, 99, 21-31. https://doi.org/10.1016/j.patrec.2017.05.004

131. Subedi S., Pradhananga N., 2021: Sensor-based computational approach to preventing back injuries in construction workers. Automation in Construction, 131, 103920. https://doi.org/10.1016/j.autcon.2021.103920

132. Breiman L., Friedman J., Stone C.J., Olshen R.A., 1984: Classification and regression trees. CRC press. ISBN 9780412048418

133. Kumar G.S., 2020: Decision trees: a step-by-step approach to building DTs. Available online at: https://towardsdatascience.com/decision-trees-a-step-by-step-approach-to-building-dts-58f8a3e82596 (Accessed 8 July 2023).

134. Haider D., Yang X., Abbasi Q.H., 2019: Post-surgical fall detection by exploiting the 5 G C-Band technology for eHealth paradigm. Applied Soft Computing, 81, 105537. https://doi.org/10.1016/j.asoc.2019.105537

135. Pajak G., Krutz P., Patalas-Maliszewska J., Rehm M., Pajak I., Dix M., 2022: An approach to sport activities recognition based on an inertial sensor and deep learning. Sensors and Actuators A: Physical, 345, 113773. https://doi.org/10.1016/j.sna.2022.113773

136. Singh R., Garg D., 2016: Hybrid machine learning algorithm for human activity recognition using decision tree and particle swarm optimization. International Journal of Engineering Science and Computing, 6(7), 8379-8389. Available online at: https://www.semanticscholar.org/paper/Hybrid-Machine-Learning-Algorithm-for-Human-Using-Singh-Garg/20eeda7b817d7f922138f8d85cb7ff5550f07996 (Accessed 24 August 2023).

137. Bussmann H.B., Reuvekamp P.J., Veltink P.H., Martens W.L., Stam H.J., 1998: Validity and reliability of measurements obtained with an "activity monitor" in people with and without a transtibial amputation. Physical therapy, 78(9), 989-998. https://doi.org/10.1093/ptj/78.9.989

138. Yang C.C., Hsu, Y.L., 2010: A review of accelerometry-based wearable motion detectors for physical activity monitoring. Sensors, 10(8), 7772-7788. https://doi.org/10.3390/s100807772

139. Han K., Yang Q., Huang, Z., 2020: A two-stage fall recognition algorithm based on human posture features. Sensors, 20(23), 6966. https://doi.org/10.3390/s20236966

140. Indumathi N., Ramalakshmi R., 2021: An evaluation of work posture and musculoskeletal disorder risk level identification for the fireworks industry worker's. In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 1-5. IEEE. https://doi.org/10.1109/ICRITO51393.2021.9596532

141. Theodoridis S., 2015: Machine learning: a Bayesian and optimization perspective. Academic press. ISBN 978-0-12-801522-3

142. Dimitrijevic M., Lepetit V., Fua, P., 2006: Human body pose detection using Bayesian spatio-temporal templates. Computer vision and image understanding, 104(2-3), 127-139. https://doi.org/10.1016/j.cviu.2006.07.007

143. Balaji E., Brindha D., Elumalai V.K., Umesh K., 2021: Data-driven gait analysis for diagnosis and severity rating of Parkinson's disease. Medical Engineering & Physics, 91, 54-64. https://doi.org/10.1016/j.medengphy.2021.03.005

144. Xanthopoulos P., Pardalos P.M., Trafalis T.B., 2013: Linear discriminant analysis. Robust data mining, 27-33. https://doi.org/10.1007/978-1-4419-9878-1_4

145. Iosifidis A., Tefas A., Nikolaidis N., Pitas I., 2012: Multi-view human movement recognition based on fuzzy distances and linear discriminant analysis. Computer Vision and Image Understanding, 116(3), 347-360. https://doi.org/10.1016/j.cviu.2011.08.008

146. Lee M., Roan M., Smith B., Lockhart T.E., 2009: Gait analysis to classify external load conditions using linear discriminant analysis. Human movement science, 28(2), 226-235. https://doi.org/10.1016/j.humov.2008.10.008

147. Qiu S., Zhao H., Jiang N., Wang Z., Liu L., An Y., Zhao H., Miao X., Liu R., Fortino G., 2022: Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges. Information Fusion, 80, 241-265. https://doi.org/10.1016/j.inffus.2021.11.006

148. Zhao J., Obonyo E., 2021: Applying incremental deep neural networks-based posture recognition model for ergonomics risk assessment in construction. Advanced Engineering Informatics, 50, 101374. https://doi.org/10.1016/j.aei.2021.101374

149. LeCun Y., Bottou L., Bengio Y., Haffner P., 1998: Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324. https://doi.org/10.1109/5.726791

150. Chai J., Zeng H., Li A., Ngai E.W., 2021: Deep learning in computer vision: A critical review of emerging techniques and application scenarios. Machine Learning with Applications, 6, 100134. https://doi.org/10.1016/j.mlwa.2021.100134

151. Harris E.J., Khoo I.H., Demircan E., 2022: A survey of human gait-based artificial intelligence applications. Frontiers in Robotics and AI, 8, 749274. https://doi.org/10.3389/frobt.2021.749274

152. Yang W., Li S., Ouyang W., Li H., Wang X., 2017: Learning feature pyramids for human pose estimation. In proceedings of the IEEE international conference on computer vision, 1281-1290. https://doi.org/10.48550/arXiv.1708.01101

153. Wang J., Ma Y., Zhang L., Gao R.X., Wu D., 2018: Deep learning for smart manufacturing: methods and applications. Journal of manufacturing systems, 48, 144-156. https://doi.org/10.1016/J.JMSY.2018.01.003

154. Russakovsky O., Deng J., Su H., Krause J., Satheesh S., Ma S., Huang Z., Karpathy A., Khosla A., Bernstein M., Berg A.C., Fei-Fei L., 2015: ImageNet large scale visual recognition challenge. International Journal of Computer Vision, 115(3), 211-252. https://doi.org/10.1007/s11263-015-0816-y

155. Krizhevsky A., Hinton G., 2009: Learning multiple layers of features from tiny images. Available online at: http://www.cs.utoronto.ca/~kriz/learning-features-2009-TR.pdf (Accessed 6 July 2023).

156. Neverova N., Wolf C., Lacey G., Fridman L., Chandra D., Barbello B., Taylor G., 2016: Learning human identity from motion patterns. IEEE Access, 4, 1810-1820. https://doi.org/10.1109/access.2016.2557846

157. Rani C.J., Devarakonda N., 2022: An effectual classical dance pose estimation and classification system employing convolution neural network–long shortterm memory (CNN-LSTM) network for video sequences. Microprocessors and Microsystems, 95, 104651. https://doi.org/10.1016/j.micpro.2022.104651

158. Vaith A., Taetz B., Bleser G., 2020: "Uncertainty Based Active Learning with Deep Neural Networks for Inertial Gait Analysis," in 2020 IEEE 23rd International Conference on Information Fusion (FUSION), 1-8. https://doi.org/10.23919/fusion45008.2020.9190449

159. Hu Q., Tang X. and Tang W., 2020: A real-time patient-specific sleeping posture recognition system using pressure sensitive conductive sheet and transfer learning. IEEE Sensors Journal, 21(5), 6869-6879. https://doi.org/10.1109/JSEN.2020.3043416

160. Long C., Jo E., Nam Y., 2022: Development of a yoga posture coaching system using an interactive display based on transfer learning. The Journal of Supercomputing, 1-16. https://doi.org/10.1007/s11227-021-04076-w

161. Krizhevsky A., Sutskever I., Hinton G.E., 2012: Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems. Available online at: https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf (Accessed 28 June 2023).

162. Zhang Y., Huang Y., Yu S., Wang L., 2019: Cross-view gait recognition by discriminative feature learning. IEEE Transactions on Image Processing, 29, 1001-1015. https://doi.org/10.1109/tip.2019.2926208

163. Newell A., Yang K., Deng J., 2016: Stacked hourglass networks for human pose estimation. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VIII 14, 483-499. Springer International Publishing. https://doi.org/10.1007/978-3-319-46484-8_29

164. Chen Y., Wang Z., Peng Y., Zhang Z., Yu G., Sun J., 2018: Cascaded pyramid network for multi-person pose estimation. In Proceedings of the IEEE conference on computer vision and pattern recognition, 7103-7112. https://doi.org/10.1109/CVPR.2018.00742

165. Wei S.E., Ramakrishna V., Kanade T., Sheikh, Y., 2016: Convolutional pose machines. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, 4724-4732. https://doi.org/10.48550/arXiv.1602.00134

166. Sun K., Xiao B., Liu D., Wang J., 2019: Deep high-resolution representation learning for human pose estimation. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 5693-5703. https://doi.org/10.1109/CVPR.2019.00584

167. Redmon J., Divvala S., Girshick R., Farhadi A., 2016; You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, 779-788. https://doi.org/10.48550/arXiv.1506.02640

168. Lee M.F.R., Chen Y.C., Tsai C.Y., 2022: Deep learning-based human body posture recognition and tracking for unmanned aerial vehicles. Processes, 10(11), 2295. https://doi.org/10.3390/pr10112295

169. Cao Z., Simon T., Wei S.E., Sheikh Y., 2017: Realtime multi-person 2d pose estimation using part affinity fields. In Proceedings of the IEEE conference on computer vision and pattern recognition, 7291-7299. https://doi.org/10.48550/arXiv.1611.08050

170. Li B., Han C., Bai B., 2019: Hybrid approach for human posture recognition using anthropometry and BP neural network based on Kinect V2. EURASIP Journal on Image and Video Processing, 2019, 1-15. https://doi.org/10.1186/s1364 0-018-0393-4

171. Chen K., Wang Q., 2015, December: Human posture recognition based on skeleton data. In 2015 IEEE International Conference on Progress in Informatics and Computing (PIC), 618-622. ieee. https://doi.org/10.1109/PIC.2015.7489922

172. Chollet F., 2017: Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, 1251-1258. https://doi.org/10.48550/arXiv.1610.02357

173. Li Y., Huang H., Xie Q., Yao L., Chen Q., 2018: Research on a surface defect detection algorithm based on MobileNet-SSD. Applied Sciences, 8(9), 1678. https://doi.org/10.3390/app8091678

174. Zhang X., Zhou X., Lin M., Sun J., 2018: Shufflenet: An extremely efficient convolutional neural network for mobile devices. In Proceedings of the IEEE conference on computer vision and pattern recognition, 6848-6856. https://doi.org/10.48550/arXiv.1707.01083

175. Ma N., Zhang X., Zheng H.T., Sun, J., 2018: Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the European conference on computer vision (ECCV), 116-131. https://doi.org/10.48550/arXiv.1807.11164

176. Zhang J., Zhu H., Wang P., Ling X., 2021: ATT squeeze U-Net: A lightweight network for forest fire detection and recognition. IEEE Access, 9, 10858-10870. https://doi.org/10.1109/ACCESS.2021.3050628

177. Dindorf C., Ludwig O., Simon S., Becker S., Fröhlich M., 2023: Machine learning and explainable artificial intelligence using counterfactual explanations for evaluating posture parameters. Bioengineering, 10(5), 511. https://doi.org/10.3390/bioengineering10050511

178. Alpaydin E., 2020: Introduction to machine learning. MIT press. Available online at: http://nuir.nkumbauniversity.ac.ug/xmlui/bitstream/handle/20.500.12383/1421/Introduction%20to%20Machine%20Learning,%20Second%20Edition%20(Adaptive%20Computation%20and%20Machine%20Learning)%20(%20PDFDrive%20).pdf?sequence=1 (Accessed 19 June 2023).

179. LeCun Y., Bengio Y., Hinton G., 2015: Deep learning. Nature, 521(7553), 436-444. https://doi.org/10.1038/nature14539

180. Anaconda Inc., 2023: The definitive guide to AI Platforms for open-source data science and ML. Available online at: https://www.anaconda.com/definitive-guide-to-ai-platforms (Accessed 21 June 2023).

181. Hinton G., Deng L., Yu D., Dahl G.E., Mohamed A.R., Jaitly N., Senior A., Vanhoucke V., Nguyen P., Sainath T.N., Kingsbury B., 2012: Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal processing magazine, 29(6), 82-97. https://doi.org/10.1109/MSP.2012.2205597

182. Currenti J., Styduhar C., Yang C., 2023: The definitive guide to AI platforms for open-source data science and ML. Available online at: https://www.anaconda.com/definitive-guide-to-ai-platforms (Accessed 20 June 2023).

Revista Pădurilor 138(3) (2023) 001-044

Revista Pădurilor

disponibil online la: www.revistapadurilor.com

DOMNUL PROFESOR DR. ING. ARCADIE CIUBOTARU ÎMPLINEȘTE 75 DE ANI

Elena Camelia Mușat[a,*]

[a]Departamentul de Exploatări Forestiere, Amenajarea Pădurilor și Măsurători Terestre, Facultatea de Silvicultură și exploatări forestiere, Universitatea Transilvania din Brașov, Șirul Beethoven 1, 500123, Brașov, România, e-mail: elena.musat@unitbv.ro (E.C.M.).

REPERE

- Aniversarea domnului prof. dr. ing. Arcadie Ciubotaru la venerabila vârstă de 75 ani.

REZUMAT GRAFIC

INFORMAȚII ARTICOL

Istoricul articolului:
Manuscris primit la: 4 septembrie 2023
Primit în forma revizuită: -
Acceptat: 4 septembrie 2023
Număr de pagini: 4 pagini.

Tipul articolului:
Comunicare

Editor: Stelian Alexandru Borz

Cuvinte cheie:
Arcadie Ciubotaru
Aniversare
75 de ani

REZUMAT

Născut în 12 august 1948 în Buhuși, județul Bacău, domnul profesor a fost mereu apropiat de natură și de tradiții, care l-au definit și l-au ghidat în dezvoltarea profesională și personală. Astfel, între 1955 - 1962 a urmat cursurile la Școala Generală din satul Slobozia, județul Neamț, după care, în 1966, tânărul Arcadie Ciubotaru a absolvit Liceul Teoretic Roznov, din același județ. Apropierea de natură, ca urmare a locului unde și-a petrecut primii ani din viață, l-a influențat pe domnul profesor în alegerea profesiei pe care să o urmeze și căreia să i se dedice întreaga viață. Așa că, în 1968 a dat admitere la Facultatea de Silvicultură din Brașov, iar în 1973 i s-a îndeplinit visul de a deveni inginer silvic. Pe parcursul celor 35 de ani în care a activat ca și cadru didactic, domnul profesor a pregătit generații și generații de ingineri silvici, prezentându-le cu măiestrie și dăruire tainele exploatării și prelucrării primare a lemnului. Privind per ansamblu întreaga carieră a domniei sale, se poate observa cu ușurință că valorile pe care a pus accent întotdeauna domnul profesor au fost profesionalism, seriozitate, implicare, organizare și, nu în ultimul rând, omenie. Vă mulțumim domnule profesor pentru tot ceea ce ne-ați oferit nouă, studenților, de la cunoștințe și îndrumări, până la sfaturi părintești, și vă dorim mulți ani înainte, cu sănătate, liniște și nenumărate bucurii alături de persoane dragi dumneavoastră!

* Autor corespondent. Tel.: +40-761-646-361.
Adresa de e-mail: elena.musat@unitbv.ro

DOMNUL PROFESOR DR. ING. ARCADIE CIUBOTARU ÎMPLINEȘTE 75 DE ANI

Un om deosebit ne-a spus odată nouă, studenților, că „este mare lucru să mergi la muncă cu drag" și că „atâta timp cât tu nu ești perfect, nu-i cere celuilalt să fie". Acest om este domnul profesor Arcadie Ciubotaru, care întotdeauna s-a ghidat după principii solide, bazate atât pe experiențele proprii, cât și pe cunoștințele transmise de-a lungul timpului, din moși-strămoși.

Născut în 12 august 1948 în Buhuși, județul Bacău, domnul profesor a fost mereu apropiat de natură și de tradiții, care l-au definit și l-au ghidat în dezvoltarea profesională și personală. Astfel, între 1955-1962 a urmat cursurile la Școala Generală din satul Slobozia, județul Neamț, după care, în 1966, tânărul Arcadie Ciubotaru a absolvit Liceul Teoretic Roznov, din același județ (1962-1966).

Apropierea de natură, ca urmare a locului unde și-a petrecut primii ani din viață, l-a influențat pe domnul profesor în alegerea profesiei pe care să o urmeze și căreia să i se dedice întreaga viață. Așa că, în 1968 a dat admitere la Facultatea de Silvicultură din Brașov, iar în 1973 i s-a îndeplinit visul de a deveni inginer silvic.

Ca urmare a politicilor vremii, după absolvirea facultății din Brașov, tânărul inginer a fost repartizat și mai departe de casă, la G.S.C.F.I. Râmnicu Vâlcea unde, timp de trei ani (1973-1976), și-a îmbunătățit cunoștințele dobândite în facultate, având posibilitatea de a le aplica practic, în producție, alături de alți silvici „cu state vechi" de la care a continuat să învețe, ghidându-se pe ideea că „de la oricine poți învăța câte ceva dacă ai mintea deschisă".

După perioada de așa-zisă „ucenicie" în ceea ce privește profesia de inginer silvic, domnul profesor Ciubotaru și-a continuat activitatea la I.F.E.T. Orșova, dar de această dată din postura de șef de lot și specialist silvic, nu de învățăcel. În cei doi ani (1976-1978) a trebuit să facă față multor provocări pe care, prin cunoștințele însușite, seriozitate și organizare, a reușit să le ducă la bună îndeplinire. Aici, postul ocupat a impus nu numai activități care țineau de exploatarea lemnului, ci și activități de proiectare a drumurilor forestiere, de supraveghere a construcției acestora și multe alte sarcini pe care domnul profesor le-a îndeplinit cu brio, învățând din fiecare câte ceva și îmbunătățindu-și permanent cunoștințele și aptitudinile tehnice și organizatorice.

Cu toate frumusețile din zonă și tradițiile păstrate încă de localnici și împărtășite cu drag noilor veniți, inginerul Arcadie Ciubotaru a resimțit lipsa Brașovului și, mai ales, a familiei întemeiate aici. Astfel, în 1978 a revenit în orașul de la poalele Tâmpei, unde și-a dedicat timpul, cunoștințele și experiența acumulată studenților de la Facultatea de Silvicultură.

Domnul profesor a parcurs, din aproape în aproape, toate treptele ierarhiei universitare, de la asistent universitar (1978-1991), la șef de lucrări (1991-1995), conferențiar universitar (1995-1998) și, în final, profesor universitar (1998-2013), predând ore la disciplinele Exploatarea pădurilor (curs și laborator - licență, programul de studii Silvicultură, anul III), Tehnologia prelucrării lemnului (curs și laborator - licență, programul de studii Exploatări forestiere, anul IV), Proiectarea și organizarea activității de exploatare (curs și proiect - licență, programul de studii Cinegetică ID, anul III), Ecotehnologii de exploatare a pădurilor (curs și laborator - masterat, programul de studii Management și sisteme tehnice în exploatări forestiere, anul I).

Pe parcursul celor 35 de ani în care a activat ca și cadru didactic, domnul profesor a pregătit generații și generații de ingineri silvici, prezentându-le cu măiestrie și dăruire tainele exploatării și a prelucrării primare a lemnului. Fiind un adevărat profesionist, care iubește natura și activitățile practice, domnul profesor a organizat numeroase deplasări în teren astfel încât studenții să poată observa cum se recoltează și se colectează efectiv lemnul și chiar să mânuiască ferăstrăul mecanic.

Tactul didactic și expunerile interesante făceau ca la cursurile domnului profesor sălile să fie aproape pline, chiar dacă nu făcea niciodată prezența. În plus, sfaturile, învățăturile și glumele presărate din loc în loc, întotdeauna legate de subiectul abordat, ne făceau pe noi, studenții, să-l îndrăgim și mai mult și să fim mai motivați în a deprinde noi și noi cunoștințe. Profesionalismul demonstrat la fiecare oră de curs și lucrări practice, precum și personalitatea domnului profesor au făcut ca mulți dintre studenți să aleagă să realizeze proiectul de diplomă și/sau lucrarea de disertație sub îndrumarea dânsului.

Aprecierea generațiilor de studenți îndrumați în lucrările de finalizare a studiilor sau care l-au avut pe domnul profesor doar cadru didactic pe parcursul studiilor, s-a extins și în exteriorul instituției, motiv pentru care domnul profesor Ciubotaru este întâmpinat cu zâmbetul pe buze și cu mare drag oriunde merge în țară. Aceste aprecieri se traduc și prin numeroasele solicitări din partea absolvenților de a realiza fie teze de doctorat sub îndrumarea dumnealui, fie lucrări de grad didactic I în învățământul preuniversitar.

În acest sens, domnul profesor a dobândit dreptul de a conduce doctorat în anul 1991. Această calitate presupune multe provocări, atât prin prisma seriozității celor înscriși la doctorat, cât și a subiectelor abordate. Astfel, domnul profesor a dat dovadă de spirit organizatoric, gândire logică și o dorință continuă de perfecționare, care l-au condus la îndrumarea cu succes a mai multor teze de doctorat care au abordat fie teme specifice exploatării lemnului (consumuri și pierderi tehnologice la exploatarea arborilor în diverse condiții de relief și arboret, calitatea arborilor pe picior în arborete pure de fag și arborete tinere de molid, caracteristicile defectelor vizibile la arborii de fag), fie teme apropiate acestui domeniu (calitatea arborilor din zonele publice) și chiar teme care au presupus provocări mai mari, precum utilizarea tehnologiei LiDAR în realizarea modelului digital altimetric al terenurilor acoperite cu vegetație forestieră.

Remarcându-se în cadrul colegilor ca o persoană organizată, cu gândire logică, perseverentă și dornică de implicare, domnul profesor a fost desemnat și în diverse poziții de conducere de la nivelul universității, ocupând funcțiile de director educativ, director de colegiu universitar și cancelar general al Universității Transilvania din Brașov. Dar, cu toate aceste noi responsabilități, domnul profesor nu și-a neglijat niciodată activitatea de bază, nici pe cea didactică și nici pe cea științifică. Din această perspectivă a publicat numeroase cărți și îndrumare de laborator pentru studenți, pe specificul disciplinelor predate. În plus, preocupările din cercetare s-au concretizat în 31 de proiecte de cercetare științifică, cu teme solicitate de diverse instituții din țară. De asemenea, trebuie menționate și cele peste 130 de articole publicate în reviste de specialitate, unele dintre ele fiind prezentate și la conferințe internaționale, iar altele publicate în reviste cotate la cel mai înalt nivel.

În 2013, la vârsta de 65 de ani, domnul profesor Arcadie Ciubotaru s-a pensionat, păstrându-și calitatea de cadru didactic asociat și predând ore la disciplinele Exploatarea pădurilor și Ecotehnologii de exploatare a pădurilor.

La 70 de ani a renunțat și la această calitate, păstrându-și doar statutul de conducător de doctorat. În această calitate, domnul profesor continuă să studieze, să se perfecționeze și le oferă încă îndrumare, idei și sfaturi atât doctoranzilor, cât și celor pe care i-a îndrumat, dar care și-au găsit un loc în domeniul învățământului sau a cercetării științifice, domenii pe care domnul profesor le-a onorat toată viața și continuă să o facă.

Privind per ansamblu întreaga carieră a domniei sale, se poate observa cu ușurință că valorile pe care a pus accent întotdeauna domnul profesor au fost profesionalism, seriozitate, implicare, organizare și, nu în ultimul rând, omenie. Aceste calități l-au ajutat pe domnul profesor Arcadie Ciubotaru să devină un pedagog deosebit, un prieten și un coleg de nădejde, dar, mai ales, un model de viață și profesionalism pentru mulți dintre noi.

Domnule profesor, pentru mine și mulți alții sunteți dovada vie că poți merge la muncă cu drag și că numai atunci când faci ceva cu plăcere vei obține și rezultatele așteptate. Vă mulțumim domnule profesor pentru tot ceea ce ne-ați oferit nouă, studenților, de la cunoștințe și îndrumări, până la sfaturi părintești, și vă dorim mulți ani înainte, cu sănătate, liniște și nenumărate bucurii alături de persoane dragi dumneavoastră!

La mulți ani!!!

Ș.L. dr. ing. Elena Camelia MUȘAT

Facultatea de Silvicultură și exploatări forestiere

Universitatea Transilvania din Brașov

Revista Pădurilor 138(3) (2023) 001-044

Revista Pădurilor

disponibil online la: www.revistapadurilor.com

PROF. DR. BIOL. MARIUS DANCIU (1941-2023), UN BOTANIST ÎNTRE SILVICULTORI

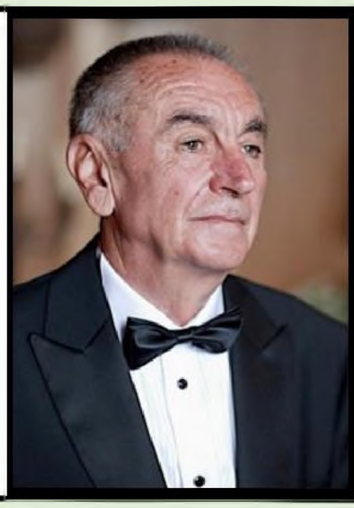
Dan-Marian Gurean[a,*], Pantelimon Ularu[a], Victor Adrian Indreica[a]

[a]**Departamentul de Silvicultură, Facultatea de Silvicultură și exploatări forestiere, Universitatea Transilvania din Brașov, Șirul Beethoven 1, 500123, Brașov, România.**

REPERE

- Cadru didactic titular la Facultatea de Silvicultură şi exploatări forestiere din Braşov, disciplina Botanică şi Fiziologia plantelor, în perioada 1964-2006.
- 108 lucrări științifice (16 cărți, 92 articole), 27 de contracte de cercetare.
- cercetări floristice - două specii noi pentru flora României identificate, cercetări fitocenologice.

REZUMAT GRAFIC



INFORMAȚII ARTICOL

Istoricul articolului:
Manuscris primit la: 4 septembrie 2023
Primit în forma revizuită: -
Acceptat: 4 septembrie 2023
Număr de pagini: 6 pagini.

Tipul articolului:
Comunicare

Editor: Stelian Alexandru Borz

Cuvinte cheie:
Profesor Marius Danciu
Activitatea didactică și științifică
Facultatea de Silvicultură și exploatări forestiere

REZUMAT

Absolvent al secției de biologie-botanică a Facultății de Biologie-Geografie din cadrul Universității „Babeș-Bolyai" din Cluj-Napoca, dl. Profesor Marius Danciu a beneficiat de repartiție ministerială în învățământul superior, fiind angajat ca șef de laborator în octombrie 1964 la Disciplina Botanică de la Facultatea de Silvicultură și exploatări forestiere din Brașov. A devenit apoi botanist, botanist principal, asistent (1972), șef de lucrări (1990), conferențiar (1993) și profesor universitar din 1998. A susținut doctoratul în geobotanică la Universitatea București, sub conducerea Prof. dr. doc. biol. Iuliu Morariu, cu teza „Studii geobotanice în sudul Munților Baraolt". A publicat 108 lucrări științifice (16 cărți, 4 ca prim autor și 92 de articole, 11 ca unic autor), a contribuit la elaborarea a 27 de contracte de cercetare ca responsabil sau colaborator, circumscrise domeniilor botanicii - cercetări floristice, fitocenologice, fenologice, ecofiziologice, privind corologia, ecologia și fitocenologia speciilor de cormofite, resursele de plante medicinale din fondul forestier sau cele trofice pentru vânatul ierbivor din diferite ecosisteme, conservarea speciilor sau comunităților rare de plante.

* Autor corespondent. Tel.: +40-740-080-430.
Adresa de e-mail: dangurean@unitbv.ro

PROF. DR. BIOL. MARIUS DANCIU (1941-2023), UN BOTANIST ÎNTRE SILVICULTORI

Domnul Prof. dr. biol. Marius Danciu s-a născut pe 16 august 1941, în satul Camna (comuna Tauţ, în prezent comuna Şilindia, judeţul Arad), în casa părinţilor săi - învăţătorul Traian Danciu şi mama - Mărioara Danciu, casnică, dedicată treburilor casei şi creşterii copiilor - Lavinia şi Marius, care au moştenit de la tatăl lor vocaţia profesiei de dascăl şi au dus mai departe această frumoasă tradiţie de familie, ca învăţătoare în Arad, şi respectiv profesor universitar la Braşov.

Cursurile școlii elementare le-a urmat în perioada 1948-1955, clasele I-II în satul natal, clasele III-IV în satul Chier (comuna Târnova, judeţul Arad) iar la numai 11 ani a plecat de acasă pentru a-şi continua studiile cu clasele V-VII (1952-1955) în oraşul Ineu (judeţul Arad), unde a urmat şi cursurile liceale la „Școala Medie Mixtă", secţia reală, între 1955 şi 1959.

În perioada 1959-1964, domnul Profesor Danciu a frecventat cursurile secţiei de biologie-botanică a Facultăţii de Biologie-Geografie din cadrul Universităţii „Babeş-Bolyai" din Cluj-Napoca, obţinând titlul de diplomat (licenţiat) în biologie, specialitatea botanică. Pe baza rezultatelor obţinute în anii de studii universitare, a beneficiat de repartiţie ministerială într-o instituţie de învăţământ superior, fiind încadrat pe 28.10.1964 ca şef de laborator (funcţie ce corespundea atunci celei de preparator universitar), la Disciplina Botanică din structura Catedrei de Botanică şi Zoologie forestieră a Facultăţii de Silvicultură şi exploatări forestiere, din cadrul Institutului Politehnic Braşov. Şeful catedrei - Prof. dr. doc. biol. Iuliu Morariu, solicitase repartizarea unui biolog-botanist pe postul menţionat, devenit vacant ca urmare a transferului domnului dr. biolog Pantelimon Ularu, ca asistent universitar, la nou înfiinţata Facultate de Ştiinţe Naturale din cadrul Institutului Pedagogic de 3 ani al Universităţii din Braşov.

În perioada 1965-1969 domnul Profesor Danciu a deţinut în cadrul aceleiaşi discipline funcţia de botanist, apoi, din 1969, odată cu modificarea titulaturii disciplinei, botanist principal la Botanică şi fiziologia plantelor, asistent suplinitor în anul universitar 1971-1972 concomitent cu preluarea poziţiei de titular de către Prof. dr. ing. biol. Darie Parascan iar din 01.10.1972, este titularizat prin concurs, când acumulase deja 8 ani vechime, pe post de asistent universitar - poziţia 6 în Statul de funcţii al noii Catedre de Silvicultură, constituită prin includerea, alături de cea veche, a catedrelor desfiinţate de Botanică şi Zoologie forestieră şi a celei de Împăduriri şi Amelioraţii silvice. Domnul Profesor Danciu s-a integrat cu succes în noul colectiv de catedră, dominat evident de silvicultori, în timp ce biologii alături de care îşi începuse activitatea s-au retras, pe rând, prin pensionare (Prof. dr. doc. biol. Iuliu Morariu, pensionat în 1970), transfer (dr. biol. Pantelimon Ularu), sau ca urmare a plecării din ţară (dr. biol. Heinz Heltmann).

Colegii mai vechi sau noi, dar şi zeci de promoţii de studenţi ce l-au cunoscut, au apreciat unanim şi permanent calităţile remarcabile ce au definit personalitatea Profesorului Marius Danciu - ţinuta morală ireproşabilă, onestitatea, modestia, delicateţea, dedicarea, meticulozitatea, rigoarea ştiinţifică, conştiinciozitatea şi, nu în ultimul rând, tenacitatea.

În 1966 domnul profesor şi-a unit destinul cu cel al d-rei Knobloch Catalena, absolventă a aceleiași universități clujene - Facultatea de Filologie, secția limbă şi literatură maghiară, profesoară la Covasna, apoi corector, translator, redactor şi secretar de redacție la ziarul „Brassoi Lapok" din Braşov, căsătoria lor fiind binecuvântată cu un copil - Daniel, născut în 1975.

Toate calitățile menționate ale domnului profesor, credința fermă a domniei sale că munca asiduă, conştiinciozitatea de excepție, meritele şi rezultatele incontestabile vor trebui să fie la un moment dat recompensate, dar şi susținerea permanentă a familiei l-au ajutat să depășească parcursul nefiresc de lung și întru totul nemeritat al treptelor ierarhiei didactice, o primă şi importantă neîmplinire a carierei domniei sale.

După 12 ani de activitate ca asistent şi alți 8 anterior ca șef de laborator, botanist şi botanist principal, timp în care a susținut doar ore de lucrări practice, în 1984 domnul Danciu preia cursul de Botanică şi fiziologia plantelor de la anul I ingineri seral şi doi ani mai târziu părea să apară oportunitatea unei promovări, conform adeverinței nr. 8851, eliberată de Universitatea din Braşov la data de 25.11.1986, spre a-i servi la completarea dosarului în vederea susținerii concursului pentru ocuparea postului de Şef de lucrări, poziția 18 în Statul de funcții al Catedrei de Silvicultură. Din păcate, din motive pe care nu le cunoaştem, acel concurs nu a mai avut loc sau a fost amânat, așa că dl. Danciu a devenit Şef de lucrări abia după Revoluția din decembrie 1989, mai exact de la 1.10.1990, la 26 de ani vechime, când în Fișa de prezentare din 27.02.1990 a candidatului - Asist. dr. biol. Marius Danciu, la concursul pentru postul de Şef de lucrări, este consemnat că a publicat singur sau în colaborare 61 de lucrări științifice, este doctor în biologie din 1974, a participat în calitate de responsabil sau colaborator la elaborarea a 19 contracte de cercetare.

Ca semn al unei relative normalizări a promovărilor, şi al fundamentării acestora preponderent pe criterii obiective de performanță științifică și didactică, dl. Danciu este titularizat, prin concurs, pe post de conferențiar universitar, începând cu 1.10.1993, din 1994 devine titularul cursului de Botanică, succedându-i Prof. dr. ing. biol. Darie Parascan şi, la 34 de ani vechime în învățământul superior, devine profesor universitar, de la 01.10.1998, deși întrunea condițiile necesare în acest sens de multă vreme.

A funcționat pe acest post până în 2006, dar din 2005 s-a confruntat cu a doua neîmplinire din carieră, şi anume reducerea, prin Reforma Bologna şi restrângerea învățământului superior tehnic de la 5 la 4 ani, de la un an întreg la un singur semestru a timpului acordat cursului şi lucrărilor practice de Botanică în Planul de învățământ al programelor de studii Silvicultură, Exploatări forestiere şi Cinegetică, situație care le-a creat domnilor profesori Danciu şi Parascan o mare dezamăgire. Nu a trecut mult şi, din păcate, în 2006 Profesorul Danciu trăiește nemeritat o a treia neîmplinire - imposibilitatea de a obține conducerea de doctorat în domeniul fundamental Științe agricole şi silvice, domeniul Ecologie forestieră sau Botanică forestieră, datorită faptului că era doctor în biologie, specializarea geo-botanică. Nu a contat faptul că, deși biolog, cu doctoratul în domeniul de formare, şi-a desfăşurat activitatea timp de 42 de ani preponderent între silvicultori, nici că a făcut eforturi majore - în continuarea celor ale predecesorilor săi, Prof. dr. ing. biol. Darie Parascan, şi Prof. dr. doc. biol. Iuliu Morariu, pentru a adapta conținutul cursului şi lucrărilor practice de Botanică specificului forestier, în sensul exemplificării termenilor consacrați de morfologie, ori de câte ori a fost posibil, la specii lemnoase de interes forestier, al realizării de preparate microscopice cu structurile diferitelor organe vegetative sau reproducătoare tot la specii lemnoase sau ierboase de pădure, dar şi în sensul focusării în cadrul sistematicii asupra familiilor şi ordinelor care includ plante ierboase indicatoare de pădure, deci specii cu evidente afinități pentru mediul forestier. Nu au contat nici recomandările, oferite cu generozitate, de către Prof. consult. dr. ing. biol. dr. Honoris Causa Darie Parascan, membru titular A.S.A.S. şi şef al Catedrei de Silvicultură în perioada 1985-1990, cu care dl. Prof. Danciu a colaborat practic pe întreg parcursul activității la catedră, Prof. dr. ing. Dumitru Târziu, membru titular A.S.A.S, şef al Catedrei de Silvicultură în perioada 1990-2004 dar şi Prof. consult. dr. biol. Vasile Ciocîrlan de la Universitatea de Științe Agronomice şi Medicină Veterinară din București, Catedra de Botanică şi Fiziologie vegetală.

Informat că nu poate primi conducerea de doctorat decât în biologie - geo-botanică, ceea ce evident nu îl avantaja în contextul activității domniei sale la Facultatea de Silvicultură şi exploatări forestiere, ai cărei absolvenți nu aveau posibilitatea de a se înscrie la un astfel de doctorat, domnul Profesor Danciu a ales să nu își mai depună dosarul şi, în consecință, conform reglementărilor momentului, nu a putut să își prelungească activitatea în calitate de titular, fiind nevoit să se pensioneze la împlinirea vârstei de 65 de ani, în 2006. A mai predat cursul de Botanică până în anul 2007 şi apoi, timp de câțiva ani a mai ajutat disciplina prin susținerea unor ore de lucrări practice în regim de plata cu ora sau chiar pe parcursul practicii, după care, cu toate rugămințile noastre, s-a retras din activitatea didactică, motivând, pe bună dreptate, dezinteresul tot mai accentuat al multor studenți față de școală, lipsa de motivare a acestora pentru o pregătire profesională temeinică.

Activitatea științifică a d-lui Profesor Danciu a fost orientată mai întâi, după cum însuşi dumnealui afirma într-un memoriu de activitate, „cu precădere asupra cercetărilor floristice, materializată îndeosebi în dezvoltarea şi continua perfectare, prin verificare critică şi punerea de acord cu lucrările taxonomice moderne, a colecției științifice de plante presate a facultății".

În perioada 1964-1990, „stocului comparativ de materiale științifice ale herbarului i s-au adăugat 25.600 de coli noi, reprezentând taxoni (specii, subspecii, varietăți) din diferite unități sistematice", în această cifră fiind incluse specimene recoltate şi de ceilalți membri ai colectivului disciplinei sau chiar de întregul colectiv pe parcursul unor deplasări (de exemplu pe Măgura Codlei), dar şi materialele herbaristice obținute prin schimburi cu alte colecții din țară (Institutul de Biologie din București, Universitățile din Iași, Cluj-Napoca, Craiova, Institutul Pedagogic din Bacău etc.) sau din străinătate (Muzeul din Lund, Suedia). Fără îndoială însă, profesorul Marius Danciu a contribuit în cea mai mare măsură la îmbogățirea Herbarului Facultății de Silvicultură şi exploatări forestiere din Braşov şi a investit extrem de mult timp în verificarea atentă a taxonilor herborizați, mai recent sau cu mai multă vreme în urmă, ceea ce l-a determinat să afirme, riguros fundamentat, că „este unul din cele mai bogate şi mai bine sistematizate din țară". Ținând cont de acestea, apreciem că ar fi pe deplin meritat ca acest herbar să-i poarte numele, şi vom face toate demersurile necesare în acest sens.

Activitatea publicistică a domnului profesor a debutat în 1967 cu articolul Vegetația stâncăriilor de pe Măgura Codlei, autori Morariu I., Ularu P., Danciu, M., Lungescu E., publicat în Buletinul Institutului Politehnic Braşov, 9, pg. 15-24. Din cele 108 lucrări științifice, 16 (4 ca prim autor) sunt cărți, capitole în cărți sau îndrumare de lucrări practice, publicate în edituri centrale ca Editura „Ceres" - Morfologia şi fiziologia plantelor lemnoase, cu elemente de taxonomie vegetală, 1983, 363 p., autori Parascan D., Danciu M., care a primit premiul „Traian Săvulescu" al Academiei Republicii Socialiste România sau Edit. Silvică - Plante vasculare periclitate, vulnerabile şi rare din pădurile României, 2007, 258 p., autori Danciu M., Gurean D., Indreica A., indexată în baza internațională de date UNPD (United Nations Programs for Development) Romania, edituri locale ca Editura „Pentru Viață", Braşov - Botanică forestieră, 2002, 324 p., autori Danciu M., Parascan D., Gurean D. (colaborator), Editura şi Reprografia Universității „Transilvania" din Braşov. Din cele 92 de articole științifice publicate în diverse reviste sau periodice de prestigiu din țară sau din străinătate, în volumele unor conferinţe sau sesiuni de comunicări științifice, 11 îl au pe dl. Prof. Danciu ca unic autor, 16 au fost elaborate în colectivul de biologi alături de care şi-a început activitatea (dr. P. Ularu - prim autor la 3 dintre acestea, dr. E. Lungescu), sub coordonarea Prof. dr. doc. Iuliu Morariu, 23 în colective mai largi din care a făcut parte şi Prof. dr. ing. biol. Darie Parascan, 21 în colaborare numai cu dânsul, fiind alternată coordonarea.

Studiile doctorale le-a început în 1968, în specialitatea geobotanică, sub îndrumarea Prof. dr. doc. Ion Popescu-Zeletin, membru corespondent al Academiei Române, şi le-a continuat după decesul acestuia în 1974, sub conducerea Prof. dr. doc. Iuliu Morariu. A susținut la Universitatea București, pe data de 23.12.1974, teza de doctorat „Studii geobotanice în sudul Munților Baraolt", obținând în același an titlul științific de doctor în biologie.

Lucrările de cercetare științifică ale domnului Prof. dr. biol. Marius Danciu se circumscriu diferitelor domenii ale botanicii - cercetări floristice, fitocenologice, referitoare la corologia, ecologia şi fitocenologia speciilor de cormofite, conservarea speciilor sau comunităților rare de plante, cunoaşterea resurselor trofice pentru vânatul ierbivor din diferite ecosisteme, cercetări fenologice, ecofiziologice sau privind cunoaşterea resurselor de plante medicinale din fondul forestier, precum şi a diferitelor erbicide şi a eficienței acestora în culturile din pepiniere sau plantații. Rezultatele cercetărilor sale s-au concretizat în identificarea a două specii noi pentru Flora României (de ex. *Geranium cinereum*, semnalată în 1983 de dl. profesor de pe stâncării foarte greu accesibile din Cheile Postăvarului - **Figura 1**), numeroase stațiuni noi de răspândire a unor taxoni rari sau sporadici, precum şi prin contribuții remarcabile la vegetația anumitor teritorii, masive muntoase sau chiar, în ansamblu, la vegetația României.

Figura 1. ***Geranium cinereum*** **pe stâncării, la Porțile de Piatră ale Postăvarului. Foto: Gurean D.**

O parte din aceste rezultate au rămas din păcate nepublicate, dar ne vom strădui ca ele să vadă lumina tiparului, cum este şi cazul unui articol aflat acum în curs de publicare - Contributions to the flora and vegetation of Piatra Craiului National Park (I), autori Danciu M., Gurean D., Indreica A., comunicare susținută la Sesiunea științifică bienală „Forest and sustainable development", organizată de Facultatea de Silvicultură şi exploatări forestiere din Braşov în octombrie 2022.

Domnul Prof. Danciu a participat în calitate de colaborator sau de responsabil la elaborarea a 27 de contracte de cercetare cu diferiți beneficiari - Regia Națională a Pădurilor ROMSILVA, I.C.A.S. Bucureşti, Institutul de Biologie Bucureşti ş.a. Activitatea domniei sale a inclus şi îndrumarea cercului ştiințific studențesc de botanică, în cadrul căruia s-au redactat anual teme, unele dintre acestea fiind premiate la faza pe universitate a Sesiunii de comunicări ştiințifice studențeşti sau chiar la faza pe țară.

Retras din activitate, cu probleme de sănătate, de care însă nu s-a lăsat niciodată copleşit, tot mai îngrijorat de starea fizică fragilă a doamnei, care din păcate a trecut în neființă în anul 2022, domnul Profesor Danciu îşi reîncărca bateriile cu ocazia vizitelor fiului său Daniel şi a celor 2 nepoți - un nepoțel şi o nepoțică, de care era foarte mândru şi ori de câte ori, vizitându-l, ne arăta poze cu ei, iar sufletul i se umplea de bucurie şi ochii i se umezeau.

Zilele trecute, când ar fi trebuit să-l sărbătorim la vârsta de 82 de ani, vârstă pe care din păcate nu a mai împlinit-o, nu am putut decât să ni-l amintim aşa cum l-am cunoscut, pentru că dumnealui ne-a părăsit, trecând în eternitate, pe data de 26 aprilie 2023, la 81 de ani, 8 luni şi 10 zile.

Chiar dacă problemele din ultimii ani l-au determinat să vină mai rar pe la facultate, mentorul nostru, domnul Profesor dr. biol. Marius Danciu va rămâne, prin tot ceea ce a realizat, prin tot ceea ce am învățat de la dumnealui, pentru totdeauna în amintirea noastră, a disciplinei de Botanică şi Fiziologia plantelor, a Facultății de Silvicultură şi exploatări forestiere de la Braşov şi a numeroase generații de absolvenți ai acesteia.

Vă mulțumim Domnule Profesor şi vă asigurăm de întreaga noastră gratitudine şi recunoştință ! Dumnezeu să vă odihnească !