Review Article

A Systematic Review of the Applications of Artificial Intelligence in the Study of Occupational Cancers

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Abstract

Background: Occupational exposures contribute to approximately 8% of all cancer cases. Artificial intelligence (AI), encompassing machine learning and deep learning, presents a promising avenue for the prevention and management of these cancers. This systematic review explores the current applications of AI in the detection, assessment, diagnosis, and control of occupational cancers.
Methods: This systematic review adhered to PRISMA guidelines, conducting a thorough search of the Web of Science, Scopus, and PubMed databases between October and November 2023. The search utilized keywords related to occupation, cancer, and AI. Articles were included if they examined occupational cancers, occupational exposure to carcinogens, and the application of AI tools. A screening process was followed by data extraction, focusing on study details, populations, and AI applications.
Results: The initial search yielded 2426 articles, from which 34 were selected for full-text review. Ultimately, 23 studies were included in the analysis. These studies covered a range of occupational cancers and AI applications, broadly categorized into: 1) AI for risk assessment of occupational exposure to carcinogens, 2) AI for cancer prediction and detection, and 3) AI for cancer diagnosis and clinical evaluation. Lung cancer was the most frequently studied type of occupational cancer.
Conclusion: The application of AI in the study of occupational cancers is relatively nascent, with a limited number of studies identified. However, given AI's significant capabilities in disease assessment and management, future research is strongly recommended to leverage these tools for investigating the most prevalent occupational cancers, including lung, bladder, laryngeal, leukemia, and liver cancers.

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Introduction

Various hazardous agents in workplaces may cause diseases in exposed workers.[1-4] Cancers are a group of diseases that may occur in occupational settings due to exposure to carcinogenic chemicals.[5,6] Cancer is the uncontrolled growth of abnormal cells in the body[7] and is one of the biggest challenges faced by the medical community.[8] The number of cancers diagnoses worldwide was about 18.1 million in 2018.[9] Approximately 8% of cancer cases could have their origin in occupational exposures.[10] Cancer is of interest to the medical community due to its incidence, prevalence, and mortality.[11] Throughout history, a series of substances, agents, and situations have been linked to cancer.[12] The most important risk factors include smoking, obesity/overweight, certain pathogens, and, to a lesser extent, alcohol, diet, and a sedentary lifestyle.[13] Another important risk factor is occupational exposure to carcinogens.[14] The International Agency for Research on Cancer (IARC) has classified 150 agents as human carcinogens, many of which are encountered in the workplace.[15] Occupational cancers are those that result from exposure to carcinogenic agents in the workplace.[16, 17] The Occupational Cancer Research Center (OCRC) in Canada published a report, "The Burden of Occupational Cancer," in 2019, highlighting 13 occupational carcinogens, including solar ultraviolet (UV) radiation, asbestos, diesel engine exhaust, crystalline silica, welding fumes (nickel and chromium (VI) compounds), radon, night shift work, polycyclic aromatic hydrocarbons (PAHs), arsenic, and benzene.[18]

Assessing and managing occupational cancers is critical for better understanding risk factors and preventing new cases. Artificial intelligence (AI) can be utilized in various ways to evaluate cancers.[19] AI has a relatively long history in assessing cancers.

1. **Early Data Mining Techniques (1990s):** The early use of AI involved identifying patterns and correlations in large datasets related to occupational exposures and health outcomes.

2. **Machine Learning (ML) Algorithms (2000s):** More sophisticated algorithms emerged, enabling more effective data analysis and cancer risk assessment.

3. **Natural Language Processing (2010s):** Advances in extracting information from unstructured text, such as medical records and research articles, helped identify cancer risks.

4. **Big Data Analytics (mid-2010s):** The ability to analyze large amounts of data from multiple sources provided a better understanding of cancer risk factors.

5. **Deep Learning Applications (late 2010s–present):** Deep learning techniques have helped identify patterns in complex data and improve cancer detection, early diagnosis, and prognosis in occupational settings.[20, 21]

AI plays a significantly different role than traditional methods in cancer diagnosis and management. While traditional methods often rely on statistical analyses, biopsies, and clinical procedures, which can miss complex patterns, AI uses advanced ML and deep learning algorithms to identify patterns in big data more accurately. AI can also process data in real-time, provide personalized treatments, and assist physicians in managing cancer more effectively by predicting disease progression and improving decision-making. These unique capabilities are bringing significant improvements in diagnostic accuracy and treatment strategies.[22-24]

AI-based deep learning (DL) models can predict an individual's response to a specific treatment, aiding in personalized therapy selection.[25] AI's ability to handle large datasets makes it suitable for cancer diagnosis and treatment.[26] Furthermore, AI can serve as a tool for early detection and diagnosis of cancers, ultimately improving prognosis and outcomes.[27] Additionally, AI-based radiomic analysis can be applied to medical data, including imaging features, to develop predictive models for noninvasive cancer diagnosis and management.[28]

Types of AI models include:

1. **ML Models:** Such as Decision Trees, Support Vector Machines (SVM), and Random Forest.

2. **DL Models:** Such as Deep Neural Networks (DNN).

3. **Reinforcement Learning Models:** Such as the Q-learning algorithm.

However, there are challenges to address. Substantial obstacles must be overcome to fully leverage the vast amount of data required to train AI models in cancer research and therapeutic applications.[29] This systematic review aims to systematically review the applications of AI techniques in the identification, evaluation, diagnosis, control, and management of occupational cancers.

Methods

Search Strategy and Study Selection

This systematic review was reported in accordance with the PRISMA guidelines. The systematic review was conducted using a comprehensive search strategy for English-language articles, with no time restrictions, by two independent researchers. Data were collected from October 2023 to November 2023 using the Web of Science, Scopus, and PubMed Databases. The search utilized the following keywords based on the PICO principle:

("Job" OR "Work" OR "Occupation" OR "Employ Worker" OR "Technician" OR "Staff" OR "Occupational Exposure") AND ("Cancer" OR "Neoplasm" OR "Malignant" OR "cancer") AND ("ML" OR "AI" OR "DL").

Data Extraction

Two independent investigators reviewed the titles and abstracts of the identified papers to assess their eligibility for the review. The full texts of the remaining articles were then read. Studies investigating the use of an AI technique in the identification, evaluation, diagnosis, control, and management of occupational cancers were included.

The following types of studies were excluded:

- Review studies
- Conference papers
- Animal studies
- Studies on non-occupational cancers
- Studies related to drug prescription and consumption

A third researcher resolved disagreements between the two researchers through discussion. Articles were imported into EndNote software, and duplicate studies were removed before screening according to the selection criteria. A checklist was developed to obtain the following descriptive information: first author's name, year of publication, study design, participants, AI tools, type of cancer, carcinogenic chemicals, and study aims.

Results and Discussion

Search Results and Study Selection

A total of 2426 articles were initially identified. After removing duplicates, 1571 articles were screened based on titles, keywords, and abstracts. Out of these, 1537 articles were excluded, leaving 34 studies for competency evaluation. Following data extraction, 23 studies were included in this review. These studies comprised: 1 case-control study, 8 cross-sectional studies, 5 cohort studies, 4 observational studies, and 5 computational studies. (A diagram of the search results is indicated in Figure 1).

Characteristics of the Included Studies

The included articles cover a range of topics related to occupational exposure to carcinogens across various industries. They explore the application of AI technologies, including ML algorithms, deep learning, predictive models, and other innovative technologies for:

- Assessing carcinogenic effects and health risks associated with occupational hazards.[30-33]
- Predicting and detecting cancers.[34-38]
- Monitoring exposure to toxic substances.
- Evaluating health risks associated with occupational hazards.[39-41]

The studies investigated various types of cancer, including: Skin cancers,[42] Bladder cancers,[36] Lung cancer,[38] Malignant pleural mesothelioma,[43] Endocrine-related cancers (e.g., cell proliferation and thyroid cancer),[40] Colorectal cancer, Prostate cancer, and Gastric cancer, among others.[44]

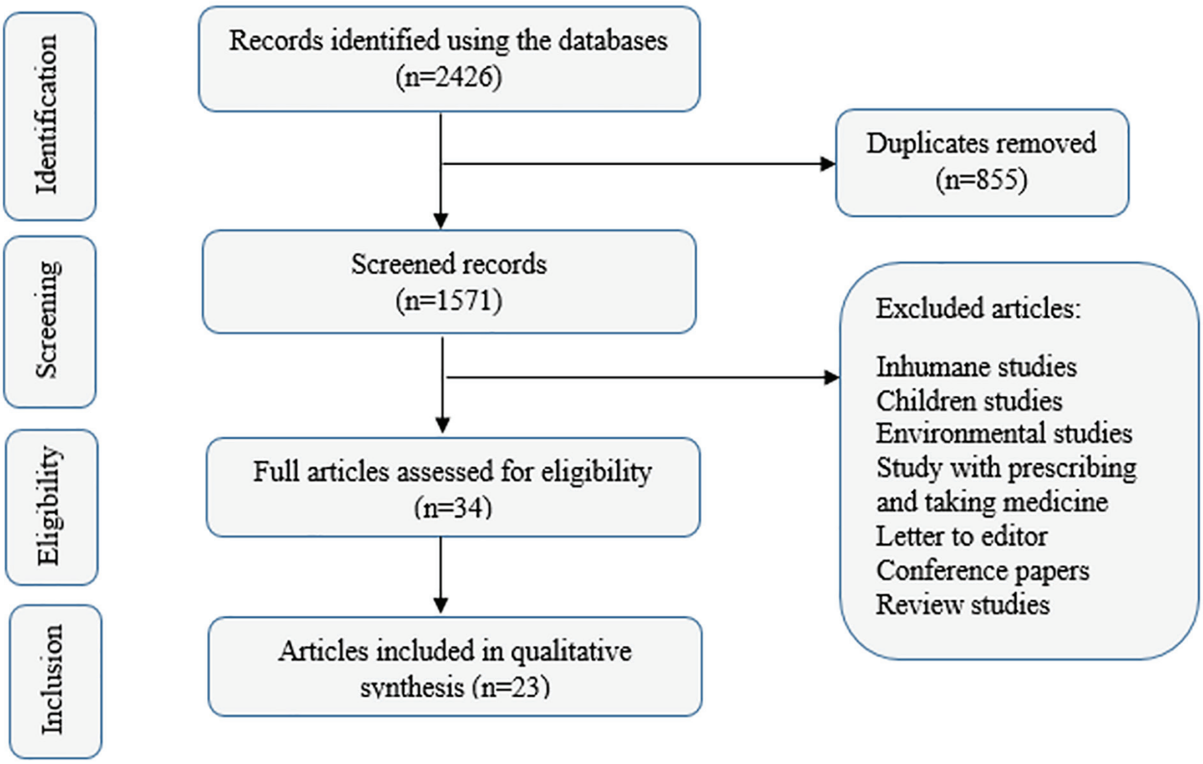

Figure 1: Flowchart of the systematic review.

Additionally, some studies investigated specific potentially carcinogenic compounds, including PAHs,[31] pesticides,[32] benzene, toluene, ethylbenzene, and xylenes (BTEX),[45] asbestos-contaminated minerals,[38] antineoplastic drugs,[33] welding fumes,[44] diesel engine exhaust,[30] and medical radiation.[46] Based on the application of AI, the studies were categorized into the following three groups:

1) Studies assessing the risk of exposure to carcinogenic agents,

2) Studies on the prediction and detection of cancers, and

3) Studies on the diagnosis and clinical evaluation of cancers.

1) Studies Assessing the Risk of Exposure to Carcinogens

These studies, listed in Table 1, utilize AI for more accurate and efficient prediction of subjects' exposures, assessment of relationships between environmental stressors and their effects, and a comprehensive understanding of potential health effects from exposure to carcinogenic agents. One study employed advanced analytical and bioinformatics techniques to examine the effects of DEE exposure on specific adducts in human serum albumin. This approach precisely identified additive changes in antioxidant activity, offering valuable insights into the biological mechanisms underlying the health effects of DEE exposure. The use of ML methods in this context facilitates the identification of important compounds and features, contributing to a comprehensive understanding of DEE's potential health effects.[30]

Decision-making models and neural networks demonstrated potential for predicting personal PAH exposures. The developed models can be utilized in epidemiological studies and health risk assessments related to PAHs exposures.[31]

A computational approach combining text mining and biology was used to investigate the toxicological effects of BPF. This study identified BPF protein interactions, integrated protein pathway information to pinpoint biological pathways associated with BPF targets, and correlated BPF with adverse outcome pathways (AOPs). This established a comprehensive framework linking BPF to an AOP network, including different cancer types. The findings can support surveillance evaluations of BPF and initiate new epidemiological and experimental studies.[40]

AI was employed to customize an integrated wearable device with sensors to record biomarkers such as skin temperature, blood oxygen level, and heart rate, and to detect falls for miners.

Table 1: Cancer risk assessment using artificial intelligence

Authors (year)	Study design	Population/ Occupation	AI tools	The type of cancer/ Carcinogenic compound	The purpose of the study	Reference
Wong et al. (2022)	Cross-sectional study	54 male workers exposed to diesel engine exhaust and 55 unexposed male workers	Machine learning approach Random forest	Lung cancer/ DEE	provide insights into the biological mechanisms and the health effects of DEE exposure	30
Aquilina et al. (2010)	Observational study	100 healthy adults	Neural networks and Decision models	The type of cancer is not mentioned/PAH	Compare different modeling approaches for predicting personal exposure to PAHs	31
Rugard et al. (2020)	Computational analysis study	Industries with Biphenyl F	Text mining and scoring modules, The study developed the AOP-help Finder tool for computational toxicology.	Endocrine-related cancers - Thyroid cancer/ BPF	The study aimed to explore the toxicological effects of Bisphenol F (BPF) using a computational approach that combines text mining and integrative systems biology.	40
Ranjan et al. (2019)	Observational study	Underground coal miner	Data analytics frameworks and algorithms	Lung cancer/ Carcinogenic compound not mention	Discussion of implementing wireless health monitoring systems	38
Rezaali et al. (2021)	Cross-sectional	47 samples in a multi-story parking garage in Qom	WRF	The type of cancer is not mentioned / BTEX	The utility of machine learning in forecasting the health risk assessment of the BTEX emissions	45

DEE: Diesel Exhaust Emissions; BPF: Bisphenol F; BTEX: Benzene, Toluene, Ethylbenzene, Xylene; PAHs: Polycyclic Aromatic Hydrocarbons; WRF: wavelet-based random forest model

This system proved highly useful for improving responses to unforeseen conditions and preventing occupational health hazards. A wireless health monitoring system was proposed, with experimental results on wireless communication in underground coal mines presented to enhance miner health and safety in harsh working environments.[39]

A wavelet-based random forest model was used to estimate BTEX concentrations and assess the health risks associated with their emissions.[45]

2) Studies on the Prediction and Detection of Cancers

These studies highlight AI's potential in predicting cancer risk, carcinogenesis, and factors influencing cancer progression (Table 2). They investigate various aspects, including mutagenicity, pneumoconiosis, risk of nodular thyroid disease, and genotoxicity, using diverse ML models. ML methods show promise in predicting the probability of bladder cancer, offering a more comprehensive and accurate understanding of its risk factors with varying degrees of sensitivity, specificity, and accuracy.[36] A hybrid neural network model has been developed to predict the carcinogenicity of various heterogeneous chemicals. ML algorithms and deep learning approaches can be used for the comprehensive classification and prediction of carcinogenic compounds.[47]

Some studies identified common gene expression changes and pathways affected by welding fumes

Table 2: Cancer prediction and detection by artificial intelligence

Authors (year)	Study design	Population/ Occupation	AI tools	The type of cancer/ carcinogenic compound	The purpose of the study	Reference
Shakhssalim et al. (2023)	Case-control study	692 bladder cancer patients and 692 healthy individuals/ petroleum, paint, and leather exposure	RF-DT, SVM, KNN	Bladder cancer/ petroleum, paint, and leather exposure	Predicting the probability of developing bladder cancer.	36
Limbu et al. (2022)	Computational modeling study	Not mentioned	Hybrid neural network model, HNN-Cancer	The type of cancer not mentioned/ Potential carcinogens of chemicals	Predicting the carcinogenicity Identify potentially carcinogenic chemicals	47
Rana et al. (2020)	Computational analysis study	8 welders who were exposed to welding fumes	ML and bioinformatics models	Colorectal cancer, Prostate cancer, Lung cancer, Gastric cancer/ welding fumes	to identify the gene expression effects of welding fumes that influence the progression of cancer	44
Shahid et al. (2020)	Cross-sectional study	90 radiology and nuclear medicine personnel and 30 radiation-unexposed workers	MLP, LR, and RF	Liver cancer/ Radiation exposure	Predict alterations in liver enzymes	46
Borroni et al. (2023)	Cross-sectional study	Female hospital nurses	RF	The type of cancer is not mentioned/ Cancer risk	Effect of night shift work on serum metabolites	34
Tomasz et al. (2018)	Observational, Prospective, and Cross-sectional study	120 Agricultural workers	ANN, SVM, KNN, DT	The type of cancer not mentioned/ Genotoxic pesticides	Evaluate the genotoxic effects of the pesticide	32
Yang et al. (2019)	Cross-sectional study	140 stone workers	ML algorithms	Mesothelioma / Asbestos-contaminated minerals	Investigate the use of biomarkers and development of a prediction algorithm	35
Zhao et al. (2022)	Retrospective Cohort & Clinical Study	1708 coal miners	XG Boost, LR, GNB, MLP, CNB	Thyroid cancer / Carcinogenic compound not mention	Early risk assessment and targeted treatment strategies	48
Ladeira et al. (2023)	Observational study	Nurses who handled antineoplastic drugs	PCA-LDA model	Not explicitly mentioned	Predict genotoxicity in occupational exposure to antineoplastic drugs	33
Badreau et al. (2023)	Constances Cohort	683 breast cancer survivors were diagnosed in the CONSTANCES cohort.	ML methods	Breast cancer	Identifying the occupational determinants of return to work of breast cancer survivors.	49

RF: Random Forest; DT: Decision Tree; SVM: Support Vector Machine; ML: Machine Learning; MLP: Multilayer Perceptron; ANN: Artificial Neural Network**;** KNN: K Nearest Neighbor. PCA-LDA: Principal Component Analysis- Linear Discriminant Analysis; XGBoost: eXtreme Gradient Boosting; LR: Logistic Regression; GNB: Gaussian Naive Bayes; CNB: Complement Naive Bayes and cancers. AI was used to identify potential new mechanisms by which fume exposure can influence cancer behavior and progression, employing ML and bioinformatics models to pinpoint mediating pathways.[44]

Accurate predictive models of radiation-induced changes in liver enzymes were developed using ML algorithms. These models identify the potential effects of low-dose medical radiation on liver function and predict changes in liver metabolism.[46]

AI, particularly ML algorithms, provided valuable insights into the potential health impacts of night shift work on nurses. Statistical models and ML algorithms were used to analyze the data and comprehensively evaluate the relationship between night shift work and serum metabolite levels in nurses.[34]

AI, especially ML algorithms, facilitates the detection of genotoxic effects from pesticide exposure, smoking, and alcohol consumption on DNA damage. AI also aided in classifying pesticide-exposed populations, showing promise for biomonitoring and disease prevention in agricultural workers. This underscores the importance of monitoring xenobiotic exposure to prevent diseases like oral cancer in this group.[32]

AI has been applied to analyze large datasets from coal miners to predict the risk of thyroid gland diseases. ML models, such as XGBoost, effectively identified important predictor variables and provided insights into the relationship between environmental factors and thyroid dysfunction in this population. AI and ML enable early risk assessment and targeted treatment strategies, potentially improving health outcomes for coal miners.[48]

Table 3: Diagnosis and clinical evaluation of occupational cancer by artificial intelligence

Authors (year)	Study design	Population/ Occupation	AI tools	The type of cancer/ carcinogenic compound	The purpose of the study	Reference
Anderson et al. (2020)	Retrospective Cohort study	The dataset included 123 CT images from 108 MPM patients	DL	Lung cancer/ Asbestos	Accurately measuring Malignant Pleural Mesothelioma (MPM) tumor volume	38
Devnath et al. (2022)	Cross-sectional	The dataset included 153 X-ray images Coal workers	ML classifiers	Lung cancer / Carcinogenic compound not mention	To improve the accuracy of pneumoconiosis detection in chest X-rays	53
Fletcher et al. (2023)	Cross-sectional, Mixed-methods	501 farmers	Use of mobile phone photos and AI	Skin cancer/ Carcinogenic compound not mention	Approaches to detect skin cancer	42
Kidds et al. (2022)	Retrospective Cohort study	183 CT datasets patients with malignant pleural mesothelioma (MPM)	DL-CNN	Lung cancer / Carcinogenic compound not mention	To develop a technical system that could accurately measure MPM tumor volume on CT images	50
Benlala et al. (2022)	Retrospective Cohort	141 retired workers with pleural plaques	DL	Lung cancer/ Asbestos	Validate a novel fully automated quantitative method for Preprocessing evaluation based on DL.	51
Hakkarainen et al. (2023)	Cross-sectional	Bronchoalveolar lavage samples with suspicion of asbestos exposure	DLNN	Lung cancer/ Asbestos	Describe a novel diagnostic method for the detection of asbestos bodies.	43
Zhang et al. (2022)	In silico and in vitro	An investigation of AhR signaling pathway disruption, cellular transcription, and bladder cancer cell metastasis induced by exposure to Mercaptobenzothiazole (MBT) as an industrial chemical	ML	Bladder cancer	Creating molecular insight into bladder cancer risk in exposure to MBT and an effective tool for rapid screening of AhR agonists	54
Gupta et al. (2023)	Computational modeling study	324 patient records on the UCI repository	ML and ANN	Malignant Mesothelioma Lung cancer	The proposed ensemble-based approaches performed well enough to predict MPM diagnosis.	52

DL: Deep Learning; CNN: Convolutional Neural Network; DLNN: Deep Learning Neural Networks; ML: Artificial Neural Network; ANN: Artificial Neural Network

AI was used to develop PCA-LDA (Principal Component Analysis-Linear Discriminant Analysis) models that accurately detect genotoxicity induced by exposure to anticancer drugs. These models demonstrated high accuracy, sensitivity, and predictive features, enabling the simultaneous analysis of 92 samples in an economical and fast manner.[33]

3) Studies on the Diagnosis and Clinical Evaluation of Cancers

These studies investigate the potential of Machine Learning (ML) and Deep Learning (DL) techniques for accurate cancer identification and classification, aiming to aid in early detection and treatment (Table 3). AI serves as a valuable tool for clinical assessment, potentially improving clinical decision-making, enhancing clinical trials, and increasing the accuracy of cancer detection. AI tools may even eliminate the need for a minimal measurable disease threshold, potentially leading to earlier cessation of toxic treatments and reduced costs in clinical trials.

AI offers a fully automated method for measuring MPM tumor volume from CT images, showing potential value for drug trials and routine care in evaluating tumor progression. The algorithm demonstrates accurate segmentation of MPM tumors with high reproducibility relative to manual measurements, highlighting the benefits of AI tools for clinical care and experimental studies. A Convolutional Neural Network (CNN) achieved accurate measurement of MPM tumor volume on CT images without human input, making it a valuable tool for clinical evaluation and research in MPM.[50]

AI-based segmentation of pleural plaques offers several advantages over visual or semi-automated assessments, enabling the segmentation of entire plaques in seconds with near-perfect reproducibility.[51] The detection of asbestos bodies using Deep Learning Neural Networks (DLNN) in bronchoalveolar lavage samples is considered reliable and can be used in the diagnosis of related diseases. Several ML approaches and computational models were compared for diagnosing malignant mesothelioma, with most performing well. Artificial Neural Networks (ANN) combined with a resampling technique achieved the best accuracy.[52]

Several DL models have been proposed for detecting pneumoconiosis on chest X-ray (CXR) images. Currently, the diagnosis and monitoring of pneumoconiosis in coal miners heavily rely on expert radiologists. A robust DL model and ensemble framework achieved 91.50% accuracy in the automatic diagnosis of pneumoconiosis.[53]

Given the limited access to specialists and time/travel constraints for farmers seeking medical help, AI can improve skin cancer diagnosis and facilitate remote diagnoses.[42]

An ML-based model was developed to successfully predict mercaptobenzothiazole analogs, creating an effective tool for rapid screening of Aryl Hydrocarbon agonists.[54]

Conclusion

The reviewed studies consistently highlight the critical importance of early detection, monitoring, and prevention of occupational cancers in workers exposed to carcinogens.

AI plays a pivotal role in this regard by:

• **Predicting Treatment Response:** AI models can predict an individual's response to specific treatments.

• **Identifying Cancer Stages:** AI assists in identifying different stages of cancer.

• **Analyzing and Synthesizing Data:** AI can analyze and synthesize multi-dimensional data to identify complex patterns and forecast outcomes, thereby enhancing shared decision-making in clinical oncology.

The studies demonstrate numerous advantages of using AI in the evaluation of occupational cancers:

1. **Risk Prediction:** AI models are capable of predicting the risk of developing occupational cancers.

2. **Big Data Analysis:** AI excels at identifying patterns and relationships within large datasets that may contribute to the development of occupational cancers.

3. **Early Detection:** AI techniques, particularly image processing, can significantly aid in the early detection of cancers.

4. **Decision Support Systems:** AI can enhance decision support systems for researchers and responsible individuals, contributing to the prevention of occupational cancer and the improvement of workplace safety.

5. **Time and Cost Efficiency:** AI can analyze and categorize complex data in less time and at a lower cost compared to traditional methods.

6. **Facilitating Treatment Selection:** AI assists in making informed decisions regarding treatment selection.

Recommendation for Future Studies

It is recommended that future research endeavors utilize AI for assessing the most common occupational cancers, including lung, bladder, laryngeal, leukemia, and liver cancers.

Authors' Contribution

Zohreh Fazli, Reza Pourbabaki, and Nahid Fazli: Methodology, Investigation, Data curation, Writing Original Draft; Esmael Soleimani: Conceptualization, Supervision, Methodology, Writing - Review and Editing, Project Administration, Funding Acquisition.

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Conflict of Interest

The authors declare no conflict of interest.

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