

Predicting Mesothelioma Using Artificial Intelligence: A Scoping Review of Common Models and Applications

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Abstract

Introduction: Mesothelioma is a type of lung cancer caused by asbestos exposure, and early diagnosis is crucial for improving survival chances. Artificial intelligence offers a potential solution for the timely diagnosis and staging of the disease. This study aims to review the latest research conducted in artificial intelligence applications to predict mesothelioma.

Methods: Until April 24, 2023, PubMed, Scopus, and Web of Science databases were searched comprehensively for articles on artificial intelligence in mesothelioma management. The data was gathered using a standardized extraction form, and the findings were reported in figures and tables.

Results: One hundred and seventy-three articles were identified from database searches, which were then reduced to 151 after eliminating duplicates. Finally, 19 articles were selected for inclusion in our study. The applications of artificial intelligence in these articles primarily focused on tumor diagnosis and classification (73.69%), followed by prevention and prognosis (21.05%) and tumor volumetric measurement of malignant pleural mesothelioma (5.26%). The most frequently used AI models include types of neural networks (NN), decision trees (DT), random forests (RF), logistic regression (LogR), Naïve Bayes (NB), and support vector machines (SVM). SVM, DT, and RF emerged as prominent models, achieving high accuracies ranging from 78.3% to 99.97%. Genetic algorithms, correlation-based algorithms, and Neural Networks were employed for risk factor identification and feature selection.

Conclusion: Artificial intelligence, particularly machine learning models such as neural networks, decision trees, support vector machines, and random forests, holds promise in predicting and managing mesothelioma, potentially enhancing early detection and improving patient outcomes.

Keywords

mesothelioma, lung neoplasms, artificial intelligence, machine learning, support vector machine, logistic regression

Received: 8 January 2025; revised: 27 March 2025; accepted: 16 April 2025

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Introduction

Mesothelioma is a rare and malignant cancer that mainly originates from mesothelial cells,¹ with around 80% of cases globally attributed to asbestos exposure.² Due to varying levels of asbestos exposure, mesothelioma incidence significantly fluctuates worldwide. By 2025, mesothelioma in Western countries is predicted to increase by 5 to 10% annually.³ Mesothelioma incidence was estimated at 1 to 2 million in states with low asbestos exposure and 10 to 15 million in states with high asbestos exposure.⁴ Furthermore, Australia has one of the highest age-standardized rates globally, primarily due to its extensive asbestos industry and long-standing mining operations.⁵

Mesothelioma progresses very slowly; sometimes, it takes more than ten years from the onset of cancer cells to the manifestation of symptoms. Nevertheless, unfortunately, when the symptoms appear, the disease has significantly progressed.⁶ Moreover, diagnosing mesothelioma based on its symptoms and signs can be challenging, as many other diseases exhibit similar symptoms. However, one of the specific characteristics of mesothelioma symptoms is that they persist for more than six months. Mesothelioma patients usually present with symptoms of shortness of breath, often accompanied by chest pain, cough, and systemic disease symptoms such as weakness, atrophy, fatigue, and anorexia.¹

Additionally, due to the hidden signs and non-specific symptoms of mesothelioma (such as cough, chest pain, and shortness of breath), many patients are diagnosed in their advanced stages. Medical imaging is essential in diagnosing, staging, and managing mesothelioma patients.⁷ Multimodal imaging can provide valuable information during various diagnosis, treatment, and follow-up phases. Common approaches to multimodal imaging include Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET).⁸ However, these traditional methods are expensive, dangerous, and painful.⁹ In addition, medical imaging requires enormous infrastructure, facilities, and skilled personnel, which makes it costly, particularly in developing countries. Since, after diagnosis, the probability of patient survival until one year later is less than 50%, the need for innovative approaches to improve the management process of this cancer seems necessary.¹⁰

Recent advancements in artificial intelligence (AI) have significantly enhanced disease prediction and diagnosis across various medical fields, including oncology.^{11,12} AI, a cutting-edge field in computer science, seeks to enhance various technologies, especially in medicine, by equipping computers and machines with intelligence for improved disease diagnosis and treatment success rates.¹³ AI-driven models have been successfully applied to lung and colon cancer classification using secure and transparent frameworks, such as blockchain and Microsoft Azure, ensuring reliability in medical decision-making.¹⁴ Additionally, feature reduction techniques have been explored to improve hepatocellular carcinoma prediction, optimizing model performance through machine learning algorithms.¹⁵

AI has also been instrumental in identifying synergistic drug combinations for FDA-approved cancer treatments, facilitating

more effective therapeutic strategies.¹⁶ In medical imaging, new edge detection techniques based on Shannon entropy have enhanced feature extraction in grayscale images, improving diagnostic accuracy.¹⁷ Given these advancements, AI-based approaches hold great potential for mesothelioma prediction, where precise diagnosis and early detection remain critical challenges. This study aims to comprehensively review common AI models and their applications in mesothelioma disease prediction by leveraging insights from these related works. Choudhury et al¹⁸ suggested using AI models to develop the optimal system for early diagnosis and prognosis of malignant pleural mesothelioma (MPM). In a 2020 study, Alam et al¹⁹ used association rule extraction to identify prognostic factors of malignant mesothelioma. They concluded that the proposed algorithm successfully predicted the disease's risk factors. Courtiol et al,²⁰ showed that deep learning, through models such as MesoNet, improves mesothelioma outcome prediction by analyzing whole-slide images without relying on pathologist annotations. MesoNet offers higher accuracy than traditional methods and identifies key histological regions linked to patient survival, revealing potential new biomarkers for better diagnosis and treatment.

To our knowledge, no review has been conducted on predicting mesothelioma disease using AI techniques, and only a few original studies have been undertaken on mesothelioma diagnosis.^{21–23} Therefore, this study aims to review the current state of AI technologies, such as machine learning and deep learning, in predicting mesothelioma disease.

Materials and Methods

Study Design

This scoping review is reported according to the PRISMA extension for scoping reviews (PRISMA-ScR) checklist.²⁴

Search Strategy

This scoping review aimed to explore the application of AI in mesothelioma prediction. Our investigation encompassed articles published up to April 24, 2023, with no temporal restrictions. We reviewed the literature using the PubMed, Scopus, and Web of Science databases to identify relevant studies. The search strategy involved utilizing Medical Subject Headings (MeSH) terms, keywords, and synonyms related to concepts such as mesothelioma and artificial intelligence, as detailed in Table 1.

Inclusion and Exclusion Criteria

The inclusion criteria encompassed original and English-language articles investigating the use of AI and its models in managing mesothelioma prevention, diagnosis, and treatment. Conversely, the exclusion criteria included studies that did not align with the study's objectives, those published in non-English language, review articles, short communications, conference abstracts, editorials, and letters to the editor.

Table 1. Keywords Used in the Search Strategy.

#1	“Mesothelioma” * OR “Malignant Mesothelioma” OR “Malignant Pleural Mesothelioma”
#2	“Decision support techniques” OR “Data mining” OR “Artificial intelligence” * OR “Machine Intelligence”
Search	#1 AND #2

*Note: MeSH terms are written in bold.

Data Extraction Process

Initially, the titles and abstracts of the articles were independently evaluated by three researchers (EE, MR, and MSKH). Subsequently, relevant data from the selected articles were meticulously extracted using a researcher-designed form, carefully crafted to align with the study’s objectives. This form collected essential information, including the article’s title, publication year, and country; the first author’s name; the study’s aim; the type and number of algorithms used; the application of AI in disease management; and the key findings derived from the research.

Risk of Bias and Quality Assessment

The assessment of bias risk in the studies included in this scoping review was meticulously conducted by three independent evaluators (MR, AG, and AS), employing the Prediction Model Study Risk of Bias Assessment Tool (PROBAST). PROBAST, specifically developed for application in systematic reviews focusing on prediction model studies, is a comprehensive quality assessment instrument. It is structured around four critical domains: participant selection, predictors, outcome, and analysis, each crucial for ensuring the reliability and validity of the studies under review. Moreover, the tool includes 20 detailed signaling questions that guide the appraisers in thoroughly examining potential biases within each domain.²⁵

Synthesis of Results

To provide a structured overview of the reviewed studies, we categorized them based on key attributes, including publication year, country, algorithm type, AI applications, AI models used in mesothelioma prediction, and the contributions and limitations of each study. This systematic categorization enhances clarity, facilitates a deeper understanding of relationships among studies, and supports a comprehensive synthesis of existing knowledge. A descriptive analysis incorporating frequency and percentage parameters was also performed based on the study variables and presented through tables and figures.

Results

After searching the databases, we identified 173 relevant articles. Subsequently, we removed duplicates, narrowing the total to 151 articles. Finally, we examined the full texts of 36 articles, of which 19 were selected for the current study (Figure 1).

Main Characteristics of the Selected Studies

Table 2 offers an overview of the studies included.

The Geographical and Temporal Distribution of Included Studies

The highest frequency of articles was related to the USA (n = 5, 26.32%),^{18,27,28,32,35} followed by China (n = 4, 21.05%)^{21,34,37,39} (Figure 2). The year of publication of articles varied from 2015 to 2022; no relevant articles were found that were published in 2017. The most frequent publication of articles was in 2021 (n = 7, 36.86%),^{18,19,22,33–36} followed by 2022^{37–40} and 2018^{21,28–30} (n = 4, 21.05%) (Figure 3).

AI Application for Mesothelioma

Figure 4 illustrates that the most common application of AI in mesothelioma management was tumor diagnosis and classification. As shown in this figure, AI has been used for tumor diagnosis and classification (n = 14, 73.69%),^{18,19,21,22,26–32,34,36,39} prevention and prognosis (n = 4, 21.05%),^{33,35,37,38} and tumor volumetric measurement of MPM (n = 1, 5.26%).⁴⁰

AI Models Used in the Prediction of Mesothelioma

According to Figure 5, the most commonly used AI models include various neural networks (NN) (n = 9), decision trees (DT) and random forests (RF) (n = 8), statistical models such as logistic regression (LogR) and Naïve Bayes (NB) (n = 7), and support vector machines (SVM) (n = 4). Furthermore, GAs, correlation-based algorithms, and NN were used to determine risk factors and feature selection.

Comparison of Included Studies

The comparison of various AI models for diagnosing mesothelioma reveals significant advancements in accuracy and efficacy across different studies. For instance, Mukherjee²⁹ utilized SVM on a dataset of 324 patients, achieving an impressive accuracy of 99.87% through metrics such as sensitivity and AUC. Similarly, Hu and Yu²¹ employed a SSAE with 97 patients and 227 healthy controls, achieving 100% accuracy. Win et al³⁰ demonstrated the effectiveness of multiple models, including DT and RF, on the same patient cohort, securing a perfect accuracy rate. In contrast, Chicco and Rovelli³¹ reported a lower accuracy of 75% using RF on clinical data from 192 patients. Choudhury et al¹⁸ utilized AdaBoost on 324 patients, achieving an accuracy of 71.29%. Notably, this study reported the lowest accuracy among the reviewed studies. These studies collectively highlight the potential of machine learning techniques, particularly deep learning models, to enhance diagnostic performance, identify critical biomarkers, and improve patient outcomes in mesothelioma detection (Table 3).

Moreover, Table 3 reveals that in disease classification using CT scans, the most widely used models and algorithms were

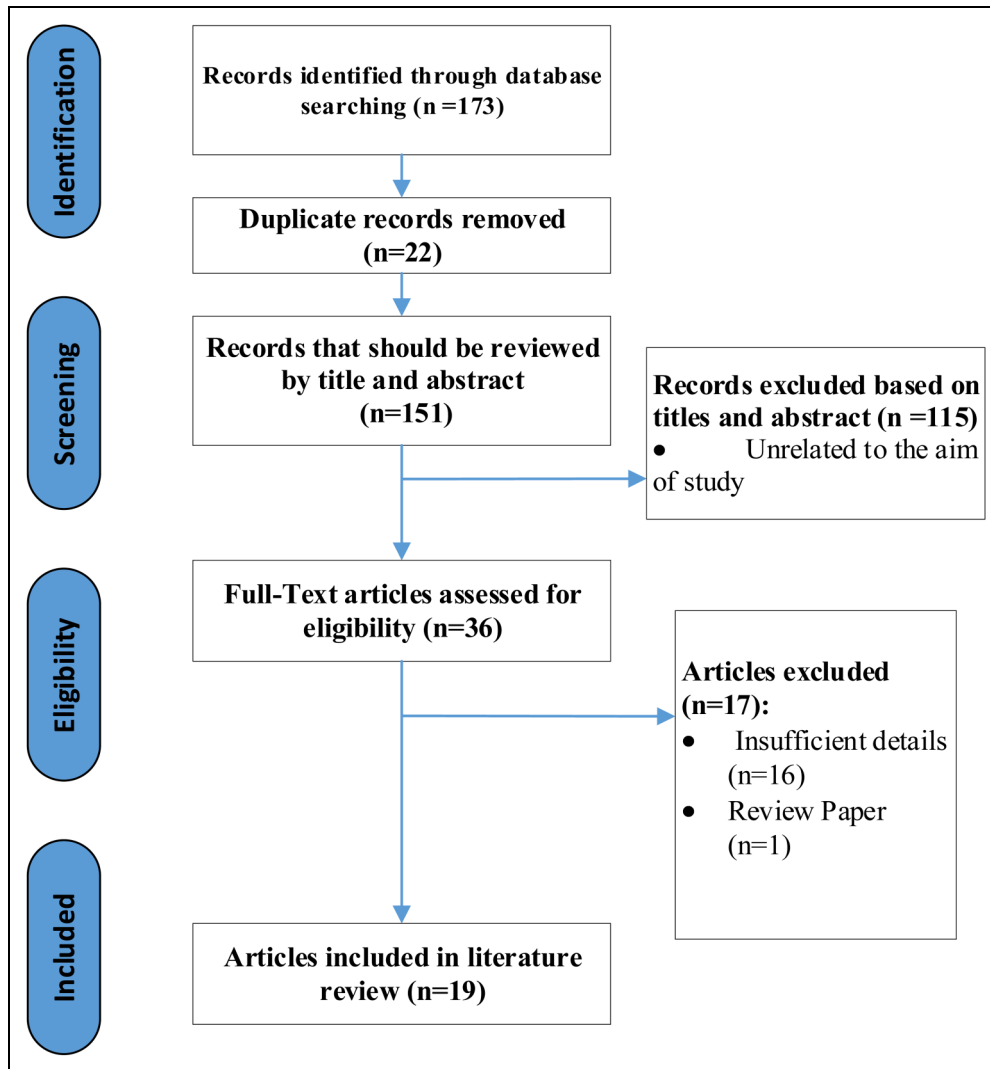


Figure 1. PRISMA Extension for ScR Flow Diagram of the Screening Process.

DCNNs, and these models were mainly evaluated using the Bland-Altman and DSC methods.^{28,32,40} RF and SVM were the most widely used machine learning models and algorithms for disease diagnosis using clinical data and vital biomarkers,^{29–31} outperforming other methods and algorithms. Furthermore, the RF was the most widely used model in disease prediction and prognosis using gene expression data and clinical parameters.^{34,37}

Comparison of Accuracies Obtained from Different AI Models

Table 4 presents the accuracy of various models used to diagnose and classify mesothelioma. Among the most used models in this field, the SVM model was used four times with an accuracy of 99.97%; the RF model was used four times with an accuracy of 93.75%; five times the DT model with an accuracy of 88.36%; and three times the NB model with an accuracy of 78.3%. In addition, in the two studies that used the LogR model,

the accuracy was 100%. In the two articles that used the KNN model, the accuracy was 91.68%.

Discussion

This study investigated the state of AI research on mesothelioma prediction. Researchers have utilized AI in tumor diagnosis, classification, prevention, prognosis, and mesothelioma treatment. The SVM model achieved an impressive average accuracy of 99.97%. In comparison, the RF model had an average accuracy of 93.75%, while the DT model averaged 88.36%. Additionally, the NB model recorded an average accuracy of 78.3%. Notably, the two studies that employed the LogR model both reported an average accuracy of 100%.

Furthermore, the average accuracy in the two articles that utilized the KNN model was 91.68%. The most common uses of AI applications for mesothelioma were tumor diagnosis and classification, prevention and prognosis, and tumor

Table 2. The Main Characteristics of Included Studies.

Authors	Year	Country	Aim of the study	Algorithm Type	Number of algorithms	AI application	Main Results
Parodi et al ²⁶	2015	Italy	Assessment of LLM classification accuracy and comparison with three alternative methods (Decision Tree (DT), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN)) using leave-one-out cross-validation	Logic Learning Machine (LLM)	1	Diagnosis	_ The LLM model outperformed other models _ Provide helpful classification rules
Podolsky et al ²⁷	2016	USA	Assessing the efficiency of machine learning (ML) algorithms in categorizing lung cancer using gene expression levels	KNN, Naive Bayes (NB), Support Vector Machine (SVM), C4.5 DT	4	Tumor Segmentation, Diagnosis	SVM achieved better accuracy than other models in classification
Gudmundsson et al ²⁸	2018	USA	Exploring the use of U-Net deep CNN architecture in deep convolutional neural networks (DCNNs) for the automated segmentation of MPM tumors in CT scan images	DCNN (U-Net architecture)	1	Tumor Segmentation	The DCNN-based approach yielded notably higher dice similarity coefficient (DSC) scores
Mukherjee ²⁹	2018	India	_ Discovering the optimal classifier _ Identifying crucial input variables for the detection of malignant mesothelioma disease	SVM, Multi-Layer Perceptron (MLP) neural network	2	Diagnosis	SVM obtained better classification accuracy
Hu and Yu ²¹	2018	China	Creating a deep learning approach to diagnose malignant mesothelioma automatically	Back Propagation (BP), Extreme Learning Machine (ELM), Stacked Sparse Auto-Encoders (SSAE), Genetic algorithm (GA), Relief-F	5	Diagnosis	SSAE and GA + SSAE models obtained the best classification accuracy
Win et al ³⁰	2018	Japan	Performance assessment of different supervised ML models for the detection of malignant mesothelioma	Linear Discriminant Analysis (LDA), NB, SVM, DT, KNN, Logistic Regression (LogR), Random Forest (RF)	7	Tumor Segmentation, Diagnosis	The SVM, DT, LogR, and RF techniques obtained 100% accuracy, sensitivity, and specificity in diagnosing the disease
Chicco and Rovelli ³¹	2019	Canada	Predicting the diagnosis and selecting features in the medical records of a patient with mesothelioma using computational models	Probabilistic Neural Network (PNN), perceptron-based NN, DT, RF, One Rule	5	Diagnosis	RFs outperformed the other models
Gudmundsson et al ³²	2020	USA	Exploring the application of deep learning in segmenting MPM tumors in CT scans	DCNN	1	Tumor Segmentation	The suggested approach obtained an average DSC of 0.690 in the tumor and effusion test set
Latif et al ³³	2021	Pakistan	Identification of factors that increase the risk of developing malignant mesothelioma	Apriori algorithm	1	Prevention	The algorithm has predicted the risk factors associated with malignant mesothelioma
Li et al ³⁴	2021	China	Developing a diagnostic approach involving the use of plasma-based metabolomics combined with ML algorithms to detect malignant mesothelioma	RF	1	Diagnosis	The RF algorithm achieved 100% specificity
Kirajima et al ²²	2021	Japan	Analysis of AI deep learning model using 3D DCNN for differentiating MPM from benign pleural disease based on FDG-PET/CT results	VGG12, 3D DCNN	2	Diagnosis	PET/CT, SUVmax, gender, and age combination outperformed other protocols with an accuracy of 0.82
Zauderer et al ³⁵	2021	USA	Development and validation of OncoCast MPM	OncoCast algorithm	1	Prognosis	OncoCast-MPM provided precise risk assessment scores for patients with MPM
Naso et al ³⁶	2021	Canada	_ Investigating whether deep learning can accurately distinguish between benign and malignant spindle cell mesothelial proliferation _ Analyzing the features used for prediction by a trained NN	Convolutional Neural Network (CNN) (called "SpindleMesoNET")	1	Diagnosis	SpindleMesoNET accurately distinguishes sarcomatoid mesothelioma from benign spindle cell mesothelioma

(continued)

Table 2. Continued.

Authors	Year	Country	Aim of the study	Algorithm Type	Number of algorithms	AI application	Main Results
Alam et al ¹⁹	2021	Australia	Examining prognostic factors in malignant mesothelioma across clinical, radiological, and histopathological aspects	Growth algorithm, Apriori model	2	Diagnosis	Improved early detection and more effective management of malignant mesothelioma
Choudhury et al ¹⁸	2021	USA	Predicting mesothelioma cancer using supervised ML	Stochastic Gradient Descent (SGD), Adaptive Boosting M1, Kernel Logistic Regression (KLR), MLP, Voted Perceptron (VP), Hoeffding Tree, Clojure Classifier (CC), Primal Estimated sub-Gradient Solver for SVM	8	Diagnosis	- In Phase I, SGD, Adaptive Boosting (AdaBoost), M1, KLR, MLP, and Very Fast Decision Trees (VFDT) achieved optimal results with 100% classification accuracy - AdaBoost performed the best in Phase 2, achieving a classification accuracy of 71.29%
Xiao et al ³⁷	2022	China	Investigating the link between glycolytic pathway genes and the prognosis of MPM through the construction of prognostic risk models using bioinformatics and ML	SVM, RF	2	Prognosis	A risk model based on six glycolytic genes (with Area Under Curve (AUC) = 0.830) was developed to predict the prognosis of MPM patients
Massafra et al ³⁸	2022	Italy	Identifying clinical characteristics of advanced pleural mesothelioma patients and exploring the potential link between prognosis and treatment results	The sequential forward selection algorithm	1	Prognosis	A positive correlation exists between advanced pleural mesothelioma patients and their response to innovative therapies
Li et al ³⁹	2022	China	Developing a ML model to differentiate MPM from other malignant pleural diseases using early CT signs	multivariate LogR	1	Diagnosis	The proposed model can differentiate between MPM and malignant pleural disease, serving as a diagnostic tool
Kidd et al ⁴⁰	2022	Scotland	Comparison of tumor volume responses using manual human assessment and fully automated AI algorithm on CT scans of 30 patients before and after chemotherapy	CNN	1	Tumor volumetric measurement of MPM	Agreement between human and AI volume responses was observed in 20 out of 30 cases (67%) with a kappa value of 0.439 (0.178 to 0.700)

volumetric measurement of MPM. These models and applications are discussed below.

Application of AI in Tumor Classification and Diagnosis

In a study by Koul et al,⁴¹ AI methods have shown superior predictive abilities for airway disorders compared to pulmonologists. They suggested that linear regression, SVM, RF, DT, NB, LogR, and fuzzy particles, the most commonly used machine learning models in this field, can identify airway conditions like pulmonary edema, COVID-19, lung cancer, asthma, and mesothelioma. The results of this study align with our findings.

Win et al³⁰ conducted a study that utilized different ML techniques under the proper supervision of LDA, NB, SVM, KNN, DT, LogR, and RF to diagnose malignant mesothelioma. In this study, the performance of these techniques was evaluated in diagnosing mesothelioma, and the researchers found that RF, LogR, SVM, and DT models can diagnose the disease with an accuracy, sensitivity, and specificity of 100%. These models can be used as decision support systems for physicians to diagnose malignant mesothelioma. In Khan et al's study,⁴² the efficiency of the SVM model for mesothelioma diagnosis was 98%. In addition, the study of Mukherjee et al,²⁹ which was conducted to diagnose malignant mesothelioma using data mining techniques, showed that the SVM algorithm achieves the best classification with an accuracy of 99.87% through ten cross-validation in 5 times runs compared to the MLP neural network, which has been obtained with 99.56% classification accuracy. In another study, Li et al³⁴ conducted a study to improve the prognosis of malignant mesothelioma by optimizing clinical diagnosis. This study employed a combined untargeted metabolomic strategy and ML models to investigate the differential metabolites in plasma samples from malignant mesothelioma patients compared to age- and sex-matched healthy controls (HCs). Both metabolite-based ROC models and multiple metabolite-based RF models distinguished between malignant mesothelioma and HC to better clarify the diagnostic significance of these metabolites. They found that the RF algorithm used in this study could diagnose malignant mesothelioma with 100% sensitivity. In addition, the combination of metabolomics and ML revealed outstanding diagnostic value for malignant mesothelioma and indicated a new and effective strategy for diagnosing this disease.

Chicco et al,³¹ in a study with the aim of computational prediction of diagnosis and feature selection in the health records of patients with mesothelioma, analyzed the health records of 324 Turkish patients with symptoms of mesothelioma who were previously exposed to asbestos and showed symptoms consistent with mesothelioma. They compared PNNs, RFs, and DTs to predict the diagnosis of patient records. This study demonstrated that ML can predict the diagnosis of mesothelioma patients with high accuracy, sensitivity, and specificity in a few minutes. In addition, RF can efficiently identify the most critical features of this clinical dataset (lung side and platelet count) in just a few seconds. Pleural plaques and blood

platelets are significant in diagnosing mesothelioma, so doctors should concentrate on these two features when reviewing the records of patients with mesothelioma symptoms. As AI techniques evolve, there is a growing trend towards combining different AI models to improve classification accuracy, such as hybrid models combining deep learning and traditional machine learning algorithms. Furthermore, a new classification method based on histological features and imaging data could emerge, potentially providing more personalized predictions for patients. These findings emphasize the transformative potential of AI in healthcare, particularly in mesothelioma diagnosis, and underscore the significance of leveraging advanced computational techniques for improved patient outcomes.

Application of AI in Tumor Volumetric Measurement

Tumor volume is relevant for prognostic assessment, treatment response assessment, and MPM staging. In a study, Koul et al⁴¹ stated that CNNs are often used as deep-learning models for disease diagnosis and tumor volume assessment. Two of the 19 studies we reviewed also identified this issue. In another study, Gudmundsson et al³² implemented a deep learning-based method for automatically segmenting mesothelioma tumors in CT scans to improve segmentation performance in scans of patients who presented with pleural effusion. Deep CNNs were developed using a two-dimensional U-Net architecture to segment left and right hemithorax tumors. These networks utilized layers that were pre-trained on the ImageNet dataset. The training was conducted using a dataset of 5230 axial sections taken from 154 CT scans of 126 mesothelioma patients. This study demonstrated improved segmentation performance for deep learning-based mesothelioma segmentation using an extensive validation method and a more diverse set of training segments representing both tumor and pleural effusion. They agreed strongly with supervised tumor lines regarding segmentation overlap and the average distance between computerized and manual tumor lines.

Kidd et al⁴⁰ measured and compared the volumetric responses of the primary tumor using a fully automatic algorithm of AI, manually by humans, and on CT scans of 30 patients before and after the chemotherapy according to modified RECIST criteria by an MPM-certified radiologist. In a multicenter retrospective cohort study, 183 CT datasets were divided into training internal validation and external validation. Comprehensive manual annotations were utilized to train the CNN using a two-dimensional U-Net architecture. CNN's performance was assessed using correlation, Bland-Altman analysis, and Dice agreement. These results were compared with the mRecist using Cohen's Kappa. Survival was also evaluated using the Kaplan-Meier method, as a result of which human and AI volumetric responses agreed in 30/20 (67%) validation cases, $\kappa = 0.439$ (0.178 to 0.700). AI and mRecist agreed in 16/30 (55%) validation cases, $\kappa = 0.284$ (0.026 to 0.543). A higher baseline tumor volume was associated with shorter survival. In the independent validation set comprising 60 CT

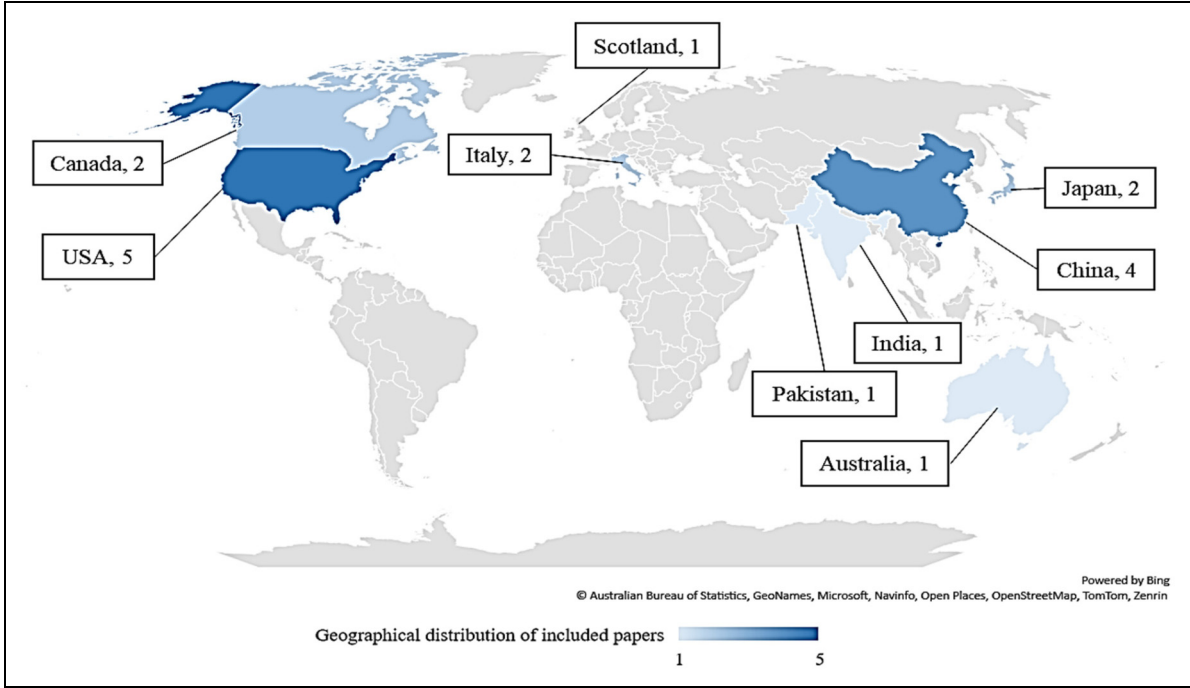


Figure 2. The Geographical Distribution of Included Studies.

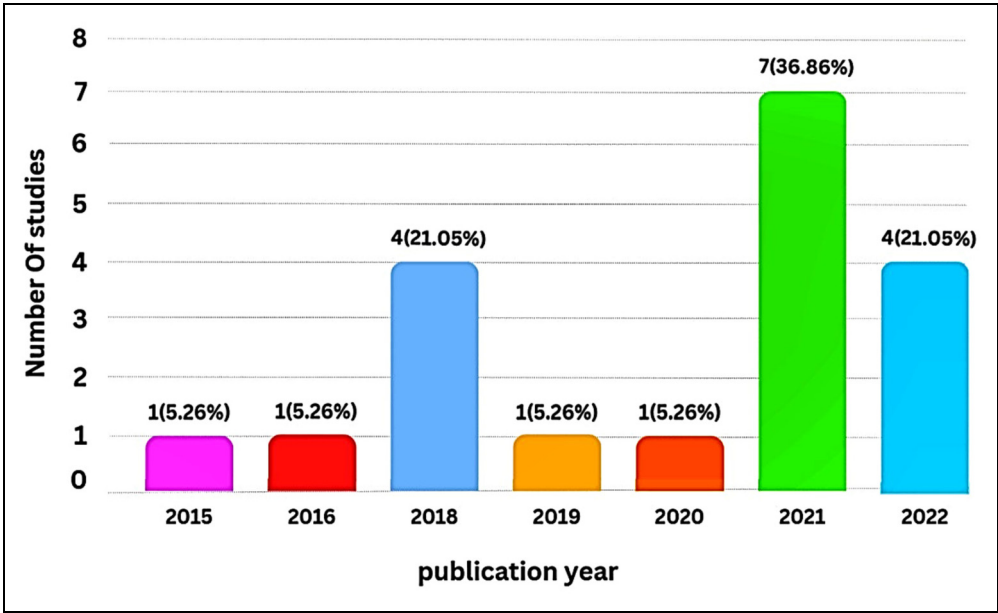


Figure 3. Temporal Distribution of Included Studies.

datasets, the mean difference between tumor volumes measured by AI and humans was not significantly different from zero.

The application of AI in tumor volumetric measurement, particularly in the context of MPM, holds significant promise for enhancing diagnostic accuracy and treatment assessment. Studies such as those by Koul et al,⁴¹ Gudmundsson et al,³² and Kidd et al⁴⁰ demonstrate the efficacy of deep learning models, particularly CNNs, in accurately segmenting tumors and measuring their volumes from CT scans. A notable trend in

AI for tumor volumetric measurement is the increased focus on multi-modality imaging, where AI models combine CT and MRI scans to enhance measurement accuracy. These advancements streamline the assessment process and offer insights into treatment response and prognostic evaluation. Moreover, the agreement between AI-generated volumetric measurements and manually obtained ones highlights the reliability and potential clinical utility of AI-driven approaches in oncology. As a result, AI could lead to the development of real-

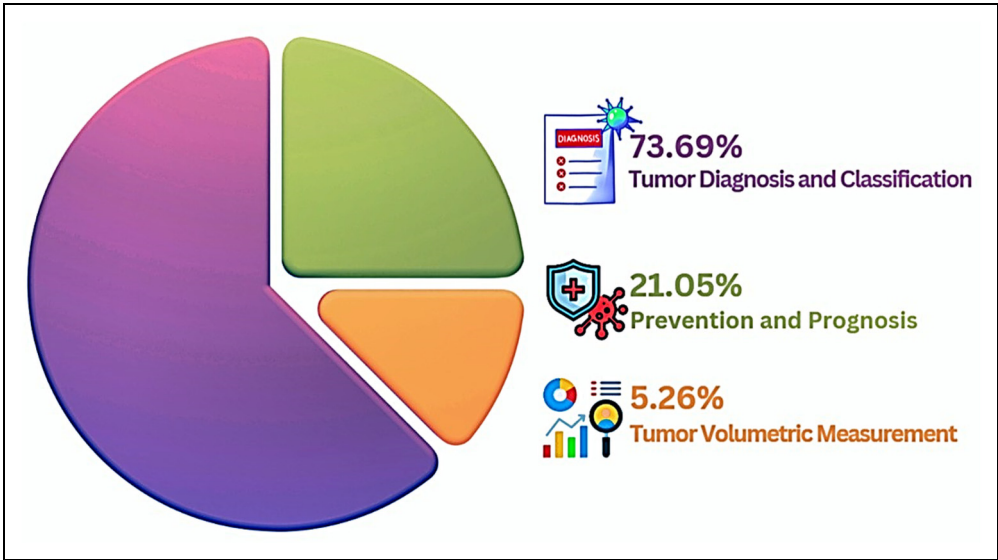


Figure 4. AI Application for Mesothelioma.

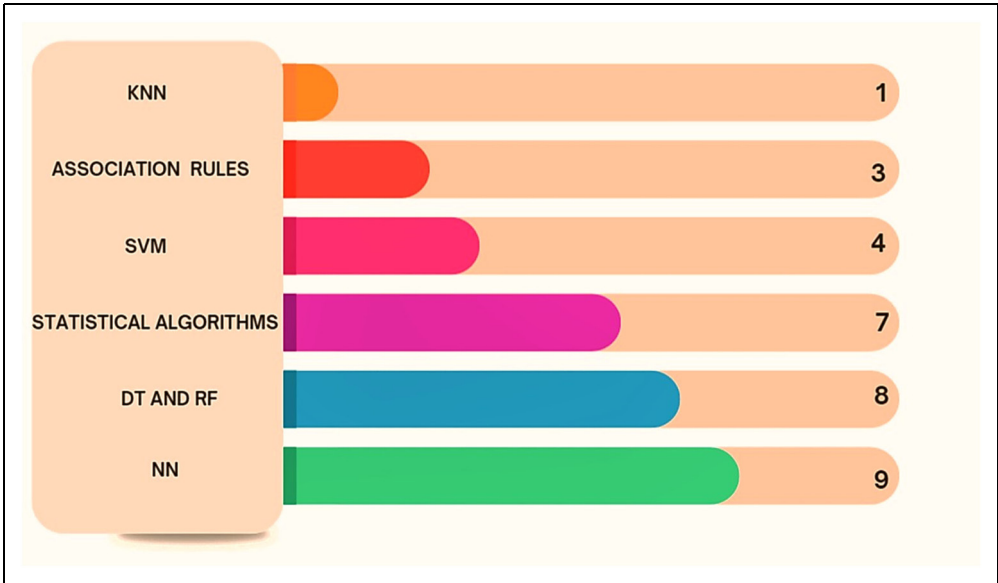


Figure 5. Frequency of Different AI Models Used in the Management of Mesothelioma.

time volumetric monitoring systems that can assist clinicians in making timely treatment decisions. As research in this field continues to evolve, integrating AI into routine clinical practice can significantly improve patient care and outcomes in managing MPM and other cancers.

Application of AI in Disease Prevention and Prognosis

Choudhury et al¹⁸ illustrated that the diagnostic approach (including biopsy and imaging findings), C-reactive protein, duration of symptoms, gender, pleural protein, platelet count, and pleural protein are crucial for diagnosing pleural mesothelioma. However, effective diagnostic procedures such as

thoracoscopy, laparoscopy, thoracotomy, laparotomy, and imaging tests (CT scan and MRI) are expensive. This study recommends AdaBoost models for pleural mesothelioma prognosis. Alam et al¹⁹ proposed a new framework for identifying prognostic indicators using non-invasive and cost-effective methods based on different techniques. It assists doctors, patients, physicians, and other healthcare professionals in early diagnosis and better treatment of malignant mesothelioma, considering critical prognostic factors. In a study, Latif et al³³ identified the risk factors associated with malignant mesothelioma. They found that the algorithm obtained 75% support, and the proposed algorithm successfully predicted the risk factors for malignant mesothelioma. LLM is an innovative method for

Table 3. Comparison of Included Studies.

Authors	Dataset	Application	Data type	Best proposed model	Accuracy of the proposed model	Model evaluation methods
Mukherjee ²⁹	324 patients	Diagnosis	Biomarkers	SVM	99.87	Sensitivity, Accuracy, AUC, F-score
Hu and Yu ²¹	97 patients with MM and 227 healthy controls	Diagnosis	Biomarkers	SSAE	100	Sensitivity, Accuracy, AUC, F-score
Win et al ³⁰	324 patients	Diagnosis	Biomarkers	DT, SVM, LogR, and RF	100	Sensitivity, Specificity, Accuracy, Recall, F-score, Precision
Chicco and Rovelli ³¹	192 patients	Diagnosis	Clinical Data, Biomarkers	RF	75	MCC, Sensitivity, Specificity, Accuracy, F-score
Choudhury et al ¹⁸	324 patients	Diagnosis, Prognosis	Clinical Data, Biomarkers	AdaBoost	71.29	Sensitivity, Accuracy, Specificity, AUC
Li et al ³⁹	297 patients	Diagnosis	Clinical data and CT signs	multivariate LogR	Not Mentioned	AUC, F-score
Kitajima et al ²²	Training: 525 patients Test: 176 patients	Diagnosis	PET/CT scan, clinical features	3D DCNN	82.4	Sensitivity, Accuracy, Specificity, AUC
Gudmundsson et al ²⁸	Training: 2663 CT scan sections from 76 scans from 61 patients Test: 2567 CT scan sections from 78 scans from 65 patients	Classification	CT scan	DCNN (U-Net)	Not Mentioned	DSC
Gudmundsson et al ³²	Training: 154 CT scans of 126 patients Test: 224 CT scans of 77 patients	Classification	CT scan	CNN	Not Mentioned	Bland-Altman Method, DSC
Kidd et al ⁴⁰	Training: 108 patients Test: 30 patients	Classification and tumor volume measurement	Tumor morphological features, CT scan	DCNN (U-Net)	Not Mentioned	Bland-Altman Method, DSC
Li et al ³⁴	25 patients with MM and 32 healthy controls	Prediction	Plasma samples	RF	100	Accuracy, AUC
Zauderer et al ³⁵	194 patients	Prognosis, Prediction	Clinical, pathological and genomic data	Oncocast-MPM	Not Mentioned	OncoPrint charts
Xiao et al ³⁷	84 patients	Prognosis	Gene expression data	RF	Not Mentioned	AUC
Massafra et al ³⁸	46 patients	Prediction	Clinical Data, Biomarkers	The sequential forward selection algorithm	75	Sensitivity, Accuracy, Specificity, AUC
Latif et al ³³	234 participants (96 patients and 128 healthy controls)	Discovering the association rules of risk factors	Clinical Data	Apriori	Not Mentioned	Support, Confidence, and Lift
Alam et al ¹⁹	96 patients with MM and 228 healthy controls	Discovering the association rules of risk factors	Critical risk factors	Apriori	Not Mentioned	Support, Confidence, and Lift

Table 4. Comparison of Accuracies Obtained from Different AI Models.

First author	Model type	Model accuracy (%)
Chicco ³¹	RF	75
	DT	69
	MLP	52
	PNN	57
Mukherjee ²⁹	SVM	99.87
	MPE	99.56
	Artificial Immune Systems (AIS)	97.7
	PNN	96.3
	MLP	94.41
	NN	91.3
	Learning Vector Quantization (LVQ)	91.14
Li ³⁴	RF	100
	ELM	93.9
	BP	94.9
	GA + BP	98
	GA + ELM	98
	SSAE	100
	GA + SSAE	100
Li ³⁹	Multivariate LogR	83
Kitajima ²²	3D DCNN	77.3%
Naso ³⁶	SpindleMesoNET	92.5%
Parodi ²⁶	LLM	77.5
	DT	72.8
	ANN	63.9
	LLM	54.4
Win ³⁰	LDA	61.73
	NB	67.90
	KNN	91.36
	SVM	100
	DT	100
	LogR	100
	RF	100

analyzing supervised data to build classifiers with understandable rules, including simple conditions on their priors. It efficiently implements the switching NN model, achieving excellent classification accuracy while decreasing computational demand.

Parodi et al,²⁶ in their study aimed at the differential diagnosis of malignant mesothelioma using three tumor markers (CEA, CYFRA 21-1, and SMRP), concluded that LLM is an innovative method that can offer helpful classification rules from the complex multivariate correlation between the different analyzed features and provide classification rules in excellent agreement with the previous knowledge about the biological role of mesothelial proliferation. Accurate differentiation of benign and malignant spindle cells can be an essential diagnostic challenge for pathologists. Naso et al³⁶ used the SpindleMesoNET NN in their study to distinguish between sarcomatoid mesothelioma and benign spindle cell mesothelial proliferation. The SpindleMesoNET NN predicted cases' benign or malignant status with AUCs of 0.932, 0.925, and 0.989 in cross-validation, reference, and external validation sets, respectively. The accuracy of this trained NN in the

reference set cases was 92.5%, higher than the average accuracy of 91.7% of three experienced pathologists in a slide set. As a result, SpindleMesoNET can accurately distinguish sarcomatoid mesothelioma from benign spindle cell mesothelial proliferation. In disease prevention and prognosis, AI models are beginning to explore integrating genomic and histopathological data to refine prognostic predictions. Furthermore, novel algorithms for dynamic prediction modeling are emerging, which allow real-time updates based on patient data, improving the accuracy of prognosis over time.

Therefore, in disease prevention and prognosis, the integration of AI demonstrates promising potential across various aspects of diagnosing and managing malignant mesothelioma. Studies by Choudhury et al,¹⁸ Alam et al,¹⁹ and Latif et al³³ underscore ML's importance in predicting cancer and finding critical prognostic indicators. This approach will help with early diagnosis and better treatment plans. Remarkably, the implementation of AdaBoost models and innovative frameworks highlights AI's role in harnessing non-invasive and cost-effective methods for prognostic assessment. Also, improvements in AI algorithms like the LLM were studied by Parodi et al,²⁶ help with differential diagnosis by giving clinicians easy-to-understand classification rules that help them correctly tell the difference between diseases. Furthermore, the development of specialized NNs such as SpindleMesoNET, as demonstrated by Naso et al,³⁶ showcases AI's potential in accurately distinguishing between malignant and benign mesothelial proliferations, potentially surpassing the accuracy of human pathologists. These findings collectively underscore the transformative impact of AI in enhancing disease prevention, prognosis, and, ultimately, patient care in the context of malignant mesothelioma.

Study Limitations and Future Research Directions

The current study has a few notable limitations that must be addressed in future research. Firstly, we considered only studies written in English, potentially excluding valuable research conducted in other languages. Secondly, our review was limited to three databases (PubMed, Scopus, and Web of Science), which may have resulted in overlooking relevant literature available from additional reputable sources. Future research should address these limitations by including studies published in other languages and expanding the search to encompass a broader range of databases, thereby enhancing the overall comprehensiveness of the review.

In addition to these limitations, our review highlights several open research problems that offer fertile ground for further investigations. The relatively few studies and limited sample sizes underscore the need for larger, multicenter investigations to validate and refine AI-driven diagnostic and prognostic models for mesothelioma. While SVM, DT, and RF models have demonstrated high accuracy, exploring novel deep learning architectures and ensemble methods could improve predictive performance and clinical applicability. Moreover, standardizing

evaluation metrics, datasets, and feature selection techniques is essential to enhance the comparability and reproducibility of research outcomes. Finally, integrating multimodal data, including imaging, genetic, and clinical parameters, may pave the way for more comprehensive and personalized approaches to mesothelioma management. Addressing these challenges will advance the field and foster innovations that improve patient outcomes.

Conclusions

This scoping review highlights the application of AI in diagnosing and managing mesothelioma. The primary applications of AI in these studies included tumor diagnosis and classification, prevention and prognosis, and tumor volumetric measurement of malignant pleural mesothelioma. The most commonly used AI models were neural networks, decision trees, random forests, logistic regression, Naïve Bayes, and SVM. Among these, SVM, DT, and RF showed high accuracy.

The findings suggest that AI, particularly machine learning models such as neural networks, decision trees, support vector machines, and random forests, has significant potential in improving mesothelioma prediction and management. These models offer promising accuracy for early detection, which could lead to improved patient outcomes. Future research should focus on refining these models, improving their generalizability across diverse patient populations, and integrating them into clinical practice to enhance diagnostic precision. Furthermore, the use of genetic and correlation-based algorithms for risk factor identification and feature selection could be explored further to optimize the performance of AI systems in mesothelioma prediction.

Abbreviations

AI	Artificial Intelligence
MPM	Malignant Pleural Mesothelioma
NN	Neural Network
DT	Decision Tree
RF	Random Forest
LogR	Logistic Regression
NB	Naïve Bayes
GA	Genetic Algorithm
ML	Machine Learning
SVM	Support Vector Machine
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
MeSH	Medical Subject Headings
PROBAST	Prediction Model Study Risk of Bias Assessment Tool
KNN	K-Nearest Neighbors
ANN	Artificial Neural Network
LLM	Logic Learning Machine
CE	Cytology Examination
BE	Benign Disease
MLPE	Multilayer Perceptron Ensemble
ALP	Alkaline Phosphatase

HU	Hounsfield Unit
SUVM _{ax}	Standardized Uptake Value
MSK-IMPACT	Memorial Sloan Kettering
DCNN	Deep Convolutional Neural Networks
DSC	Dice Similarity Coefficient
MLP	Multi-Layer Perceptron
BP	Back Propagation
ELM	Extreme Learning Machine
SSAE	Stacked Sparse Auto-Encoders
LDA	Linear Discriminant Analysis
PNN	Probabilistic Neural Network
CNN	Convolutional Neural Network
SGD	Stochastic Gradient Descent
KLR	Kernel Logistic Regression
VP	Voted Perceptron
CC	Clojure Classifier
AUC	Area Under Curve
AIS	Artificial Immune Systems
LVQ	Learning Vector Quantization
HC	Healthy Control
ROC	Receiver Operating Characteristic
mRECIST	Modified Response Evaluation Criteria in Solid Tumors
ESR	Erythrocyte Sedimentation Rate
LDH	Lactic Dehydrogenase
BMI	Body Mass Index
CPP	Calcified Pleural Plaque
CEA	Carcinoembryonic Antigen
TCGA	The Cancer Genome Atlas

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Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

All data generated or analyzed during this study are included in this published article.

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