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# Artículo Especial

## Role of artificial intelligence in predicting disease-related malnutrition – A narrative review

*El papel de la inteligencia artificial en la predicción de la desnutrición relacionada con la enfermedad: una revisión narrativa*

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## Abstract

**Background:** disease-related malnutrition (DRM) affects 30-50 % of hospitalized patients and is often underdiagnosed, increasing risks of complications and healthcare costs. Traditional DRM detection has relied on manual methods that lack accuracy and efficiency.

**Objective:** this narrative review explores how artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL), can transform the prediction and management of DRM in clinical settings.

**Methods:** we examine widely used ML and DL models, assessing their clinical applicability, advantages, and limitations. The integration of these models into electronic health record systems allows for automated risk detection and optimizes real-time patient management.

**Results:** ML and DL models show significant potential for accurate assessment of nutritional status and prediction of complications in patients with DRM. These models facilitate improved clinical decision-making and more efficient resource management, although their implementation faces challenges related to the need for large volumes of standardized data and integration with existing systems.

**Conclusion:** AI offers promising prospects for proactive DRM management, highlighting the need for interdisciplinary collaboration to overcome existing barriers and maximize its positive impact on patient care.

**Keywords:**

Artificial intelligence. Disease-related malnutrition. Machine learning. Deep learning. Clinical implementation.

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## Resumen

**Antecedentes:** la desnutrición relacionada con la enfermedad (DRE) afecta al 30-50 % de los pacientes hospitalizados y, a menudo, está infradiagnosticada, lo que incrementa los riesgos de complicaciones y los costos sanitarios. Los métodos tradicionales para detectar la DRE se han basado en técnicas manuales que carecen de precisión y eficiencia.

**Objetivo:** esta revisión narrativa analiza cómo la inteligencia artificial (IA), en particular el aprendizaje automático (AA) y el aprendizaje profundo (AP), puede revolucionar la predicción y el manejo de la DRE en entornos clínicos.

**Métodos:** se analizan modelos ampliamente utilizados de AA y AP, centrándose en su aplicabilidad clínica, ventajas y limitaciones. También se revisa la integración de estos modelos en los sistemas de registros electrónicos de salud, destacando su potencial para la detección automatizada del riesgo y la optimización de la gestión en tiempo real de los pacientes.

**Resultados:** los modelos de AA y AP muestran un gran potencial para evaluar con precisión el estado nutricional y predecir complicaciones de la DRE. Estas tecnologías mejoran la toma de decisiones clínicas y la gestión de recursos. Sin embargo, su implementación enfrenta desafíos como la necesidad de grandes volúmenes de datos estandarizados y la integración con los sistemas existentes.

**Conclusión:** la IA ofrece perspectivas prometedoras para el manejo proactivo de la DRE, subrayando la necesidad de una colaboración interdisciplinaria para superar las barreras existentes y maximizar su impacto positivo en la atención al paciente.

**Palabras clave**:

Inteligencia artificial. Desnutrición relacionada con la enfermedad. Aprendizaje automático. Aprendizaje profundo. Implementación clínica.

## INTRODUCTION

Disease-related malnutrition (DRM) is a form of malnutrition driven by acute or chronic illness, resulting from inflammation, reduced nutrient intake and absorption, or metabolic disturbances associated with the underlying disease. In 2023, the World Health Organization (WHO) reported that DRM is highly prevalent, affecting 30-50 % of hospitalized patients (1). However, it remains significantly underdiagnosed, leaving many patients without adequate treatment. DRM represents a significant challenge in healthcare, particularly among vulnerable populations such as 38-78 % of patients in intensive care, 30-70 % of the elderly, 40 % of patients with cancer or 24 % of inpatients suffering from cardiovascular or pulmonary disease. The implications of this are profound, as DRM heightens the risk of complications and mortality, significantly diminishing patients' quality of life (1). All of this increases the risk of postoperative complications, prolongs hospital stays, and raises healthcare costs (1-3). Therefore, it is crucial for nutrition healthcare professionals to be equipped with the appropriate tools to effectively prevent, diagnose, manage, and monitor patients affected by DRM (1). However, traditional detection methods, primarily based on manual assessments and clinical scoring, have significant limitations in terms of accuracy and efficiency (3). Innovative technologies, such as artificial intelligence (AI), offer an opportunity to overcome these limitations and transform DRM management. Particularly machine learning (ML) and deep learning (DL), have emerged as innovative tools with significant potential to enhance the prediction of malnutrition in hospitalized patients. AI creates systems capable of performing tasks that usually require human intelligence. Through advanced algorithms, it enables the automated analysis of large data volumes, identifying complex patterns within clinical, demographic, and laboratory variables. This facilitates the creation of predictive models that can integrate nutritional, inflammatory, and metabolic information, allowing for a more accurate assessment of malnutrition risk than conventional tools (4,5).

ML, also known as automated learning, is a subdiscipline of AI that focuses on developing algorithms that enable machines to learn from data without needing to be explicitly programmed for each task. In this way, these models can improve their accuracy as they are trained on patient databases. These algorithms range from supervised models, which allow for the classification of at-risk patients, to unsupervised models that can uncover hidden patterns within data subsets without the need for prior labels (2,5). However, what has genuinely transformed how we analyze large volumes of information is DL, a specific branch of ML that uses artificial neural networks, inspired by the workings of the human brain. These networks process extensive datasets in a complex, layered manner, such as time series of biomarkers, which is especially useful for capturing subtle interrelationships between different nutritional risk factors (6) (Fig. 1).

The clinical applicability of ML and DL in the hospital setting has shown significant potential. These models facilitate not only the assessment of patients' nutritional status but also the prediction of malnutrition-related complications, including mortality and readmission rates. For instance, predictive algorithms have successfully identified high-risk patients in intensive care units, enabling timely interventions that reduce complications and hospital stays (7). This makes them essential tools for improved clinical decision-making and efficient resource management (5). The integration of these models into electronic health record (EHR)

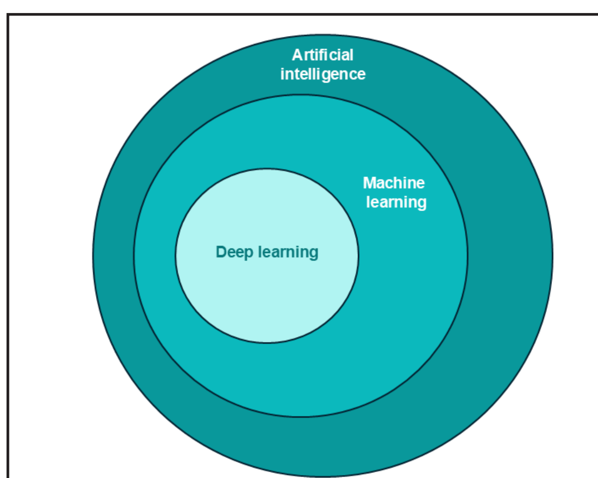


**Figure 1.**

Illustration of the existing relationship between artificial intelligence, machine learning, and deep learning.

systems enables automated risk detection and provides healthcare professionals with real-time alerts, optimizing workflow and ensuring continuous assessment of patients' nutritional status (2,3).

Building on these challenges and opportunities, this narrative review aims to explore the role of AI, specifically ML and DL, in predicting and managing DRM. It examines the clinical applicability of the most widely used models, including their advantages and limitations, and discusses the challenges to their effective implementation in hospital practice. Additionally, it offers recommendations on accessible tools for developing these models and explores the future prospects of AI in clinical nutrition.

## PREDICTIVE MACHINE LEARNING MODELS FOR MALNUTRITION

ML models have been implemented to facilitate more accurate and timely identification of at-risk patients. These models are statistical and computational tools that use algorithms to analyze and predict outcomes based on data. There are several types of learning; however, the most prominent are supervised and unsupervised learning. Supervised models are those that are trained using labeled datasets, wherein each entry in the dataset is associated with a corresponding known output (8). This type of model is especially effective for classifying patients according to their risk of malnutrition. Some of the supervised learning algorithms used for both predicting the risk of malnutrition and classifying different forms of malnutrition in various patient populations are Random Forest (RF), logistic regression (LR), support vector machine (SVM), decision tree (DT), Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), LightGBM and XGBoost among others (3-5,9).

Unlike supervised models, unsupervised learning, though less prevalent, has also been applied in some studies, particularly for tasks that require identifying patterns or clusters within malnutrition-related data without predefined labels. These models do not require labeled data, making them valuable for identifying hidden patterns within datasets and uncovering correlations that might not be immediately evident. One common application is clustering, an unsupervised method that categorizes patients based on similarities in clinical data and biomarkers. For example, algorithms such as k-means and neural networks (NN) have been used for clustering, with the aim of grouping data based on inherent similarities, which can be particularly useful in scenarios with complex, high-dimensional data and unexpected relationships. This approach facilitates personalized interventions and improves the management of nutritional treatments. As emphasized by Sharma et al., these approaches have demonstrated potential in identifying not only broad trends but also critical subpopulations of malnourished patients, particularly in resource-limited settings (10). In hospital settings, clustering is especially advantageous for segmenting patients according to distinct malnutrition patterns, thereby enabling more targeted and efficient interventions (3,11). This was demonstrated in patients suffering from cancer who were classified according to malnutrition severity using a system based on clustering in China developed by Yin et al. (12) (Table I).

**Table I.** AI algorithms in DRM prediction

| Algorithm type | Classification (ML/DL) | Model (supervised/ unsupervised) | Purpose |
|---|---|---|---|
| Random Forest (RF) | ML | Supervised | Classification of patients by malnutrition risk; prediction of major adverse postoperative events in malnourished patients |
| Logistic Regression (LR) | ML | Supervised | Prediction of continuous outcomes such as nutritional status or malnutrition severity |
| Support Vector Machine (SVM) | ML | Supervised | Classification of patients at risk of malnutrition |
| Decision Tree (DT) | ML | Supervised | Classification and prediction of factors associated with malnutrition |
| K-Nearest Neighbors (KNN) | ML | Supervised | Identification of patterns in clinical data related to malnutrition |
| LightGBM | ML | Supervised | Prediction of mortality and hospital stay length in patients at risk of malnutrition |
| XGBoost | ML | Supervised | Prediction of hospital readmissions in malnourished patients |
| K-means | ML | Unsupervised | Grouping of patients based on similarities in clinical data and biomarkers for personalized nutritional interventions |
| Neural Networks (NN) | ML | Supervised/Unsupervised | Identification of hidden patterns in high-dimensional data; grouping patients based on malnutrition patterns |
| Convolutional Neural Networks (CNN) | DL | Supervised | Processing of clinical images like ultrasounds or CT scans to assess body composition, muscle mass, and adipose tissue |
| Recurrent Neural Networks (RNN) | DL | Supervised | Analysis of biomarker time series like albumin or CRP to monitor changes in nutritional status |
| Hybrid Models | ML/DL | Supervised/Unsupervised | Combination of multiple algorithms to enhance predictive accuracy in complex clinical scenarios |

Despite its potential, reinforcement learning, which allows algorithms to learn and adapt from real-time feedback, was not prominently featured in the reviewed studies. However, this method could offer valuable applications in clinical decision-making processes, where the model could continuously improve based on patient outcomes. Sharma et al. also note that while supervised and unsupervised approaches dominate current applications, integrating reinforcement learning could significantly enhance adaptability, enabling dynamic updates in patient management strategies as new data become available (10).

The choice of algorithms is closely tied to the specific problem being addressed in malnutrition detection. For classification tasks, Random Forest (RF) and Support Vector Machines (SVM) have been particularly effective, as demonstrated in studies that focus on identifying malnutrition. Talukder et al. (13) utilized RF and other algorithms to classify malnourished children in Bangladesh, achieving high predictive accuracy, Kar et al. (14) employed machine learning algorithms, including SVM, to predict child malnutrition, highlighting their utility in handling complex classification tasks. Rahman et al. (15) expanded on this by using these models to classify children into categories of stunting, wasting, and underweight, further validating their application in diverse clinical contexts. For regression analysis, like Logistic Regression (LR) and Neural Networks (NN) have been commonly employed to predict continuous outcomes such as nutritional status or malnutrition severity. Kishore et al. (16) demonstrated the effectiveness of LR and NN models in predicting malnutrition levels in newborn infants, focusing on their ability to process large datasets and generate precise predictions. Additionally, some studies as hybrid models that combine multiple algorithms to enhance predictive accuracy, particularly in complex clinical scenarios where a single model may not suffice. This approach reflects the adaptability and robustness of machine learning in addressing multifaceted issues in malnutrition detection. They underline the importance of hybrid approaches in improving model reliability, particularly when dealing with heterogeneous patient data or integrating diverse biomarkers (10).

In summary, while supervised learning models dominate the current research landscape in the application of ML for expanding the use of unsupervised learning and reinforcement learning techniques. These advances could enhance the flexibility and adaptability of predictive models, ultimately improving the early detection and treatment of malnutrition in clinical settings.

## DEEP LEARNING: NEURAL NETWORKS FOR EARLY DRM DETECTION

Deep neural networks, also named DL, represent an advanced subcategory of ML that employs complex architectures to analyze large volumes of clinical or nutritional data. Two types of neural networks particularly useful in the context of DRM are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are commonly applied to clinical image processing, such as ultrasound scans or scans, allowing indirect assessment of nutritional status by analyzing body composition and levels of fat and muscle mass (17-19). For example, the use of CNN applied on ultrasound images to measure the subcutaneous fat thickness, muscle thickness and cross-sectional area of the rectus femur muscle has demonstrated its consistency and reliability for the quantification of these muscular parameters, which are key indicators of malnutrition. Therefore, information regarding rectus femur can help in DRM prediction (17). On the other hand, RNNs are suitable for time series analysis of biomarkers, such as albumin or C-reactive protein (CRP) levels, which can reflect changes in the patient's nutritional status over time (20). Furthermore, recent studies utilizing computed tomography (CT) imaging have shown that deep learning techniques, including CNNs, can extract features from the psoas muscle area at the third lumbar vertebra (L3) level. These features, when integrated with clinical predictors such as BMI, lymphocyte counts, and albumin levels, improve predictive accuracy for malnutrition in gastric cancer patients. A mixed-model approach combining DL features with clinical data demonstrated a robust ability to identify malnutrition risk and stratify patients by survival outcomes, highlighting the transformative potential of DL in clinical nutrition management (21).

These DL architectures offer key advantages in nutritional prediction that outperform traditional models by capturing hidden relationships between complex clinical variables (22). For example, DL models can combine biomarker data with other indicators such as red blood cell distribution, inflammatory values, and metabolic parameters to generate a predictive profile of malnutrition risk (23). This ability to identify complex patterns and nonlinear correlations allows for a more accurate assessment of nutritional risk, facilitating early detection of DRM.

## CLINICAL APPLICABILITY AND EXAMPLES OF PREDICTIVE MODELS IN DRM

The implementation of ML and DL models in the hospital setting is bringing significant improvements in the detection and management of DRM, particularly in high-risk populations, such as the elderly, patients with cancer or those undergoing complex surgical interventions (1,24,25). These models have demonstrated the ability to automate the identification of at-risk patients, facilitating preventive interventions that reduce both clinical complications and hospital costs (26). Preventive interventions for malnutrition focus on optimizing oral intake through personalized diet therapy tailored to the patient's clinical condition, preferences, and socioeconomic context. Early identification of at-risk individuals allows for timely adjustments, such as balanced diets, oral nutritional supplements, and addressing barriers to adequate nutrition. Educational initiatives and resource accessibility further support prevention, reducing the risk of malnutrition and its complications (27).

The systematic review published by Janssen et al. (3) reveals that the most frequently used algorithm in articles applying ML for early detection of DRM is RF, characterized by combining the results of several decision trees to obtain a single result. Its ease of use and flexibility have driven its adoption, as it deals with both classification and regression problems (3,28). As previously mentioned, DRM is frequently underdiagnosed, with potentially fatal outcomes. To address this, hospitals implement screening systems to assess patients' nutritional status and their risk of malnutrition. Various tools are used for this purpose, including the Malnutrition Universal Screening Tool (MUST), which assigns scores ranging from 0 to 6 based on five criteria: body mass index (BMI), percentage of body weight loss over a specified period, presence of specific diseases, nutritional intake, and the likelihood of not consuming any nutrition for more than 5 days. Patients with scores of 2 or higher are considered at high risk for malnutrition. Due to limitations in the MUST's applicability, machine learning-based classifiers such as MUST-plus have been developed. These utilize RF models and have shown superior performance in identifying DRM, thereby enhancing patient management (29). Similarly, there are also studies that use RF to determine the risk of major adverse events (MAEs) in post-surgical patients with type A aortic dissection (4). These MAEs include: cardiovascular, respiratory and wound complications, new-onset acute kidney injury, gastrointestinal bleeding and death. The importance of this fact lies in the high mortality rate caused by comorbidities that these patients suffer after the appropriate surgical intervention, malnutrition being one of the most prevalent. Thus, the development of a model with the ability to predict the clinical outcomes of patients suffering from this cardiovascular disease with concurrent malnutrition following surgical treatment was needed. The algorithm developed by Liang-wan Chen´s group (4) showed to be effective in detecting MAEs risk, which makes the model a useful tool to mitigate MAEs that may arise from the clinical condition associated with malnutrition in these patients. Recent research further underscores the role of machine learning (ML) models in addressing malnutrition-related health concerns. A study by Göl et al. (30) highlighted the potential of Random Forest (RF) algorithms in predicting anemia related to malnutrition among geriatric patients. Using a dataset incorporating malnutrition and physical activity scores, the RF model achieved an accuracy of 85.39 %, demonstrating its utility in identifying nutritional risks even without extensive biochemical data. This reinforces the applicability of supervised ML algorithms in clinical nutrition contexts, especially for populations where detailed laboratory data might not be consistently available.

Other ML algorithms that are gaining ground in DRM prediction include LightGBM and XGBoost. These models use an optimized decision tree structure, which allows them to efficiently analyze large volumes of clinical and demographic data (31,32). LightGBM, for example, has shown high accuracy in predicting length of stay and probability of mortality in DRM patients, which is crucial in resource planning and bed management in hospitals. Recent studies have shown that LightGBM can achieve Area Under the Curve (AUC) values above 0.90 in these predictions, which supports its clinical applicability in informed decision making. On the other hand, XGBoost is especially effective in predicting hospital readmissions. These models have proven to be effective in identifying complex patterns in longitudinal patient data, including variables such as BMI, dietary intake, hematocrit, albumin, CRP or leukocyte and lymphocyte levels, since these inflammatory parameters can correlate with the prognostic outcomes in malnourished patients. These variables, when integrated into a predictive model, allow patients to be classified into different levels of readmission risk, which facilitates personalized post-discharge follow-up and decreases unplanned readmission rates (4,5).

Oncology stands out as a critical field for applying AI to the prevention of DRM, given the proven benefits of early nutritional interventions in reducing mortality risk in cancer patients. Recent studies have leveraged AI techniques to develop predictive models based on a range of factors associated with DRM. For instance, one study (33) used age, tumor type, BMI, and left arm phase angle to create decision tree and RF models, achieving solid predictive performance with an AUC of 0.813. However, the retrospective design limited the inclusion of additional influential factors such as smoking, alcohol consumption, or socioeconomic variables. Similarly, another study (34) analyzed data from nearly 4,000 patients with cancer to build a decision tree model incorporating key variables such as age, recent weight loss, calf circumference, BMI, and nutritional screening scores (NRS 2002). This model demonstrated exceptional accuracy, with an AUC of 0.964, although it too faced constraints, including the omission of inflammatory markers and steroid use, which could impact malnutrition risk. In oncology, the integration of ML models has shown promising results in improving malnutrition risk prediction. Wu et al. (35) explored the use of machine learning to enhance the GLIM criteria for malnutrition diagnosis in colorectal cancer patients. Their Random Forest (RF) model, trained on anthropometric and clinical variables, demonstrated robust performance with an AUC of 0.83. This study highlights the potential for ML algorithms to complement traditional screening tools, offering more nuanced and data-driven approaches to patient stratification and nutritional risk assessment. Another example is the study developed by Duan et al. (36), who developed a predictive model for assessing malnutrition in elderly hospitalized cancer patients, achieving an impressive AUC of 0.945. The model identified key predictors, including BMI, albumin levels, and activities of daily living (ADL), demonstrating the critical role of comprehensive data integration in enhancing predictive accuracy. These findings highlight the potential of AI to refine DRM predictions by integrating diverse patient data, though further refinement and validation are necessary to enhance generalizability (37) (Table II).

## APPLICATION OF DEEP LEARNING IN NUTRITIONAL ASSESSMENT THROUGH CLINICAL IMAGING

In the context of DRM, CNNs, a common architecture of DL, are increasingly being used for the interpretation of clinical images, such as ultrasounds or computed tomography (CT) scans (38,39). CNNs enable the extraction of detailed information about patients' body composition by analyzing critical variables such as the amount of muscle mass and adipose tissue, which are essential indicators of nutritional status, for example, measuring rectus femur muscle of muscle in L3 levels on abdominal CT scan, as mentioned above (17,38,39). These data are particularly useful in surgical patients or those with advanced chronic diseases, where the visual and direct assessment of nutritional status allows for the design of nutritional intervention plans tailored to the specific needs of the patient (40). An example of this is the use of DL to assess muscle mass loss in patients suffering from non-Hodgkin´s lymphoma. This technology allows for the detection of sarcopenia through the analysis of different muscles tomography images, which is crucial for proactively adjusting nutritional support and improving health outcomes in patients undergoing cancer treatment (41). Moreover, a bibliometric analysis published in 2023, although based on pediatric malnutrition data, highlights that malnutrition can be effectively predicted using ML algorithms to analyze BMI. However, it also emphasizes that the future of malnutrition prediction lies in DL techniques (42). One such example is the use of a DL framework for the diagnosis of malnutrition using a 3D facial points cloud, whereby a 3D camera captures the spatial configuration of facial features as a "points cloud", which is a set of points in three-dimensional space representing the geometry of the face. This representation retains detailed facial structural information that can reflect health-related attributes, including malnutrition (43).

**Table II.** Studies with AI in DRM prediction

| Author and reference | Sample size | AI method used | Variable used | Outcome achieved |
|---|---|---|---|---|
| Garcia Herreros, 2024 | 100 | CNN | To validate an AI-based system compared to the classic method of reading ultrasound images of the rectus femur (RF) muscle in a real cohort of patients with disease related malnutrition | The Intraclass. Correlation Coefficient (ICC) for reliability and consistency analysis between methods A and B showed correlations of 0.912 and 95 % CI [0.872-0.940] for fat thickness, 0.960 and 95 % CI [0.941-0.973] for Muscle Thickness, and 0.995 and 95 % CI [0.993-0.997] for area |
| Göl M et al., 2024 | 438 | J48 and Random Forest | Hemogram and biochemistry blood values, malnutrition, physical and cognitive activity scores | J48: 97.77 % accuracy; Random Forest: 85.39 % accuracy without blood values |
| Wu T et al., 2024 | 4487 | Random Forest | Malnutrition based on GLIM and NRS-2002 criteria | AUC of 0.830 (95 % CI, 0.805-0.854), accuracy of 0.775, sensitivity of 0.835 and specificity of 0.742 |
| Duan R et al., 2024 | 450 | XGBoost | Activities of daily living, albumin, body mass index and age | AUC of 0.945, accuracy of 0.872 and sensitivity of 0.968 |
| Liu M-Y et al., 2024 | 4368 | LightGBM and XGBoost | 15 variables (not specified) | LightGBM: AUC 0.92-0.96 for long hospital stays and mortality rates predictions; XGBoost: AUC ~0.99 for predicting readmission |
| Xie LF et al., 2024 | 708 | Random Forest | gender, age, body mass index, past medical history including hypertension, diabetes, and coronary artery disease. Preoperative comorbidities such as chronic kidney disease, aortic valve regurgitation, and pericardial effusion. Preoperative laboratory test results. Intraoperative details such as operation time, cardiopulmonary bypass time, and aortic cross-clamp time. Postoperative clinical outcomes: ICU stay time, mechanical ventilation time, 48 hours thoracic drainage, and postoperative complications | Hhigh clinical and predictive performance of Random Forest evaluated with SHAP |
| Truijen S et al., 2021 | 1518 | Logistic Regression | Routine biochemical diagnostic test data, micronutrient deficiency biomarkers, and established malnutrition indicators (plasma vitamin C, vitamin B6 Pyridoxal 5'-Phospate, selenium, zinc and serum vitamin B12) | AUC of 0.79 (95 % CI: 0.76-0.81), sensitivity 66.0 %, specificity 78.1 % |

*(Continues on next page)*

**Table II (cont.).** Studies with AI in DRM prediction

| Author and reference | Sample size | AI method used | Variable used | Outcome achieved |
|---|---|---|---|---|
| Timsina P et al., 2020 | 8479 | Random Forest (MUST-Plus) | Admission-discharge-transfer events; structured clinical assessments within nursing documentation flowsheet; physiologic data (e.g., vital signs including pulse and respiratory rates); laboratory results; and automated electrocardiogram results | Sensitivity of 73.07 % (95 % CI: 69.61 %-76.33 %), specificity of 76.89 % (95 % CI: 75.64 %-78.11 %), AUC 83.5 % (95 % CI: 82.0 %-85.0 %) |
| López-Gómez JJ et al., 2024 | 65 | AI-supported ultrasonography | Demographic and clinical characteristics, height, weight, Body Mass Index, arm circumference, calf circumference, rectus femoris muscle area and thickness, subcutaneous fat and grey level non-uniformity matrix | Significant reduction in malnutrition and improvement in muscle indicators |
| Jullien M et al., 2021 | 656 | Convolutional Neural Networks (DLASA) | Anthropometric data from pretherapeutic CT | Muscle hypodensity as an independent risk factor for mortality. OS (HR = 2.80 (95 % CI 1.58-4.95), $p < 0.001$) and PFS (HR = 2.22 (95 % CI 1.43-3.45), $p < 0.001$) |
| Yuliansyah H et al., 2023 | Not applicable | Machine Learning, Deep Learning, Neural Networks | Not applicable | ML is the predominant method for prediction, followed by DL for future tasks |
| Wang X et al, 2024 | 482 | Deep Learning | 3D facial data obtained using a 3D camera and represented as a 3D facial points cloud | AUC of 0.7240 ± 0.0416 |

## POTENTIAL ROLE OF GENERATIVE AI IN DRM

On the other hand, it is necessary to take into account that AI can also be used in the field of clinical nutrition through generative AI, such as the popular ChatGPT (44). ChatGPT's AI capabilities offer a promising tool for personalized DRM treatment. It can provide tailored dietary guidance, suggest protein-rich food options, and even propose culturally appropriate meal plans. By delivering real-time information and psychological counselling, ChatGPT could enhance patient adherence to treatment. Furthermore, its ability to analyse treatment data enables policymakers and healthcare professionals to refine strategies and assess intervention efficacy. Applications include integration into health apps, educational tools, public health campaigns, and research facilitation. For instance, ChatGPT has been successfully used in nutritional counselling and educational platforms to improve understanding and dispel common misconceptions. Despite these advantages, ChatGPT have some significant limitations. ChatGPT cannot conduct physical examinations or assess vital signs, limiting its diagnostic accuracy. Its reliance on text-based inputs can propagate biases from flawed or culturally insensitive data. Complex medical cases requiring nuanced human expertise also fall beyond its scope. Additionally, while it can simulate empathetic responses, it lacks genuine emotional intelligence crucial for comprehensive care. Ethical concerns, such as privacy risks and over-reliance, must also be addressed. Moreover, marginalized communities are often underrepresented in training datasets, raising concerns about equitable access to accurate information (45).

## INTEGRATION OF PREDICTIVE MODELING IN ELECTRONIC HEALTH RECORD (EHR) SYSTEMS

The integration of ML and DL models into electronic health record (EHR) systems represents a significant advance in automating the care and follow-up of patients with DRM (46). By linking these models with EHRs, hospitals can implement real-time alerts that notify clinicians when a patient is at high risk for malnutrition. This allows healthcare staff to act proactively, adjusting diet or introducing nutritional supplementation before the patient's condition deteriorates. In addition, automating these alerts minimizes the reliance on professionals to manually assess nutritional status, freeing up time for other clinical tasks and ensuring that risk assessments are performed consistently, uniformly and based on up-to-date data (2,47). Big data tools like EHRead enhance the integration of ML/DL models into EHRs by utilizing natural language processing (NLP) to extract structured data from unstructured clinical narratives, such as discharge summaries and progress notes. Although not a predictive model itself, EHRead supports predictive modeling by transforming raw text into actionable data, enabling more comprehensive and accurate analyses. For instance, in a study conducted in Spain, EHRead analyzed over 180,000 hospitalization records, identifying malnutrition diagnoses in only 2.47 % of cases, despite its well-documented prevalence. This analysis revealed key patterns, such as increased in-hospital mortality (7.08 %) and prolonged hospital stays (8 days vs. 5 days) among patients with DRM, highlighting the critical need for improved detection and management. Other studies, including one conducted in a Taiwanese hospital (5), the integration of a LightGBM model with the EHR system allowed accurate prediction of length of stay and mortality in patients with pneumonia and risk of malnutrition, significantly improving resource allocation. This type of implementation facilitates continuous and automatic monitoring of nutritional status, allowing interventions to be tailored in real time to the needs of each patient. Other studies, including one by Kramer et al. in Austria (2), demonstrated 83 % accuracy in the model they used to predict malnutrition in surgical in-patients, further supporting the substantial value of integrating predictive AI models with EHRs. These findings suggest that automated malnutrition screening could potentially replace manual screening tools in hospital settings.

## GUIDANCE FOR THE IMPLEMENTATION OF ML AND DL MODELS IN DRM PREDICTION

The integration of ML and DL models for predicting DRM offers significant potential to streamline clinical workflows and improve patient outcomes. However, effective implementation requires addressing several key factors. There are guidelines in the literature that try to elucidate the steps that should be followed to start using these powerful tools in clinical practice, since, despite the proven benefits, their use is still not common in the day-to-day work of healthcare professionals involved in clinical nutrition (3). In 2022, de Hond et al. (48) published a scoping review that examined the relevant literature on the development, evaluation, and implementation of AI prediction models (AIPMs). The review provides guidance and quality criteria, utilizing a comprehensive multi-stage screening approach. It outlines six distinct phases, which can be applied to the context of DRM.

## DATA COLLECTION AND PREPARATION

The first step in developing a machine learning (ML) model for predicting malnutrition risk is gathering comprehensive clinical data. This includes key patient information such as demographics, anthropometric measurements, biochemical markers, medical history, nutritional intake, and disease-specific parameters. Ensuring the quality and consistency of the data is critical for model accuracy. This can be achieved by thoroughly cleaning and preprocessing the data, addressing any missing values appropriately, and normalizing or scaling features as needed.

## DEVELOPMENT OF THE AIPM

This second phase focuses on selecting the appropriate modeling technique, considering factors like performance, interpretability, and computational needs. The model should be interpretable to ensure acceptance in healthcare and help identify biases. Training involves optimizing parameters and hyperparameters, with transparency in the process. Internal validation is done using separate training, tuning, and test datasets, assessing discrimination and calibration through metrics like AUC. Overfitting is prevented through strategies like feature selection and regularization. Addressing algorithmic bias is key, with fairness metrics integrated into the model evaluation. Transparency in documenting the model and development process is essential for reproducibility.

## VALIDATION OF THE AIPM

External validation is a critical step in evaluating the performance of an AIPM for predicting DRM in new populations or healthcare settings, as performance may vary across different contexts. This phase involves testing the model using metrics such as discrimination (e.g., AUC, sensitivity, specificity) and calibration, similar to the internal validation process, and comparing its results to existing prediction models or clinical decision rules for DRM. While prospective external validation is preferred for its real-world applicability and ability to identify errors in real time, retrospective validation may also be used. Generalizability refers to the model's ability to maintain its predictive accuracy when applied in different settings, such as a model developed in a tertiary care hospital being applied in primary care or smaller facilities. Developers should ensure that validation data are representative of the new healthcare setting and report any differences between the development and validation data. Depending on the results, the AIPM may need to be updated, recalibrated, or retrained for the new context. Additionally, performance should be assessed by patient subgroups, such as those with different comorbidities or age groups, to detect any algorithmic bias, especially if certain groups are underrepresented. Any identified sources of bias should be explicitly reported, helping healthcare professionals understand the limitations of the AIPM's predictions for specific populations and ensure its appropriate application in DRM diagnosis and treatment.

## DEVELOPMENT OF THE SOFTWARE APPLICATION

In phase 4, the AIPM software must integrate with existing healthcare systems, following standards like International Organization for Standardization (ISO), Fast Healthcare Interoperability Resources (FHIR), and Health Level Seven International (HL7) to ensure data exchange compatibility. The design should focus on usability, clarity of the AIPM's intended use, and safety features to prevent overconfidence in predictions. Regular user testing, transparency, and inclusivity are also essential. In addition, the software should include monitoring capabilities to track performance and detect issues, with strong security measures and regular testing for vulnerabilities. Furthermore, an incident response plan should be in place to address any security breaches.

## IMPACT ASSESSMENT OF THE AIPM WITH SOFTWARE

Phase 5 focuses on evaluating the clinical utility of the AIPM for predicting DRM. Before the impact study, a feasibility pilot is recommended to ensure safe and effective integration into clinical workflows. The impact study should ideally be a randomized controlled trial (RCT) comparing outcomes between AIPM-assisted DRM prediction and standard care. Key outcomes include clinical improvements, cost-effectiveness, changes in decision-making, and user satisfaction. Findings should be communicated to healthcare professionals and policymakers to encourage widespread adoption of the AIPM in DRM prediction.

## IMPLEMENTATION AND USE IN DAILY HEALTHCARE PRACTICE

Finally, the focus shifts to the actual deployment and integration of the AIPM into healthcare settings. Prior to implementation, it's critical to identify and document the necessary conditions for deployment, such as hardware requirements. Ideally, the AIPM should be directly integrated into the existing clinical workflows, such as being embedded in the EHR system, with clear guidance on how the AIPM's predictions will influence decision-making. To ensure a smooth transition from testing to real-world use, automated deployment processes and shadow deployment strategies should be implemented, enabling local validation of updates and new versions. It is also important to have contingency plans in place, including mechanisms for halting operations in case of safety concerns or security breaches.

Ongoing maintenance is crucial for the AIPM to remain accurate and reliable. Regular updates should be made to improve performance and adapt to changes in clinical practice, though some updates may require recertification. Security and data integrity must be prioritized during updates to ensure the system continues to function effectively. Educating healthcare professionals on the proper use of the AIPM is essential, with training focusing on the system's probabilistic nature, limitations, and potential risks. This should be an ongoing process, with periodic retraining and specific guidance on recognizing and addressing potential automation biases.

Post-deployment, continuous monitoring and auditing are necessary to ensure the AIPM performs as expected and maintains safety standards. Monitoring should cover a range of factors, including predictive accuracy, data quality, user feedback, and clinical outcomes. Special attention should be paid to monitoring fairness, dataset shifts, and feedback loops. An auditing system must be in place to track the AIPM's decisions, performance, and use, ensuring compliance and helping identify any failures or risks. This framework should also include mitigation strategies to address any incidents and update the AIPM as needed based on the findings (48,49).

## CHALLENGES AND FUTURE IN THE CLINICAL IMPLEMENTATION OF ML AND DL

The applicability of ML and DL in the context of DRM allows for a more proactive and personalized approach to nutritional care, where decisions are based on objective, real-time data. However, several challenges exist. The adoption of these technologies requires specialized training to interpret the results generated by the models and to adjust them according to the specific characteristics of each clinical environment. Additionally, the reliance on large volumes of accurate and up-to-date data is essential for the success of these models; the lack of integration and standardization of data across different hospital systems represents a significant barrier (2,4) (Fig. 2).


**Figure 2.**

Implementation of AI in the field of clinical nutrition.

Another significant challenge is improving the interpretability of DL models, as their predictions are often not easily understandable by clinicians. This is especially important in hospital settings, where decisions need to be clearly explained and supported by clinical evidence. Approaches like Shapley Additive Explanations (SHAP) can help clarify the influence of each variable on the prediction, making it easier for medical professionals to comprehend and trust the model's outputs.[4] Furthermore, effective implementation requires skilled personnel and seamless integration with established hospital workflows. In addition to this, ethics is a critical consideration that must be continuously addressed as AI becomes more integrated into healthcare. The challenges posed by AI systems, including issues of bias, data protection, and explainability, require careful attention from governments and regulatory bodies to ensure ethical and regulatory standards are met. Efforts should focus on creating effective strategies to enhance the comprehensiveness, precision, and standardization of nutritional and health data (50).

As these models are refined and better adapted to the specificities of clinical data, their impact on the management of malnutrition could revolutionize patient care, optimizing both health outcomes and the use of hospital resources.

## CONCLUSION

The implementation of AI tools, particularly those based on ML and deep learning DL, has demonstrated significant potential in addressing the challenges associated with DRM.

These technologies not only enhance early detection and diagnosis but also optimize clinical management and patient outcomes. ML and DL models, such as RF, LightGBM, and deep neural networks, have shown high levels of accuracy in identifying at-risk patients and predicting related complications, enabling personalized interventions that reduce clinical complications and hospital costs. Nevertheless, their adoption in clinical practice faces notable challenges, including the need for large volumes of standardized data, integration into EHR systems, and improving model interpretability to ensure healthcare professionals' trust. Ethical considerations, such as ensuring equitable outcomes and data protection, must also be addressed to guarantee the responsible use of these tools. Despite these challenges, advancements in AI hold great promise for transforming clinical nutrition care, enabling a proactive and data-driven approach to managing DRM. Interdisciplinary collaboration among clinicians, AI specialists, and regulators will be essential to overcoming existing barriers and maximizing the positive impact of these technologies on patient health.

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