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A review of the application of deep learning in obesity: From early prediction aid to advanced management assistance

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ABSTRACT

Background and aims: Obesity is a chronic disease which can cause severe metabolic disorders. Machine learning (ML) techniques, especially deep learning (DL), have proven to be useful in obesity research. However, there is a dearth of systematic reviews of DL applications in obesity. This article aims to summarize the current trend of DL usage in obesity research.

Methods: An extensive literature review was carried out across multiple databases, including PubMed, Embase, Web of Science, Scopus, and Medline, to collate relevant studies published from January 2018 to September 2023. The focus was on research detailing the application of DL in the context of obesity. We have distilled critical insights pertaining to the utilized learning models, encompassing aspects of their development, principal results, and foundational methodologies.

Results: Our analysis culminated in the synthesis of new knowledge regarding the application of DL in the context of obesity. Finally, 40 research articles were included. The final collection of these research can be divided into three categories: obesity prediction (n = 16); obesity management (n = 13); and body fat estimation (n = 11).

Conclusions: This is the first review to examine DL applications in obesity. It reveals DL's superiority in obesity prediction over traditional ML methods, showing promise for multi-omics research. DL also innovates in obesity management through diet, fitness, and environmental analyses. Additionally, DL improves body fat estimation, offering affordable and precise monitoring tools. The study is registered with PROSPERO (ID: CRD42023475159).

1. Introduction

Obesity is a persistent metabolic ailment that characterized by the excessive accumulation of adipose tissue and aberrant distribution of body fat. Its insidious ramifications encompass a spectrum of complications, including diabetes, dyslipidemia, nonalcoholic fatty liver disease, hypertension and different types of cancers [1,2]. A recent comprehensive study encompassing 128.9 million individuals underscores the dramatic surge in global obesity prevalence, with a particularly heightened vulnerability observed among younger cohorts [3]. This underscores the need for the prevention and management of obesity.

The multifaceted nature of obesity's etiology, intertwined with genetic susceptibilities, cultural norms, dietary habits, and urban environments, has posed a challenge for comprehensive understanding and effective intervention [4]. Traditional research methodologies have often fallen short of capturing the intricacies of its causative network. However, recent advancements in genome-wide association studies (GWAS), image-based radiomics studies, and metabolites analyses, have ushered in novel insights in the realm of obesity research. Particularly the integration of advanced computational techniques, notably artificial intelligence (AI), offers new avenues for unravelling this complexity [5]. In this intricate landscape, ML emerges as a potent approach, capable of handling extensive parameters and deciphering the complex, nonlinear interrelationship among variables [6]. Nevertheless, a groundbreaking paradigm, deep learning (DL), has recently eclipsed traditional ML

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predictive models across various health domains [7,8]. It has been used to determine and optimize the most important factors for overweight and obesity in preschool-aged children [9]. Distinguished from conventional ML methods, DL empowers the direct use of raw data, leveraging the backpropagation algorithm to unveil intricate structure patterns [10]. Its capability of extending predictive variables across diverse domains, encompassing text, visual object recognition, and speech, enables the identification of novel factors [11–13].

While numerous literature reviews have extensively discussed the application of ML in obesity research, comparing methodologies with traditional statistical models, an existing gap pertains to a systematic exploration exclusively focusing on DL within obesity research [14–22]. This gap became evident with DeGregory *et al.*'s [23] seminal work in 2018, which highlighted the absence of dedicated DL applications in the field of obesity. Subsequently, in 2020, Colmenarejo *et al.* [5] conducted an overview of diverse ML models in predicting childhood obesity, with only one DL-related article included. Despite an escalation in reviews encompassing ML and obesity from 2018 to 2023, a comprehensive overview of DL and obesity remains limited [14–22]. Safaei *et al.* [17] (2021) described several ML methods for understanding the causes and consequences of obesity, without specifically clarifying the unique role of DL. Zhou *et al.* [22] (2022) briefly investigated the application of DL in food recommendation and geographic information systems, but didn't relate it to obesity. Addressing this gap, our study uniquely explores the application of DL in obesity, providing novel insights beyond current literature.

Emerging as a promising approach, DL has exhibited competitive performance in significant fields related to metabolic diseases, such as diabetes and cardiovascular diseases [24,25]. Therefore, the present study aims to elucidate the latest advances in DL technologies for obesity. By clearly defining our research objectives, we seek to enhance our understanding of DL's potential to unravel the complexities of obesity, contributing to innovative strategies for its prevention, management, and resolution.

2. Deep learning overview

DL is a branch of AI, developed upon the traditional ML algorithm—artificial neural networks (ANNs), which mimics the structure of biological neurons in the brain [26]. A standard ANN, as illustrated in Fig. 1, consists of three processing layers: input, output, and hidden layers. Each layer consists of multiple neurons, each is an abstract unit that uses its parameters to "multiply" the input vector to generate an output [24]. DL expands the architecture of ANN into deep neural networks (DNN) by incorporating additional hidden layers [27]. This augmentation enables the utilization of thousands or even millions of parameters for the extraction of data features and the acquisition of representations, thereby enhancing generalization capabilities (Fig. 1) [28]. Software packages including TensorFlow, PyTorch, Caffe, MXNet and Theano, formed the basis of DL implementation and can be executed over distributed grids of GPUs and CPUs [26,29]. The evaluation of DL classifier performance is assessed through the F1-score, confusion matrix, precision, recall and accuracy [23]. While regression problems involve a distinct set of metrics tailored to the nature of regression tasks. Commonly employed evaluation metrics for regression tasks encompass relative squared error (RSE), mean absolute error (MAE), root means square error (RMSE), mean squared logarithmic error (MSLE), and R-squared (R^2) coefficient [30]. These are frequently used evaluation metrics in body mass index (BMI) estimation tasks.

Generally, DL can be categorized into supervised learning, unsupervised learning and reinforcement learning, based on the learning method. Both classification and regression problems are common tasks for supervised learning in obesity research, where labelled input data is employed to optimize classifier parameters during model training [24]. Unsupervised learning, on the other hand, deals with datasets lacking explicit output labels. The model learns patterns and structures inherent in the data without predefined categories. In obesity research, unsupervised learning may be employed to identify natural groupings of patients based on shared characteristics or to uncover latent features in the data. Reinforcement learning introduces an interactive element, where an agent learns by interacting with an environment and receiving feedback in the form of rewards or penalties. While less common in traditional medical research, reinforcement learning can find applications in personalized treatment planning or optimizing interventions over time. For instance, it can be employed to tailor treatment plans for individual patients based on their responses to interventions [31]. Supervised algorithms of DL encompass a range of models including convolutional neural networks (CNNs), recurrent neural networks (RNNs), transformers, and others. While autoencoders (AE), deep belief networks (DBNs), and restricted Boltzmann machines (RBMs) are commonly applied unsupervised learning algorithms. Within the context of reinforcement learning, notable models include deep Q networks (DQN), deep deterministic policy gradient (DDPG) and, Monte Carlo tree search (MCTS), etc. [31].

Multilayer perceptron (MLP) and CNNs are presently among the most widely used DL algorithms. MLP often serves as a versatile architecture, and CNNs are particularly specialized for image-based tasks. Some notable examples within the CNN family include the visual geometry group network (VGG) and the residual neural network (ResNet). However, it's crucial to recognize that despite their successes, they encounter challenges like vulnerability to overfitting and sensitivity to initial conditions. These have propelled the evolution of algorithms. For instance, the multi-grained cascade forest (gcForest), inspired by the structure of DNNs, has effectively addressed challenges in various neural network architectures, encompassing both traditional ANNs like MLPs and specialized ones like CNNs. This unique approach demonstrates the

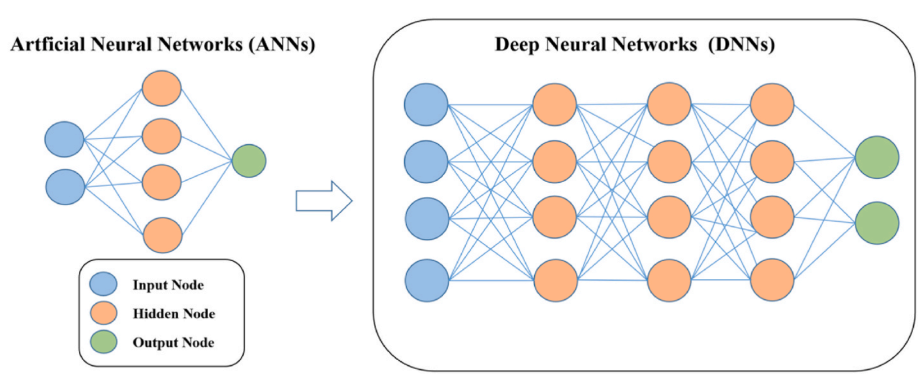

Fig. 1. Visualization of ANNs and DNNs. In contrast to AANs, the structure of DNNs exhibits a gradual increase in hidden layers, accompanied by intricate layer configurations that involve various iterations of neural nodes and cells.
Abbreviations: ANNs:artificial neural networks; DNNs:deep neural networks.

capability to achieve high accuracy even with small training datasets, requiring only minor hyperparameter adjustments [32]. Each of these DL architectures, from MLPs to advanced iterations of CNNs like VGG and ResNet, are fundamentally designed to transform raw input data into a hierarchy of features or "representations" that make the underlying patterns more discernible for prediction or classification tasks. This process is central to the power of DL and is precisely the foundation upon which the concept of "embedding" is built. Embeddings take this idea further by providing a dense, low-dimensional representation of the data, which can capture the intricate relationships within it in a way that is highly conducive to ML tasks. As we delve deeper into specialized algorithms such as gcForest, which itself performs a form of representation learning, we see a clear trajectory towards the utilization of "embeddings" to handle complex and high-dimensional data, such as genetic information, where complex relationships need to be captured efficiently.

In addressing obesity-related problems, DNNs offer a potent approach. Most problems in obesity prediction, management, and body fat segmentation are tackled through supervised learning. There are two supervised learning-based DNNs found in the literature of obesity: CNNs and RNNs. RNNs, in particular, distinguish themselves by incorporating information from previous time steps into their input, endowing them with a powerful ability to process sequential signals and capture temporal features. LSTM, which stands for long short-term memory, is a type of RNN that are designed to overcome the problem of vanishing gradients in traditional RNNs, which can make it difficult to learn long-term dependencies in sequential data. In both classification and regression tasks, the DNN process begins with collecting and preprocessing relevant data, such as patient profiles, medical records, or numerical features. This curated dataset is then input into the DNN model, featuring multiple layers of interconnected neurons. Utilizing the iterative process of forward and backward propagation, the network effectively learns intricate patterns and relationships within the data. For classification, it distinguishes between distinct obesity classes like "normal weight", "overweight", or "obese", while in regression, it predicts continuous outcomes such as numerical values "BMI", or scores based on the provided input features. By harnessing the potential of DNNs in obesity-related tasks, researchers can extract valuable insights into critical aspects such as risk factors, early detection strategies, and intervention approaches. Ultimately, this knowledge contributes significantly to the identification, assessment, and effective management of obesity-related concerns.

3. Methodology

Aiming at identifying and analyzing the benefits of DL within obesity-related research, we conducted a systematic review by searching multiple public online databases, including PubMed, Embase, Web of Science, Scopus, and Medline, following the standards introduced by Kitchenham and Charters [33]. All these databases provide open-access search engines, we restricted the search to English-language documents that were published between January 1, 2018, and September 30, 2023. The search was performed based on titles, abstracts, keywords, and metadata of original articles. We followed the preferred reporting items of the systematic review and meta-analyses (PRISMA) approach [34]. The selection process has been summarized in Fig. 2.

3.1. Research questions

The following research questions were formulated for this study:

1) What is the most commonly applied DL algorithm in obesity prediction?
2) What is the most popular domain of DL utilization in obesity management?
3) How can DL be leveraged in body fat composition estimation of obese individuals based on the current literature?

3.2. Search strategies

In the search procedures, the keywords "obesity", "overweight" and "obese" were combined with the DL terms using Boolean operators AND/OR. The specific query used in the searching process was: (obesity OR overweight OR obese) AND (deep learning OR deep neural network OR convolution neural network OR convolutional neural network OR recurrent neural network OR LSTM OR Boltzmann machine OR deep

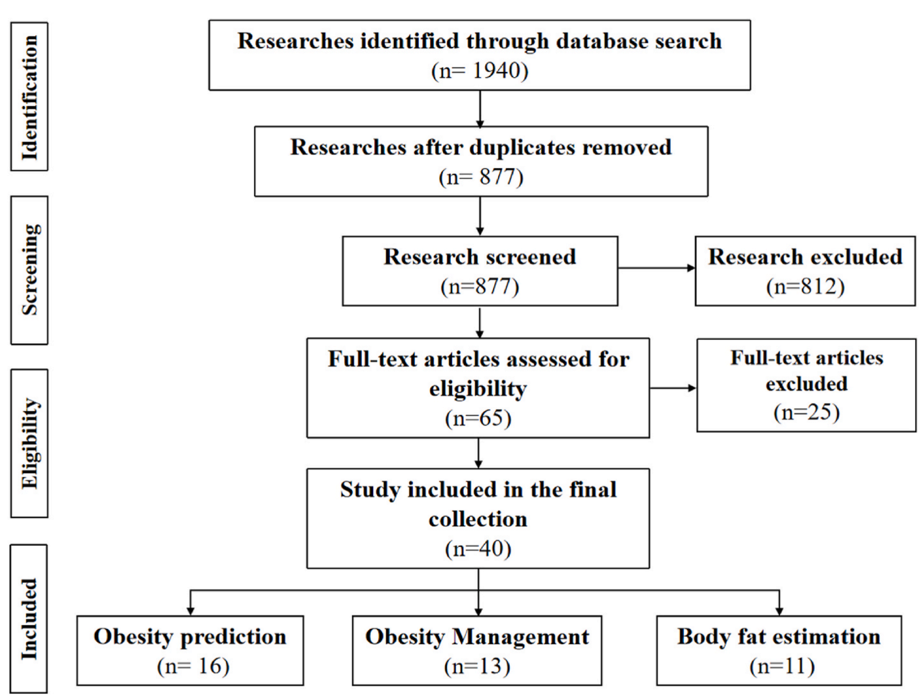

Fig. 2. Flow of the selection process.

belief network). After obtaining the initial collection of relevant articles, we removed duplicate research and manually inspected the remaining studies based on inclusion and exclusion criteria. A "forward and backward" search approach suggested by Watson and Webster was implemented in this procedure [35].

3.3. Inclusion and exclusion criteria

Studies adopted in this review are original and have full-text availability, focused mainly on the practical application of DL in obesity. The final collection of studies were allot into three categories based on application scenarios and purposes: obesity prediction, obesity management, and body fat estimation. Particularly, the included studies were expected to:

1) described the information of the data source.
2) described the methods, e.g., the structure of DNNs.
3) evaluate model performance with standard metrics or other common indicators: RSE, MAE, RMSE, etc.

The excluded studies were expected to:

1) works that are considered irrelevant to the research purpose.
2) couldn't access full-text availability, abstracts, posters, technique reports, and reviews were excluded.
3) study subjects aren't human, such as mice, sow, or adipose tissue etc.

3.4. Quality assessment

The following criteria were used in the quality assessment process:

1) Are the topics and abstracts of the study relevant to the review question?
2) Are the data sources clearly described and fully illustrated in the methodology section?
3) Does the model development procedure have a detailed description?
4) Has the model been validated on an external dataset or has practical application in the clinics?
5) Are the statistical analysis methods described specifically?

The above criteria were established regarding the quality evaluation procedure of Nidehra *et al.* [19,40]. Articles were then assessed and evaluated based on the criteria. If the study satisfied a criterion, it was given a score of 2. If it is partially satisfied, it will be given a score of 1. If it doesn't satisfy any criterion, it will be awarded a score of 0. Overall, articles that finally have a score of 7 or higher were considered high quality. Those who scored 4–6 were considered medium, and those who scored lower than 4 were removed from this SLR. After the quality assessment, a total of 40 relevant articles were collected for the next procedure.

3.5. Information extraction

We reviewed the full text and extracted key information from the selected articles to evaluate DL applications in obesity. The following categories were used to present the selected studies (Tables 1–3):

1) Cases: The study purpose and its potential application scenarios are summarized in this session.
2) Data Sources: The source of input data for model development is summarized in this session. Datasets used in some studies are publicly available. Thus, we summarized the information regarding the employed datasets including their sources, sizes, types, and formats.
3) Models: Algorithms used in developing DL models were described. Some developers may rename the prediction model, but their fundamental structures originated from the basic algorithms such as DNN and CNN, as mentioned before.
4) Development Process: We described the training strategies for DL model development in this category. Although DL can extract features from raw data without preprocessing, these development procedures still need to be carefully designed, to guarantee the model's functionality and reproducibility.
5) Main Outcomes: The major model performance evaluation index with the corresponding metrics and criteria are included in this category. Some of the evaluation estimators in obesity prediction are SE, SP, and AUC; while dice score is commonly used in body fat estimation.
6) Baselines: In most selected studies, comparison models of traditional ML algorithms are listed as baseline methods, to highlight the superior performance of the DL algorithm. Conventional ML models collected in this category include logistic regression (LR), generalized linear model (GLM), supporting vector machine (SVM), random forest (RF), extreme gradient boosting (XGboost), k-nearest neighbor (KNN), and decision tree (DT).

4. Results

A total of 1940 papers were collected through the initial search from PubMed (n = 232), Embase (n = 599), Web of Science (n = 336), Scopus (n = 658) and Medline (n = 115). After removing the duplicates (n = 877), 1063 remained. The selected articles were then manually sorted according to the inclusion and exclusion criteria. A complete inspection for full-text accessibility was carried out to evaluate the eligibility of the remaining articles. Finally, 40 research articles were included. The final collection of this research can be divided into three categories: obesity prediction (n = 16); obesity management (n = 13); and body fat estimation (n = 11). Most selected papers were published in 2022, indicating that DL application in obesity is fairly new and its development has been accelerating. The selected works are summarized in Tables 1–3. In addition, Fig. 3 summarized the application of DL in obesity. The developed models for classification and regression are evaluated with the following metrics.

- Classification metrics: accuracy score, area under curve (AUC), classification report and confusion matrix. A confusion matrix consists of two dimensions, "actual"and "predicted", each of which includes categories for "true positive (TP)", "true negative (TN)", "false positive (FP)", and "false negative (FN)". Formulas for calculating the classification metrics are stated below:

$$
\begin{gathered}
Accuracy = \frac{(TP + TN)}{TP + FP + FN + TN} \\
Precision = \frac{TP}{(TP + FP)}, \\
Recall(Sensitivity) = \frac{TP}{(TP + FN)}, \\
Specificity = (1 - Sensitivity) = \frac{TN}{(TN + FP)} \\
F1\ score = \frac{2*precision*recall}{precision + recall}
\end{gathered}
\tag{1}
$$

Accuracy measures how closely a measured value aligns with the true value. Precision measures the closeness of predicted values to true values, while Recall (or sensitivity) gauges the model's ability to identify all positive instances. The F1-score combines precision and recall to strike a balance between these aspects in model evaluation. These metrics are vital for evaluating and comparing the performance of DL models across different applications.

- Regression metrics: MAE, MSE, RMSE and R^2-score.

Table 1
Summary of research articles delving into obesity prediction.

Ref	Cases	Data Sources	Models	Development Process	Main Outcomes	Baselines	Year
Montanez *et al.* [36]	Obesity prediction	Genotypes and Phenotypes (dbGaP) dataset: 240,950 SNP genotypes of 1997 individuals	Multi-layer feedforward artificial neural network	Hyperparameters: 5 SNPs model: hidden layers: 2; neurons: 20; activation function: maxout with dropout; L1:7.1 × 10ˆ-5; L2:9.6 × 10ˆ-5. 32 SNPs and 248 SNPs model: hidden layers:2; neurons: 50; actiation function: Tanh with dropout; L1:3.0 × 10ˆ-6; L2:6.5 × 10ˆ-5; 2465 SNPs model: hidden layers:2; neurons: 10; actiation function: rectifier with dropout; and L1:9.6 × 10ˆ-6; L2:2.8 × 10ˆ-5.V alidation: internal; 10-fold cross-alidation.	AUC of validation set: 0.627 (using 5 SNPs), 0.754 (using 32 SNPs), 0.923 (using 248 SNPs), 0.9931 (using 2465 SNPs).	N/A	2018
Lapierre *et al.* [37]	Obesity prediction	Metagenomic samples from 164 obese patients and 89 non-obese controls (datasets of MetAML study)	AutoNN: neural network with autoencode	Hyperparameters: number of autoencoder layers: 1; number of feedforward layers: 5; dropout rate: 0.5; optimizer: adagrad; learning rate: 0.001.V alidation: internal; 5-fold cross-alidation.	AUC using microbial abundances: gcForest:0.6495; AutoNN:0.6031. AUC using k-mer abundances: gcForest:0.6186; AutoNN:0.5666.	gcForest; SM; RF; XGBoost.	2019
Oh *et al.* [38]	Obesity prediction	Whole-genome shotgun metagenomic studies: metagenomic samples from 164 obese patients and 89 non-obese controls	DeepMicro: arious autoencoders, including, deep autoencoder, ariational autoencoder, and conolutional autoencoder	Hyperparameters: specific hyperparameters are not mentioned.V alidation: internal; 5-fold cross-alidation.	DeepMicro (abundance-based model): AUC:0.674.	N/A	2020
Montanez et al. [39]	Obesity prediction	Genotypes and Phenotypes (dbGaP) dataset: 2193 participants; each participant contains 594,034 genetic markers	SAERMA: stacked autoencoder rule mining algorithm	Hyperparameters: not mentioned;V alidation: internal.	AUC: 77%; SE: 68% SP: Gini coefficient: 53%; log loss: 0.58; MSE: 0.20.	N/A	2020
Yao *et al.* [40]	BMI prediction	Publicly aailable datasets of human actiity recognition: 67 subjects from MobiAct and 24 subjects from MotionSense	CNN-LSTM	Hyperparameters: optimizer: Adam; learning rate: 0.001; epochs: 200; batch size: 20; dropout rate: 0.5; regularizer: L2.V alidation: internal; leae-one-subject-out cross-alidation.	Accuracy: 94.8% ± 1.5%.	kNN; SM; C4.5; DT.	2020
Kim *et al.* [41]	Body weight prediction	Lifelog mobile app: user data of 17,867 indiiduals going through the 16-week weight loss program	RNN	Hyperparameters: not mentioned.V alidation: internal; 5-fold cross-alidation.	MAE:3.50%.	N/A	2021
Lee *et al.* [42]	Obesity prediction	Walking data from mHealth APP: 170 high school students	Feedforward neural network; CNN	Hyperparameters: 1) Feedforward neural network: input layer initialized by Glorot normal initialization; input shape: 9 rotation vectors; hidden layers: 5 layers, each with 512 neurons and 50% dropout rate; output layer: 2 neurons with Softmax actiation function. 2) CNN: 3 conolution layers with the Relu actiation function; first conolution layer: 512 output filters; second conolution layer: 1024 output filters; third conolution layer: 2048 output filters; one max pooling layer for resizing; two densely connected neural network layers for the output layer; output layer: 2 neurons with Softmax actiation function; dropout rate: 50%.V	Feedforward: neural network: accuracy:61.8%, 90.5%; loss value: 4.998,0.979 CNN: accuracy: 54.8%, 79%; loss value:3.551,2.12.	N/A	2022

(*continued on next page*)

Table 1 (*continued*)

Ref	Cases	Data Sources	Models	Development Process	Main Outcomes	Baselines	Year
				alidation: internal; 10-fold cross-alidation.			
Dhanamjayulu *et al.* [43]	BMI prediction	Images: 1530 human face images scraped from the internet	Residual network 50	Hyperparameters: 50 layers; others not mentioned.V alidation: internal; multi-task cascaded conolutional neural network. were used to process facial images; training samples: 1227, test samples: 316.	MAE (5.02); RMSE (4.56).	Visual geometry group 16; Sequential multi-task sual geometry group.	2022
Eom *et al.* [44]	Obesity prediction	BIGKinds: 8830 texts data from 52 media	RNN; LSTM	Hyperparameters: *1)*RNN: 2 layers, 12 timesteps, 64 hidden nodes, 0 L^2 regularization, 0 dropout rate, 32 batch size, and 7 epochs. 2)LSTM: 2 layers, 12 timesteps, 32 hidden nodes, 0 L^2 regularization, 0.1 dropout rate, 20 batch size, and 10 epochs. The learning rate is not explicitly mentioned.V alidation: internal.	RNN: accuracy: 98.218%; precision: 97.456%; recall: 89.757%; LSTM: accuracy: 97.122%; precision: 96.717%; recall: 89.669%.	N/A	2022
Snekhalatha *et al.* [45]	Obesity detection	Fifty healthy subjects and fifty age cum sex matched obese subjects (1000 images for normal and 1000 images for obese classes)	CNN	Hypermeters: optimizer: stochastic gradient descent; learning rate: 0.01; clip alue: 0.5; epochs:20.V alidation: internal.	The highest: F1-score: 0.92; AUC: 0.948	N/A	2021
Gupta *et al.* [46]	BMI prediction	An EHR dataset of children and adolescents from Nemours Children's Health: 68,003 patients	RNN with LSTM cells	Learning rate:an Adadelta optimizer with an initial learning rate of 0.05; the epoch or batch size used for training is not mentioned V alidation: internal.	AUC for a 3-year window: 0.80 at 5 years (preschool), 0.93 at 11 years (prepubertal), 0.92 at 18 years (post-pubertal).	Linear regression; RF.	2022
Grazioli *et al.* [47]	Obesity prediction	A total of 11 different cohorts: metagenomic and metabolomic data from human gut microbiota	Multimodal ariational information bottleneck; DeepMicro with ariational autoencoder	Hyperparameters for multimodal ariational information bottleneck: learning rate: 10ˆ-4; latent dimension: 256; batch size: 256; epochs: 50 epochs. (DeepMicro not mentioned).V alidation: internal; 5-fold cross-alidation.	AUC on obesity: Multimodal variational information bottleneck: 0.743 DeepMicro with variational autoencoder: 0.731.	RF: 0.806;	2022
Jin *et al.* [48]	BMI estimation	Project webpage: 4190 images	CNN (DenseNet)	Hyperparameters: batch size:32; epochs:50.V alidation: internal; 10-fold cross-validation.	MAE: 4.00; MAPE: 12.50%	N/A	2022
Rashmi *et al.* [49]	Obesity detection	Siananda Gurukulam school: data of 150 children (Obese: n = 50; Oerweight: n = 50)	CNN (MobileNet ersion 2; isual geometry group 16; Customized Net)	Hyperparameters: batch size: 128; learning rate: 0.01; epochs:50.V alidation: internal; 5-fold cross-validation.	Accuracy: MobileNet Version 2: 74.8%V isual geometry group 16: 79.2% Customized net: 89.3%.	N/A	2022
Forte *et al.* [50]	Classify obesity risk	Portuguese project: 654 adolescents	Neural network	Hyperparameters: optimizer: adam; batch size: 16 units.V alidation: internal; 10-fold cross-alidation.	Accuracy: 75%; AUC: 0.64.	N/A	2023
Richa *et al.* [51]	Obesity detection	Siananda Gurukulam school: data of 100 children (Obese: n = 50)	Residual network 18; isual geometry group 19	Hyperparameters: not mentioned.V alidation: internal; 5-fold cross-validation.	Oerall classification accuracy: Residual network-18: 94.2%; Visual geometry group-19: 86.5%.	N/A	2023

Abbreiations: AUC: area under the cure; SVM: supporting vector machine; RF: random forest; SE: sensitivity; SP: specificity; MSE: mean squared error; BMI: body mass index; CNN: conolutional neural network; LSTM: long short-term memory; kNN: k-nearest neighbor; DT: decision tree; RNN: recurrent neural network; MAE: mean absolute error; RMSE: root mean square error; MAPE: mean absolute percentage error.

MAE measures the average absolute difference between the predicted values generated by a model and the actual observed values. MAE is often used in conjunction with other regression performance metrics, such as MSE and RMSE, to provide a comprehensive evaluation of the model's performance. MSE measures the average squared difference between the predicted values and the actual observed values. A smaller MSE also indicates better accuracy, but it amplifies the impact of large errors. RMSE is the square root of MSE, providing a measure of the average squared prediction error. R^2 measures how well the model explains the variability in the target variable. Its values range from 0 to 1,

Table 2
Comprehensie oeriew of research articles addressing the multifaceted aspects of obesity management.

Ref	Cases	Data Sources	Models	Deelopment Process	Main Outcomes	Baselines	Year
Hasan *et al.* [60]	Body weight control	Transcripts of 129 motiational interiews: 50,239 segmented and annotated utterances	LSTM; gated recurrent unit	Hyperparameters: learning rate: 0.00005; batch size: 8; epochs:100.V alidation: internal; 10-fold cross-validation.	LSTM with target replication: precision:0.8733 recall:0.8681 f1-score: 0.8677.G ated recurrent unit with target replication: precision:0.8705 recall:0.8676 f1-score: 0.8673.	Statistic model; Marko chain; hidden marko model.	2018
Mcallister *et al.* [61]	Food classification	Food image datasets: Food-5K, Food-11, RawFooT-DB, and Food-101	Google net; Residual network 152; isual geometry group 16; Residual network t-50	Hyperparameters: specific hyperparameters are not mentioned; the framework is to use DL algorithms to do feature extraction job; and then ANN, SM, RF were trained on the learned representation.V alidation: internal; 10-fold cross-validation.	ANN classifier: accuracy: 91.5%; recall: 0.915; F1 Score: 0.915; kappa: 0.83; AUC: 0.98. SM classifier: accuracy: 89.5%; recall: 0.895; F1 Score: 0.895; kappa: 0.79; AUC: 0.97. RF classifier: accuracy: 88.5%; recall: 0.885; F1 Score: 0.885; kappa: 0.77; AUC: 0.96.	N/A	2018
Nguyen *et al.* [62]	Liing enironment	Google's street iew: 430,000 images for Salt Lake City, Chicago and Charleston	CNN	Hyperparameters: not mentioned.V alidation: not mentioned.	Accuracy: commercial buildings/apartments: 84.59%; green-30%:85.40%; crosswalk recognition: 93.03%.	Manual annotations.	2018
Lee *et al.* [63]	Body weight control	Korean Genome and Epidemiology Study (KoGES): 12,206 eligible consecutie isit-pairs of 3447 participants	DNN	Hyperparameters: learning rate:5 × 10ˆ-3; epochs: 500.V alidation: external validation of national health insurance serice of Korea–National sample cohort.	AUC:0.876.	LR (0.851); NB (0.857); RF (0.867); XGBoost (0.879).	2020
Phan *et al.* [64]	Liing enironment	Google Street iew: 31,247,167 images	CNN	Hyperparameters: not mentioned.V alidation: internal.	Accuracy: 85%–93% for the separate recognition tasks.	Manual annotations.	2020
Xiao *et al.* [65]	Liing enironment	Baidu Street iew images: 8988 samples from 40 communities in Shanghai	CNN	Hyperparameters: not mentioned.V alidation: not mentioned.	N/A	N/A	2020
Kim *et al.* [66]	Dietary management	Korea national health and nutrition examination surey	DNN	Hyperparameters: learning rate:0.01; the batch size:20; epochs:100.V alidation: internal; 5-fold cross validation.	Accuracy: 0.62496.	LR: 0.62486; DT:0.54026.	2021
Exarchou *et al.* [67]	Dietary management	Food-101 dataset: 38 k images of desert and non-desert	CNN (inception3); Residual network 101; isual geometry group 16; MobileNet	Hyperparameters for inception 3: initial learning rate = 0.008; momentum:0.9; decreasing learning rate by half every 10 epochs; trained to binary cross-entropy loss 0.0910 after 27 epochs.V alidation: external; a new data collection of food images captured under challenging light and angle of capture conditions.	Accuracy: Google Inception3:95.79%; Residual network 101: 92.99%; V isual geometry group: 82.24%; mobileNet: 89.25%.	N/A	2022
Oduru *et al.* [68]	Dietary management	Google images: 23,141 food images (definitiely healthy, healthy, unhealthy, definitiely unhealthy)	Residual network 152	Hyperparameters: not mentioned.V alidation: external validation; Twitter dataset.	Accuracy: 77.25%; F1-score:78.8%.	N/A	2022
Chen *et al.* [69]	Dietary management	Business analyst: restaurants images; Google images: food images	CNN	Hyperparameters: not mentioned.V alidation: not mentioned.	Validated the model's performance using three statistical metrics: Kendall's tau rank correlation coefficient, Pearson's correlation coefficient, and Cohen's kappa coefficient using linear weights. The correlation coefficients (τ =	The calorie information obtained from a published nutrient composition database.	2022

(continued on next page)

Table 2 (*continued*)

Ref	Cases	Data Sources	Models	Delopment Process	Main Outcomes	Baselines	Year
					0.953, r = 0.961, and k = 0.846).		
Yue *et al.* [70]	Liing enironment	164 million Google street iew images	CNN	Hyperparameters: loss function: sigmoid cross entropy with logits; optimizer: adam; batch size: 20; epochs:20; learning rate: 1 × 10^{-4};Validation: internal.	Accuracy: street greenness: 88.70%; presence of crosswalks: 97.20%; non-single family homes: 82.35%; single lane roads: 88.41%; isible utility wires: 83.00%; side walks: 84.5%.	N/A	2022
Shermila *et al.* [71]	Food classification and calorie assessment	Twenty different types of fruits and egetables	RNN; LSTM	Hyperparameters: not mentioned.Validation: not mentioned.	Accuracy: 99.15%; precision: 9.8%; recall: 8.7%; specificity: 98.26%.	N/A	2023
Josephin *et al.* [72]	Food classification and calorie assessment	Twenty different types of fruits and egetables: total of oer 41,509 images	Combination of RNN and LSTM.	Hyperparameters: not mentioned.Validation: internal; 5-fold cross-validation.	Accuracy: 99.36%; precision: 98.9%; recall: 99.15%; specificity: 98.07%.	Segmentation-based multi kernel-based support vector machine; deep conolutional neural network; Faster recurrent conolutional neural network.	2023

Abbreiations: LSTM: long short-term memory; DL: deep learning; ANN: artificial neural network; SVM: supporting vector machine; RF: random forest; AUC: area under the cure; CNN: conolutional neural network; DNN: deep neural network; NB: naïe bayes; LR: logistic regression; DT:decision tree; RNN: recurrent neural network.

with 1 indicating a perfect fit and 0 indicating a poor fit. A higher R^2 score indicates a better fit and greater explanatory power of the model.

$$MAE = \frac{1}{n} * \sum \left| Predicted\ Value - Actual\ Value \right|, MSE = \frac{1}{n} * \sum (Predicted\ Value - Actual\ Value)^2,$$

$$RMSE = \sqrt{(MSE)}, R^2 = 1 - \frac{\frac{1}{n} \sum_{i=1}^{n} (Actual\ Value - Predicted\ \ Value)^2}{\left(\frac{1}{n} \sum_{i=1}^{n} \left(Actual\ Value - Mean\ \ Value \right) \right)^2} \tag{2}$$

subsequent research to explore the potential of SAEs in achieving compact representations of SNPs without losing essential information. By adjusting the hidden units in the SAEs, later studies effectively reduced the SNP count to 204 and still achieved a respectable AUC of 0.77 for obesity prediction [38]. These findings underscore the effectiveness of embeddings in condensing genetic information into a lower-dimensional space for more efficient analysis.

4.1. Obesity prediction

Prompt detection of obesity onset is crucial in preventing chronic complications associated with obesity status. Conventional ML methods have been vastly applied in obesity prediction [5,17,22]. However, compared with traditional ML methods, DL has shown superior performances [36–51].

Recently, with the flourishing of omics data, its' advantage has become evident. Conventional ML methods may suffer from computational complexity when dealing with data derived from the GWAS study. To address this, the concept of "embedding" comes into play. Embeddings can handle high-dimensional omics data by transforming it into a form that reduces computational demands for conventional ML methods. DL models facilitate this by generating embeddings of single nucleotide polymorphisms (SNPs), thereby enabling the detection of complex interactions that may contribute to obesity [36]. These embeddings effectively condense the genetic information into a lower-dimensional space that can be more readily analyzed. Montanez *et al.* [36] utilized stacked autoencoders (SAEs) to distill the complexity of SNP epistatic information into a more manageable form. Their model adeptly compressed 2465 SNPs into a lower-dimensional embedding, yielding a high AUC of 0.993 for obesity prediction. However, the number of SNPs proved to be a crucial factor for model performance; a reduction in SNP input to 5 resulted in a significantly lower AUC of 0.627, indicating sensitivity to the input size. This insight prompted subsequent research to explore the potential of SAEs in achieving compact representations of SNPs without losing essential information. By adjusting the hidden units in the SAEs, later studies effectively reduced the SNP count to 204 and still achieved a respectable AUC of 0.77 for obesity prediction [38]. These findings underscore the effectiveness of embeddings in condensing genetic information into a lower-dimensional space for more efficient analysis.

Apart from genetic variants, metagenome-based profiles also provide novel insights into obesity prediction. The MetAML (metagenomic prediction analysis based on ML) study collected microbiome samples from diseases including cirrhosis, diabetes, colorectal disorders, and obesity from 8 large cohorts, a total of 164 obesity samples and 89 normal controls were contained. Several studies have reported that ML models based on this dataset have excellent performance in liver and bowel disease prediction but poorly in obesity [52–54]. However, by then, DL models have not been evaluated. In 2019, LaPierre *et al.* [37] investigated the DL performance of gcforest and AutoNN (based on DNN) on this dataset using different feature extraction methods, the k-*mer*-based feature extraction strategy and the previously reported MetaPhlAn2-based feature extraction method. Results show that gcForest yielded the highest AUC of 0.65, while the AutoNN achieved the best accuracy on Type 2 diabetes (T2D) prediction. Later in 2020, the study further utilized DeepMicro, a framework that incorporated various AEs, including shallow autoencoder, deep autoencoder, variational autoencoder, and convolutional autoencoder, to learn a low-dimensional embedding for microbiome profiles [38]. This model outperforms the other approaches including SVM, RF and ANN in obesity prediction (AUC = 0.659) and other diseases including T2D, cirrhosis and bowel diseases [38]. Similarly, Montanez *et al.* [39]

Table 3
Summary of selected articles related to body fat estimation.

Ref	Cases	Models	Data Sources	Deelopment Process	Main Outcomes	Baselines	Year
Langner *et al.* [77]	Body fat segmentation	Fully conolutional networks (U-Net; -Net)	The study Tellus and the study BetaJudo: BMI up to 40 kg/m2	Hyperparameters: learning rate: 0.0001; batch size:1; optimizer: Adam optimizer.V alidation: external; 20 scans from the BetaJudo study.	Dice score: U-Net (0.97–0.99 for AT; 0.99 for SAT) -Net (0.92–0.98 for AT; 0.98–0.99 for SAT).	Human manual segmentation analysis.	2019
Liu *et al.* [78]	Body composition analysis	ABC-Net	The hospital of the uniersity of Pennsylania: unenhanced low-dose CT scans of 38 patients (BMI:17.27–38.28 kg/m2)	Hyperparameters: trained using a combination of dice loss and cross-entropy loss; learning rate: adjusted using a warm restarts strategy.V alidation: internal; 5-fold cross-validation.	92–98% in common accuracy metrics (F1-score, precision, recall).	DeepMedic; 3D U-Net; Net; Dense -Net.	2020
Paris *et al.* [79]	Body composition analysis	Deep CNN	Clinical centers and hospitals from Canada, United States, France, and the Netherlands: CT scans of 893 patients (BMI: 28.0 (±6.1) kg/m2)	Hyperparameters: not mentioned.V alidation: internal validation.	Dice similarity coefficient compared with manual segmentation based on CT scans: skeletal muscle: 0.983 ± 0.013 intermuscular: 0.900 ± 0.034;V AT: 0.979 ± 0.019; SAT: 0.986 ± 0.016.	Human manual segmentation analysis.	2020
Kafali *et al.* [80]	Body fat segmentation	2D U-Net; 3D U-Net; ADC 3D U-Net	Habitual diet and aocado trail: 87 participants with 164 MRI exams (BMI:31.89 ± 4.45)	Hyperparameters: not mentioned.V alidation: not mentioned.	Mean 3D dice scores: ADC 3D U-Net: 0.96 for VAT, 0.99 for SAT; 2D U-Net: 0.96 for SAT; 0.77 for VAT 3D U-Net: 0.95 for SAT; 0.74 for VAT.	N/A	2021
Langner *et al.* [81]	Body composition analysis	Residual network 50	UK Biobank: 40,264 participants (BMI: 14–62 kg/m2)	Hyperparameters: pre-trained on ImageNet and optimized with Adam at batch size 32 with online augmentation by random translations. After 5000 iterations, the base learning rate of 0.0001 was reduced by factor 10 and training continued for another 1000 iterations.V alidation: external; dataset D_c.	Test dataset: SE:0.91 SP:0.99 PP: 0.94 NP: 0.98.	Body composition measurements from the same MRI data based on volumetric multi-atlas segmentation.s	2021
Majmudar *et al.* [82]	Adiposity assessment	CNN	Recruited 134 healthy adults (BMI:18.5–51.6 kg/m2)	Hyperparameters: not mentioned.V alidation: external validation; four smartphone images of each participant in an “A" pose and associated reference measurements for total body fat percentage.	MAE: 2.16 ± 1.54%.	Commercial body composition analysis methods.	2022
Langner *et al.* [83]	Body composition analysis	Residual network 50	UK biobank: 38,916 adults' MRI scans	Hyperparameters: not mentioned.V alidation: internal; 10-fold cross-validation.	Mean absolute percentage error: <3%.	N/A	2022
Bhanu *et al.* [84]	Body fat segmentation	3D U-Net and RGA-U-Net	Geri-LABS study: MRI scans of 90 healthy community-dwelling older adults (BMI 23.75 ± 3.65 kg/m2)	Hyperparameters: batch size: 16; epoch:250.V alidation: internal; random 4:1 split of the dataset into training and validation sets.	Dynamic strength index: score for training (3 class): U-Net: 0.74–0.91); RGA-U-Net: 0.88–0.94.	N/A	2022
Wu *et al.* [85]	Abdominal adipose tissue segmentation	CNN (2D competitie dense fully conolutional network)	Generation R Study: 2920 children MRI scans	Hyperparameters: not mentioned.V alidation: internal.	Dice similarity coefficient: SAR: 0.96; VAT:0.89. v olumetric similarity: SAT: 0.98; VAT: 0.93 MAE: SAT: 2.5%; VAT: 4.7%.	Manual segmentation.s	2023
Schneider *et al.* [86]	Abdominal fat quantification	CNN	Single-center study at integrated research and treatment center: patients with obesity (BMI ≥35 kg/m^2), the dataset inolved 331	Hyperparameters: not mentioned.V alidation: internal; 5-fold cross validation.	Dice coefficient: SAT: 0.954; VAT: 0.889. MPE: SAT: 0.7%; VAT:		2023

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Table 3 (*continued*)

Ref	Cases	Models	Data Sources	Deelopment Process	Main Outcomes	Baselines	Year
			MRI examinations and 12,422 abdominal MRI slices		0.8%. RMSPE: SAT: 0.026; VAT: 0.017.		
Josephin *et al.* [87]	Abdominal fat quantification	U-Net	136 adolescents (BMI:13.20–25.19 kg/m^2)	Hyperparameters: learning rate: 0.0001; epochs:100; batch size: 8.V alidation: internal; 5-fold cross validation.	Dice similarity coefficient: outer region: 0.96; inner region: 0.89; SAT: 0.87; VAT: 0.81.	N/A	2023

Abbreiations: BMI: body mass index; VAT: visceral adipose tissue; SAT: subcutaneous adipose tissue; CT: computed tomography; CNN: conolutional neural network; SE: sensitivity; SP: specificity; PPV: positive predictiev value; NPV:negative predictive value; MRI: magnetic resonance imaging; MAE: mean absolute error; MAPE: mean absolute percentage error; MPE:mean percentage error; RMSPE: root mean squared percentage error.

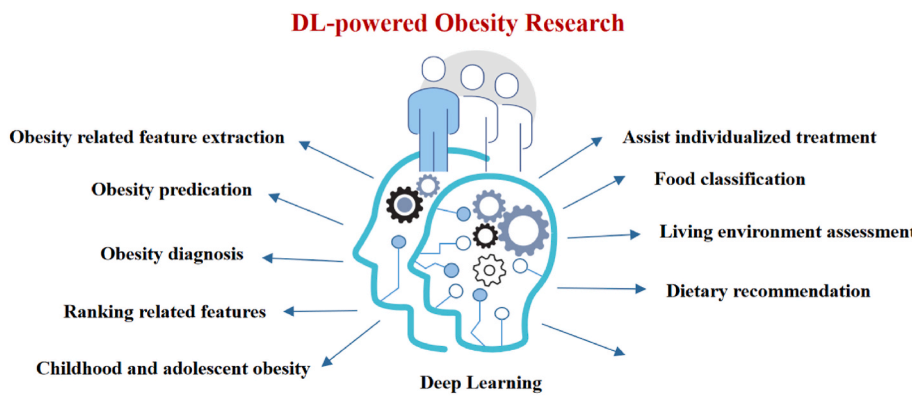

Fig. 3. Summary of deep learning application in obesity.

proposed a SAERMA (stacked autoencoder rule mining algorithm) model, which combines several techniques, including quality control, association analysis, rule mining, and DL, to extract meaningful features from the genetic data and classify individuals based on their risk of developing extreme obesity. The algorithm uses a SAE to perform deep feature extraction and initialize the weights of a multi-layer perceptron neural network (MLPNN) for classification analysis. Rule mining is used to identify the most frequent SNPs among individuals in cases and controls and extract rules from them. The resulting rules are then used as input features in the SAE to capture the relationships between SNPs and improve the performance of the MLPNN. SAERMA has been shown to outperform other methods for identifying epistatic interactions in GWAS for extreme obesity, and it has the potential to be applied to other complex diseases as well [39]. In 2022, a multimodal variational information bottleneck (MVIB) was developed, MVIB integrates abundance and marker gene data from the gut microbiome to predict three diseases: obesity, T2D, and colorectal cancer [47]. The authors demonstrate that MVIB outperforms existing state-of-the-art methods on multiple benchmark datasets, achieving an AUC of 0.743 on the obesity cohort [47]. The study also compares MVIB with other DL models, including DeepMicro, and shows that MVIB achieves better performance on all three diseases [38,47]. Additionally, the authors investigate the generalization ability of MVIB by performing cross-study experiments, which demonstrate that MVIB can generalize well to unseen datasets from different studies [47]. Overall, this work provides a valuable contribution to the field of microbiome-based obesity prediction and highlights the potential of DL models in this area.

Other than omics data processing, studies have also utilized DL to process data collected from motion sensors, media, and mobile apps to capture obesity-related traits and risk factors [40–44]. Moreover, recent developments have introduced various methods for estimating BMI values based on visual information, such as face images or 3D body images [48]. These approaches, which extrapolate anthropometric features from face images or 3D body images, have significantly enhanced the accuracy of BMI estimation [48]. A recent study shows that in addition to projections based on cross-sectional data, DL was first utilized in longitudinal obesity prediction [46]. The LSTM models using temporal data can predict childhood obesity in the next 1, 2, and 3 years with high accuracy [46]. Furthermore, DL has also been harnessed in computer-aided diagnosis systems for detecting obesity based on thermal images. Various CNN models were evaluated for their ability to classify subjects as obese or normal. Among these models, the custom CNN network (Custom-2) exhibited superior performance, achieving a weighted average F1-score of 0.92 and an AUC of 0.948 [45]. This DL-based approach delivered results comparable to traditional ML methods like scale-invariant feature transform for feature extraction.

To sum up, according to the research included in the study, CNNs are exceptional in natural language processing data analysis, including audio, text, and image processing related to obesity, and unsupervised method AEs are specialized in feature engineering and dimensionality reduction process [43,44,55,56]. Embeddings are a foundational component in DL applications within obesity prediction, providing a means to simplify and condense complex biological data into actionable insights. The exact models mentioned employ embeddings in nuanced ways, tailoring them to the specificities of the dataset at hand, which is a testament to the versatility and power of DL techniques in this field [37]. However, to our knowledge, DL has not been specifically applied in multi-omics research related to obesity yet. Therefore, further research may yield unexpected results in obesity surveys.

4.2. *Obesity management*

The goal of obesity management is to keep a healthy lifestyle and avoid undesired weight gain. Although dietary control and exercise intervention are state-of-the-art in obesity treatment, standard therapy and restricted exercise schedules remain difficult to accomplish.

Smartphone apps and portable devices have been invented to enable weekly individual coaching and health behavior monitoring, which provide opportunities for DL utilization [57–59]. There are several sub-domains in obesity management, which can be differentiated into three categories: dietary management, fitness guidance, and living environment adjustment [60–72]. Studies have shown that patients who possess the potential risks for metabolic syndrome could benefit by giving guidance with DL models [63]. After the analysis of residents' physical fitness data, DL can formulate personalized exercise programs for each individual, and provide sports education as well as intelligent guidance [73].

Dietary control is fundamental in obesity management, apps and devices that require manual input have been invented to record daily calorie intake [74]. However, automated dietary monitoring is more reliable than manually food logging. An early dietary monitor system combined with a programmable social robot can automatically track diet targeting childhood obesity prevention [75]. With the constant updating of computer versions, multiple CNN-based models have been adopted to extract the representation from photographs in the open-source food dataset [61,66–68,76]. Survey has shown that these models can segment diverse, multi-food cuisines automatically and estimate the calories, which enables image-based dietary intake monitoring [76]. A noteworthy instance of these advancements is the application of the pre-trained ResNet-152 architecture, which stands out with its depth of 152 layers and the incorporation of shortcut connections to promote better information flow. This complex architecture uses convolutional layers to perform deep feature extraction from food image datasets, efficiently preparing the data for subsequent classification by ML classifiers into distinct food categories [61]. Complementing the ResNet-152's capabilities, the Calorie Mama API, a DL-based food image recognition tool, has been employed to refine the analysis of food images further. It offers comprehensive nutritional information, including calories and nutrient content, quantified in the SI unit of Kcal/kg. This technology plays a critical role in aggregating calorie data for individual restaurants, acting as a marker of obesogenic environments, thus aligning with the Food and Drug Administration's nutritional labelling requirements [69]. In a similar vein, the proprietary models DEEPFIC (deep learning-based food item classification) and MDEEPFIC(modified deep learning-based food item classification), which also utilize DNN, have been tailored to deliver precise feature extraction and calorie calculation [71,72]. The DEEPFIC employs an architecture that integrates image preprocessing techniques—like contrast stretching and histogram equalization—to refine input images, followed by RNN and Bi-LSTM networks that capture spatial and temporal features for effective classification. The calorie values are then computed using a regression model based on these features [71]. In contrast, MDEEPFIC uses improved watershed segmentation for image processing, coupled with a modified dragonfly optimization algorithm that enhances the accuracy of calorie estimations, particularly for fruits and vegetables of varying sizes. For example, an apple with skin is calculated to have 75 kcal for a 130-g serving, and a banana has 108 kcal per 102 g, by correlating the mass of the food item with a standardized calorie chart. Both models demonstrate their efficacy by providing precise caloric values of food items, which are crucial for dietary management and obesity prevention [72].

CNN-based algorithms have been instrumental in evaluating the living environment's impact on obesity, revealing connections between greenery, urban design, and obesity prevalence [62,64,65,70]. Studies indicate that features like green streets, crosswalks, and mixed building types correlate with lower obesity prevalence [62]. Additionally, areas with greater median family income tend to have greener streets and fewer commercial buildings or apartments, indicating a socioeconomic dimension to the neighborhood characteristics contributing to obesity [62]. And both horizontal, vertical greenery and the proximity of green levels can impact body weight [65]. Within this realm of research, a noteworthy application involved employing the VGG-16 model—a deep convolutional network famed for its 16 weighted layers and high image recognition accuracy. This model demonstrated proficiency by analyzing 31, 247, 167 images from Google Street View, which facilitated the generation of neighborhood characteristic indicators with significant implications for obesity and physical activity outcomes, reaching accuracy levels ranging from 85% to 93% [64]. The utility of the VGG-16 model extended beyond mere identification of environmental traits; it was instrumental in extracting and classifying features indicative of the built environment's health impact. This was achieved through an architecture that integrates multiple convolutional layers, max-pooling layers, and fully connected layers—features it shares with other leading architectures such as AlexNet, ResNet, and Inception. These models, pre-trained on extensive image datasets like ImageNet, empower researchers to fine-tune algorithms for the precise detection of environmental factors linked to obesity [65]. This approach echoes methodologies employing the robust CNN framework to extract urban design features from Google Street View images, assessing their impact on chronic diseases including obesity in the U.S., with an effective image recognition architecture comprising convolutional, pooling, and fully connected layers, paralleling those in similar studies [70].

4.3. Body fat estimation

BMI is usually implemented as a threshold in clinical practice to define obesity and overweight. However, it cannot discern the fat component from lean tissues of body mass, therefore it can't diagnose abdominal obesity or muscular obesity [77–87]. Thus, body composition is more appropriate for accessing adiposity levels in older adults, athletes, or individuals who have lost muscle due to pathological reasons. Callipers, bioelectrical impedance analysis, computed tomography (CT) scans, and magnetic resonance imaging (MRI) are commonly used methods in determining body composition and body fat segmentation [77,82]. However, several limits of these methods such as the low accuracy of the former and the high cost of the latter have restrained their large-scale utilization. Addressing these challenges, the ABCNet emerges as an innovative DL-based approach detailed in the recent study [78]. This 3D dense-structure network is engineered specifically for the segmentation and analysis of body tissue composition from body-torso-wide low-dose CT images, employing a basic-vonv unit and a series of dense blocks to create a deep yet memory-efficient network. The ABCNet has shown proficiency in automatically segmenting key body tissues—including subcutaneous and visceral adipose tissue, skeletal muscle, and paraspinal muscle—essential for both research and clinical evaluation. Its optimization using dynamic soft dice loss and coarse-to-fine tuning has significantly improved segmentation accuracy. The network has been validated on a dataset of 200 low-dose CT scans, demonstrating high accuracy and robustness, and shows promise for implications in diseases such as cardiovascular and metabolic disorders, and monitoring post-chemotherapy outcomes [78]. These findings represent a substantial advance in DL applications for body composition analysis, potentially overcoming the constraints of traditional methods [79,81,83].

Current research indicates that excess accumulation of visceral adipose tissue (VAT) is strongly linked to a poor metabolic and inflammatory profile compared to subcutaneous adipose tissue (SAT) [88]. SAT primarily functions for long-term energy storage, while VAT has higher metabolic and hormonal activity due to adipokine release. An MRI-image-based DL method can quantify SAT and VAT, and reduce the time-consuming work of building the ground-truth images that are required to train DL models [83]. Complementing this effort, the study introduced two advanced fully convolutional network architectures, U-Net and DeepLabV3+, tailored for abdominal segmentation [86]. The modified U-Net with residual connections and the atrous convolution-utilizing DeepLabV3+, pre-trained on the COCO dataset, were fine-tuned on a dataset of 2820 abdominal MRI scans. This adjustment and training were geared towards enhancing the segmentation of SAT and VAT, employing binary cross-entropy loss and dice loss for optimization, and augmenting the training data with various transformations to bolster model robustness [86]. Similarly, 2D-CDFNet (two-dimensional competitive dense fully convolutional network) can automate the quantification of abdominal fat in adolescents using MRI scans. This model, trained on a dataset of 2820 abdominal MRI scans from children aged 13–18 years, employs a specialized 2D (two-dimensional) CNN architecture to segment SAT and VAT effectively [85]. The 2D-CDFNet includes a feature extraction module to glean details from MRI images, a context aggregation module to enhance the data's contextual integrity, and a segmentation module for accurate tissue differentiation, demonstrating strong agreement with manual segmentations [85]. Such DL approaches, including the application of the U-Net architecture for abdominal segmentation, provide precise measurements of abdominal adipose tissues, essential for a consistent evaluation of changes in SAT and VAT, especially in younger populations [87]. By using the U-Net architecture, popular for its performance on small medical image datasets, the author trained two models: one for abdominal wall segmentation and another for SAT and VAT classification. Combining region-based and pixel-based training, the technique precisely measures abdominal adipose tissue in young individuals, providing a consistent evaluation of changes in abdominal VAT and SAT [87]. However, not all metadata can be inferred with the proposed DL model because the required information may be lost by different preprocessing approaches or the images may not be acquired in a standardized manner [83]. In this case, proper quality control of the data source and the external validation of an open-sourced DL framework is necessary to overcome such obstacles [81,83,84].

5. Discussion

The primary objective of this study was to explore the application of DL techniques in various aspects of obesity research and clinical practice, including obesity prediction, management, and body fat estimation. Our results reveal the substantial potential of DL in enhancing the accuracy, efficiency, and precision of these critical processes. In comparison with traditional ML methods, our findings underscore the superiority of DL in the context of obesity prediction. We demonstrated that DL models, particularly stacked autoencoders, are exceptionally proficient at capturing complex interactions between SNPs to classify obesity subtypes. These results align with previous studies that have also recognized the promise of DL in managing the intricacies of genomic data analysis, but we extend these findings to the specific context of obesity research [39]. We extended our inquiry to the metagenome-based profiles, shedding light on the novel prospects of DL in this domain. In this respect, our work adds a novel dimension to the literature as previous studies have shown strong performance in liver and bowel disease prediction, yet have fallen short in obesity prediction. This research, however, brought DL into the limelight, exemplified by the noteworthy results from our use of gcForest and AutoNN [37]. Additionally, our exploration of DL's role in dietary management, fitness guidance, and the impact of living environments in obesity management is pioneering. These findings are aligned with emerging studies demonstrating the potential of DL in optimizing health behavior monitoring and personalized health intervention.

In the domain of obesity prediction, DL outperforms ML methods, particularly in handling complex data types like genetic variants and metagenomic profiles. Furthermore, DL's applications extend to obesity management. Smartphone apps and portable devices equipped with DL enable personalized coaching and health behavior monitoring. DL models can automatically monitor dietary intake through image-based recognition, offering a more reliable and user-friendly alternative to manual food logging. They also play a crucial role in developing personalized exercise programs based on physical fitness data. Moreover, DL aids in body fat estimation by offering innovative methods for assessing adiposity levels. Visual body composition models can estimate body fat percentage directly from 2D digital photographs, making it a convenient and cost-effective tool for daily monitoring. DL is also integrated with traditional methods, such as CT scans and MRI, to automate the analysis of body composition phenotypes, saving time and resources for clinicians.

Our results underscore the transformative power of DL in handling intricate data types across the spectrum of obesity research and clinical practice. This includes but is not limited to, managing genomics data for obesity prediction, developing personalized exercise programs and dietary management strategies, and evaluating the impact of living environments on obesity prevalence. DL's ability to uncover complex patterns in large datasets, especially in the multi-omics context, signifies its potential to elucidate the complex interplay of genetic and environmental factors contributing to obesity. Most of the selected papers of DL in obesity research were published within the late two years. To our knowledge, this is the first review focusing on the DL application in obesity research. Our study acts as a cornerstone in the growing literature on the application of DL in obesity research and clinical practice. It opens doors to innovative solutions and underscores the pivotal role of DL in advancing our understanding of obesity and its management. For future work, researchers should evaluate each DL algorithm for accuracy and robustness on external datasets when attempting to expand its utilization. Moreover, research that focuses on integrating multiple omics data to unravel the complex web of factors that contribute to obesity seems promising.

In conclusion, this comprehensive review has shed light on the transformative role of DL within the domain of obesity research and clinical practice. Our extensive analysis reveals that DL holds remarkable promise across multiple dimensions of obesity, including prediction, management, and body fat estimation. One of the key contributions of this study to the existing body of literature is the exploration of DL's untapped potential in multi-omics research related to obesity. By amalgamating genetic, proteomic, and metagenomic data, DL offers the tantalizing prospect of unveiling fresh insights and innovative solutions. DL technology can significantly enhance the precision and effectiveness of obesity diagnosis and management. With its prowess in data extraction from diverse sources, such as genetic and environmental data, motion sensor data, and even longitudinal data, DL empowers clinicians and researchers alike to gain comprehensive insights into obesity-related traits and risk factors. This review sets the stage for further research into DL applications, encouraging ongoing exploration of its potential in the multifaceted world of obesity research and clinical practice. For future research, it's crucial to assess the accuracy and robustness of DL algorithms on external datasets as they are extended for broader applications. Additionally, promising prospects lie in studies that aim to integrate various omics data to untangle the intricate web of factors underlying obesity.

5.1. Limitations and challenges

First, this study excluded conference articles, books, and unpublished full-text papers, this could have constrained access to alternative research and outcomes. Nevertheless, this selection was made to align with the anticipation of presenting verified findings through peer-reviewed journal papers, which also follow the best practices norm in academic publishing. The second limitation is the restricted search for articles to only five online databases: i.e., PubMed, Embase, Web of Science, Scopus, and Medline. However, these databases were selected because they are among the most extensively applied and acknowledged worldwide, each index covers journals and articles across various disciplines, including medicine, engineering, and computer science, which are relevant to the current study. Hence, this thorough exploration still clearly portrays the present state of obesity research with DL methods.

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Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dsx.2024.103000.

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