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Review

The Application of Artificial Intelligence in Magnetic Hyperthermia Based Research

Magdalena Osial † and **Agnieszka Pregowska** *,†

Institute of Fundamental Technological Research, Polish Academy of Sciences, Pawinskiego 5B Street, 02-106 Warsaw, Poland
* Correspondence: aprego@ippt.pan.pl; Tel.: +48-22-826-12-81 (ext. 412)
† These authors contributed equally to this work.

Abstract: The development of nanomedicine involves complex nanomaterial research involving magnetic nanomaterials and their use in magnetic hyperthermia. The selection of the optimal treatment strategies is time-consuming, expensive, unpredictable, and not consistently effective. Delivering personalized therapy that obtains maximal efficiency and minimal side effects is highly important. Thus, Artificial Intelligence (AI) based algorithms provide the opportunity to overcome these crucial issues. In this paper, we briefly overview the significance of the combination of AI-based methods, particularly the Machine Learning (ML) technique, with magnetic hyperthermia. We considered recent publications, reports, protocols, and review papers from Scopus and Web of Science Core Collection databases, considering the PRISMA-S review methodology on applying magnetic nanocarriers in magnetic hyperthermia. An algorithmic performance comparison in terms of their types and accuracy, data availability taking into account their amount, types, and quality was also carried out. Literature shows AI support of these studies from the physicochemical evaluation of nanocarriers, drug development and release, resistance prediction, dosing optimization, the combination of drug selection, pharmacokinetic profile characterization, and outcome prediction to the heat generation estimation. The papers reviewed here clearly illustrate that AI-based solutions can be considered as an effective supporting tool in drug delivery, including optimization and behavior of nanocarriers, both in vitro and in vivo, as well as the delivery process. Moreover, the direction of future research, including the prediction of optimal experiments and data curation initiatives has been indicated.

Keywords: artificial intelligence; machine learning; magnetic hyperthermia; magnetic nanoparticles; cancer treatment; drug delivery

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1. Introduction

Artificial Intelligence (AI), including Machine Learning (ML), can be used to solve various issues of information processing, including pattern recognition, classification, clustering, dimensionality reduction, image recognition, natural language processing, and predictive analysis [1]. AI-based algorithms can be applied to solve complex problems [2–4]. Recent algorithm development enables its application in many areas of everyday life, such as industry, medicine, and nanomedicine; including nanomaterials with magnetic properties [5]. Consequently, a new opportunity to predict drug influence and responsiveness based on retrospective databases became available [6]. It may contribute to the development of optimized healthcare [7].

An important direction in developing medicine is to provide an effective method of dealing with various neoplastic diseases. The heterogeneous nature of tumors contributes to the problems in selecting effective treatment mechanisms. It is crucial to deliver drugs directly to the tumor core, the area most active in proliferation but less vascularized and hypoxic. Thus, the critical challenge in choosing the optimal therapy is determining the synergy of the drug depending on its dose, administration timing, and current treatment process. The latest development in nanotechnology enables the design of nanocarriers for targeted drug delivery, improving medicine release and beating cancer cells. In turn, manufacturing the nanoparticles, which can be loaded with drugs or other agents (stabilizers, compounds for diagnostics), is a time and financial outlays-consuming process. Thus, the AI-based prediction of the effect of nanoparticles with drugs on living tissues enables the development of targeted nanomedicine [8,9].

One cancer treatment method that uses magnetized particles is magnetic hyperthermia [10,11]. It can lead to the death of cells through the modulation of cellular processes by generating heat. It relies on intravenous injection or carrying of the magnetic particles at the site of the tumor's tissue and their heating in an alternating magnetic field in the range of temperature 40–43 °C as an effect of both hysteresis and relaxation losses [12]. Magnetized nanoparticles reach the tumor by disrupting the endothelial barrier with an external magnetic field [13]. This process provides the killing or weakening of tumor cells. Nanoparticles that can be used in Magnetic Resonance Imaging (MRI) imaging are super-paramagnetic iron oxide nanoparticles (SPIONs), fluorescent agents, perfluorocarbon, and gadolinium, while X-ray and CT use High-density gadolinium or iodine as contrast agents [14]. SPIONs-based magnetic hyperthermia may destroy malignant tissues in the body [15]. Thus, magnetic hyperthermia requires selecting the proper process parameters and the properties of magnetic particles; and conditions like the position and properties of the tumor, the health status of subjects, and current and taken therapies. Artificial Intelligence has been involved in making this process more efficient and predictable [5]. In [16], *in-silico* modeling for hyperthermia using the bioinformatics tool i-TASSER was presented, namely evaluating the effect of amino acid sequences on metal binding sites. Moreover, this approach enables the prediction of the rheological properties of magnetic particles [17].

Another application field of magnetic nanoparticles is anemia treatment and diagnostics, including Computed Tomography (CT) and MRI [18–22]. In the case of such iron-based compounds, The Food and Drug Administration (FDA) has approved different formulations, where the colloidal suspension of the magnetic nanocarriers is proposed [19]. Ferumoxytol (trade named Feraheme® and Rienso®) composition is based on the colloidal iron having a hydrodynamic diameter (D_H) ranging from 17 to 31 nm coated with an organic stabilizer like polyglucose sorbitol carboxymethyl ether [23–25]. In turn, in Ferumoxide (Feridex®, Endorem®), the dextrans are used to coat iron oxide nanoparticles (IONPs) [26,27] similarly to Ferumoxtran-10 (Sinerem®, Combidex®) [28]. Another product called Ferrisat® is based on iron dextran nanostructures, and Injectafter® contains ferric carboxymaltose [26]. Ferucarbotran (Ciavist™, Resovist®) stabilizes IONPs with carboxydextran, where D_H is up to 180 nm [29,30]. In turn, in Ferumoxsil (Lumirem®, GastroMARK®), IONPs are coated with siloxanes, where D_H is up to 300 nm [31], and in Nanotherm® with aminosilanes, and VSOP C184 ultrasmall IONPs are coated with citrates [29]. As these agents contain solid-state iron-based compounds having magnetic properties, they reveal tremendous potential to be used in magnetic hyperthermia [31]. Depending on the shape, size, and concentration of nanoparticles in the solution and the magnetic properties of magnetic carriers, including coercivity, magnetic remanence, magnetization saturation, and hysteresis loop area, the particles' effectiveness in magnetic hyperthermia can vary. The ability to predict these properties with Artificial Intelligence-based algorithms can provide the opportunity to optimize the parameters of magnetic hyperthermia [5]. The AI-based algorithm was also proposed to increase the effectiveness of microbubbles, which are used in clinical diagnostics as a contrast nanocarrier in ultrasound imaging techniques and as a transport carrier in targeted delivery [32,33].

In this paper, we briefly overview the significance of the combination of AI-based methods, in particular, the Machine Learning technique with magnetic hyperthermia, to shed light on their application in the field of nanotechnologies, in particular nanomedicine, including targeting strategies and optimization of the effectiveness of existing anticancer therapies. Algorithmic performance comparison in terms of their types and accuracy, data availability taking into account their amount, types, and quality was also carried out. Finally, the direction of future research has been indicated.

2. Materials and Methods

The review methodology was based on PRISMA Statement [34] and its extensions: PRISMA-S [35,36], and our personal experience. We considered recent publications, reports, protocols, and review papers from Scopus and Web of Science Core Collection databases. In the study, the following keyword and their variations have been used: "Artificial Intelligence", "Machine Learning", "nanoparticles", "Magnetic Hyperthermia", "nanomaterials", "nanomedicine", and "prediction". As a result, in Scopus, we obtain 157 documents, including 93 articles, 12 conference papers, 34 reviews, 8 conference reviews, 3 books chapter, 3 notes, and 4 editorials. As a result, in the Web of Science Core Collection, we obtain 131 documents, including 16 research articles, 33 review articles, 13 books, 21 book chapters, 17 conference abstracts, 1 conference info, and 1 discussion. The selection process was performed according to the context of Magnetic Hyperthermia, algorithms, their efficiency, and databases. Finally, 112 documents were considered analyses.

3. Magnetic Hyperthermia

Magnetic hyperthermia (MHT) is more commonly used in various biomedical applications [37,38]. MH, a clinical alternative to tumor treatments, also became a powerful tool for cancer treatment by exposing tumor tissue to elevated temperatures to achieve a therapeutic effect [31]. It has been successfully applied to the treatment of different types of cancer including the brain [39], spine [40], lung [41], prostate [42], breast [43], and pancreas [31]. It is also a promising alternative to traditional cancer therapies, particularly in the case of aggressive brain cancer like glioblastoma [44]. MHT's huge advantages are connected with biosafety, deep tissue penetration, and a focused place of action [45]. It induces apoptosis by the magnetic carriers generating the heat in the external alternating magnetic field [46]. The heating of magnetic carriers occurs due to the relaxation that generates the heat going within the core within Néel and Brown modes, while several parameters need to be included to estimate the specific absorption rate (SAR) and the intrinsic loss power of the colloidal suspension (ILP), described by the following equations [47]:

$$SAR = C/m_{np}\ (dT/dt) \tag{1}$$

where C stands for a heat capacity of the fluid per unit mass of fluid, m_{np} is the mass of magnetic phase suspended in the fluid, and dT/dt refers to the initial slope of temperature rise T, as a function of time, t; and as follows

$$ILP = SAR/H^2f \tag{2}$$

where H defines the amplitude of the magnetic field, and f refers to the frequency of the AMF.

The SAR and ILP depend on the parameters defining the properties of the magnetic carriers: chemical composition, magnetization saturation, shape and size of nanoparticles, the density of the colloidal suspension (magnetic carriers mass in the volume of suspension), dispersant-specific heat, nanoparticles density, the viscosity, and the amplitude of the alternating magnetic field (AMF), frequency of the AMF. They also depend on the hysteresis effect, relaxation effect, eddy current, domain wall, and natural resonance influence of AMF [48]. Thus, the physicochemical and biological properties of the magnetic carriers and the medium influence the efficiency of magnetic hyperthermia-based therapies, making it crucial to be optimized for effective therapy [49]. It is important to provide a high level of efficiency and safety for the magnetic particles used.

Magnetic hyperthermia application for beating cancers is a relatively new technique facing some challenges, such as accurately determining local temperature growth or tumor heating efficiency [49]. Other important issues are optimizing magnetic nanoparticles' shape, size, and stability. For example, [50] has shown that applying nanoparticles in the form of oxide nanocubes increases the efficiency of magnetic hyperthermia. Therefore, AI tools can benefit MH research (see Figure 1).

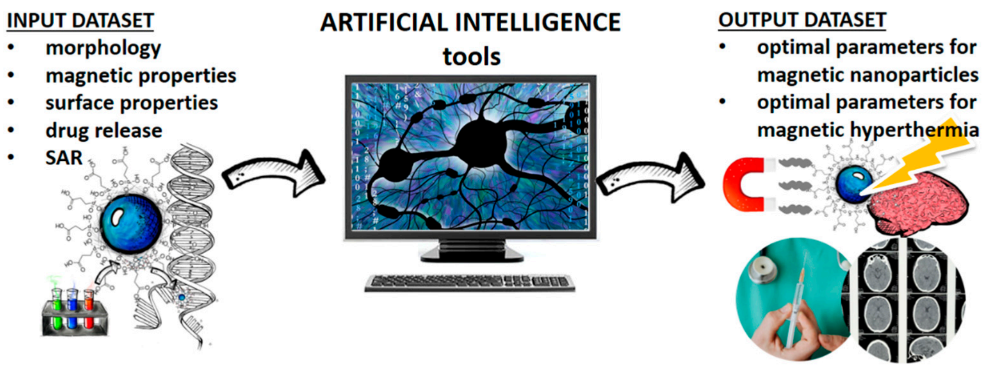

Figure 1. The general idea of magnetic hyperthermia combined with AI is applied to tumor therapies.

4. Artificial Intelligence and Machine Learning Based Approach

Artificial Intelligence is the creation of models and programs that simulate, at least partially, intelligence behavior. It enables machines to learn from experience, adapt to new information, and perform human-like tasks [51]. These activities are based on knowledge, data modeling, algorithm systems, and computing power development. AI-based approaches include Machine Learning, Natural Language Processing (NLP), and speech recognition. AI is slowly becoming an inseparable companion in most areas of people's lives, including autonomous vehicles, smart homes, and power grids. Many modern digital devices contain AI modules; even internet browsers are working on its principles to predict content based on our search habits with high efficiency, or provide capabilities spanning from sorting spam. Netflix applied AI to personalize movie offers. Also, nanomedicine, in particular magnetic hyperthermia-based research, may be beneficial with AI applications, especially throughout the increase of product quality and decrease of cost connected with their developments [5,8,9].

Recently, a huge effort has been made to apply AI-based solutions, including Machine Learning in magnetic hyperthermia-based research [51,52]. In turn, Machine Learning is an automatic improvement of computer programs through experience [53]. It includes various types of approaches, starting from traditional statistical ones, like, for example, linear regression, in fact, estimation of the best-fit line, to complex neural networks, including Artificial Neural Networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), Support Vector Machines (SVM), and Least-Squares Support Vector Machines (LS-SVM). Artificial Neural Networks are networks of computer-created artificial neurons that imitate the functioning of the human brain through applied algorithms [54]. The commonly used type of ANNs is the Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) [55].

The first, as the input, used time series and sequential data, i.e., text or video, and the size of input and output may vary, while the second used spatial data, namely images, and the size of input and output is fixed. RNN is usually applied to NLP, speech recognition, image captioning, and text translation [56], while CNN is used in image recognition and classification [57]. Both types can be applied in deep learning [58], which increases the ability to processing of raw data in comparison to conventional ML techniques. Deep learning uses the backpropagation algorithm to evaluate parameters, which are used to compute each layer's representation based on the previous layer's model. Still, the most commonly used ML form is supervised learning, which is based on the minimization of the error between the desired pattern and output sources by modification of internal parameters, often called weights. Thus, the application of AI, in particular ML, in magnetic hyperthermia-based research can be challenging, depending on the various types of materials and the amount and quality of available data.

5. Artificial Intelligence and Machine Learning as Support for Magnetic Hyperthermia-Based Research and Prediction Properties of Nanoparticles

Since each subject is different, and drug synergy gives a different output in an individual case, transforming Artificial Intelligence (AI) to nanomedicine enables the analysis of large data sets and the effective selection of the optimal therapy [51,52]. It is essential in cancer therapy, particularly in the application of magnetic hyperthermia, to predict the optimal parameters of the process. AI includes various algorithms; in this paper, we reviewed the existing solutions in the area of research, which involve the use of magnetic hyperthermia, taking into account their effectiveness, type and size of data sets, input and output parameters, and application fields. In [59], ANN was applied to predict the size of $AgNO_3$ particles. It turned out that the most sensitive parameters are both $AgNO_3$ concentration and reaction temperature. As the $AgNO_3$ suspension has no relation with magnetic hyperthermia, the literature shows the successful use of ANN in the prediction of particular properties of nanomaterials. In [60], the ANN was proposed to predict the shape and size of TiO_2 nanoparticles. In Table 1, the algorithms for the evaluation of the nanoparticle size were compared. It turned out that neural networks, in particular networks based on multilayer perceptrons, enable the prediction of the size of nanoparticles with high accuracy, i.e., 0.97 based on the experimental data.

Table 1. The comparison of the algorithm's performance takes account of the prediction of the optimal size of the nanoparticles.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Artificial Neural Network				
0.94	experimental data	- polymer concentration - drug - solvent ratio - mixing rate	- size	[61]
0.97	experimental data	- polymer molecular weight-number of blocks in the copolymer used - ratio of polymer to drug	- size	[62]
Algorithm Type: multilayer perceptron				
0.97	745 experimental data from the literature	- inherent viscosity - molecular weight - lactide-co-glycolide ratio - inner/outer phase Polyvinyl alcohol (PVA) - concentration - PVA molecular weight - inner phase volume - encapsulation rate - mean particle size - concentration - dissolution pH - number of dissolution additives - dissolution additive concentration - production method - dissolution time	- size	[63]

Table 1. *Cont.*

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
0.99	experimental data	- particle concentration - reaction temperature - UV-visible wavelength - montmorillonite d- - spacing	- size	[59]

The AI-based analysis of thermal conductivity, taking into account different shapes of nanoparticles (i.e., spherical, ellipsoidal, clubbed, and sheet), has been made in [64]. It turned out that AI-based prediction can substantially increase the relative thermal conductivity of nanofluids. In Table 2, the algorithms for the evaluation of the thermal conductivity of the nanoparticle were compared.

Table 2. The comparison of the algorithm's performance takes account of effective thermal conductivity.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: cascade-forward neural network				
0.93	1273 data collected from the literature	- temperature-solid volume fraction-solid volume fraction	- effective thermal conductivity	[65]
0.99	80 dataset experimental data and 389 data collected from the literature	- temperature concentration - shape factor - thermal conductivity	- relative thermal conductivity	[64]
Algorithm Type: Artificial Neural Network				
0.99	776 experimental data set	- average diameter - volume fraction - temperature	- the ratio of thermal conductivity	[66]
Algorithm Type: multilayer perceptron, radial basis function neural network generalized regression, Least-Squares Support Vector Machines				
0.97	80 dataset experimental data and 389 data collected from the literature	- temperature concentration - shape factor - thermal conductivity	- relative thermal conductivity	[64]
Algorithm Type: radial basis function neural network				
0.95	80 dataset experimental data and 389 data collected from the literature	- temperature concentration - shape factor - thermal conductivity	- relative thermal conductivity	[64]
Algorithm Type: Adaptive neuro-fuzzy inference system				
0.96	80 dataset experimental data and 389 data collected from the literature	- temperature concentration - shape factor - thermal conductivity	- relative thermal conductivity	[64]

One of the most important properties of nanoparticles is neurotoxicity [65]. In [67], the classification model for evaluation neurotoxicity based on Random Forest was proposed while in [68], the evaluation of antibacterial capacity using different AI-based algorithms was shown. In turn, [69] applied ML and perturbation theory to evaluate the toxicity of nanoparticles. In Table 3 the comparison of the algorithms for the prediction of the neurotoxicity of the nanoparticle was compiled. So far, the ANN can also be used to predict specific parameters for magnetic nanoparticles, see Table 4.

Table 3. The comparison of the algorithms for prediction of the nanoparticle toxicity.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Artificial Neural Networks				
0.97	260 datasets from the literature	- average values of the - descriptors for nontoxic - toxic cases with the specific value of the descriptor of each toxic or nontoxic	- toxicity	[69]
Algorithm Type: Least Absolute Shrinkage Selection Operator Regression, Ridge Regression Elastic Net Regression, Support Vector Machine				
0.78	datasets from literature	- specific surface - area - hydrodynamic size - zeta potential - core size - exposure dose - duration - shape - type - coating - bacterium - aggregation Available online: https://github.com/mahsa-mirzaei/RFR_ABA/commits?author=mahsa-mirzaei (accessed on 24 November 2022).	- core size - exposure dose - species of bacterium	[68]
Algorithm Type: Random Forest				
0.78	datasets from literature	- specific surface - area - hydrodynamic size - zeta potential - core size - exposure dose - duration - shape - type - coating - bacterium - aggregation Available online: https://github.com/mahsa-mirzaei/RFR_ABA/commits?author=mahsa-mirzaei (accessed on 24 November 2022).	- core size - exposure dose - species of bacterium	[68]
0.98		- dose - duration - nanoparticle type - nanoparticle shape - zeta potential - surface area - cell origin - cell type - cell line - assay	- cell viability	[70]

Table 4. The comparison of the algorithms for prediction of the optimal properties of nanomaterials performance.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Artificial Neural Network				
0.93 (for Young's modulus) 0.96 (ultimate tensile strength)	153 datasets from the literature	- weight percent - - particle size	- Young's modulus - ultimate tensile strength	[71]
0.97	3404 experimental dataset	- wavelength - peak intensity - full width at half-maximum - peak area of the main peak	- particle size - reaction yield - quantum yield	[72]
0.98	experimental data sets	- extraction time - temperature - pressure - modifier volume	- extraction yield of essential oils	[73]
0.99	experimental data sets	- composition	- specific absorption rate	[74]
0.99	420 experimental data sets	- particle concentration - alternating magnetic field strength - temperature - time	- optimal parameters	[75]
Algorithm Type: Random Forest				
0.75	652 datasets from the literature	- nanoparticle type - nanoparticle core - surface modification - modification type-size - zeta potential - polydispersity index - corona formation - corona isolation	- optimal composition	[76]
Algorithm Type: multilayer perceptron				
0.94 (compressive strength) 0.97 (porosity)	data collected from the literature	- elastic modulus - fracture toughness diopside - hardystonite - bredigite	- compressive strength - porosity	[73]

The following research [5] described the ML application to the prediction of power losses of magnetic particles, which is an important issue in drug targeting. This study has been done on a limited amount of data containing simulated particles' simulated properties, showing the proposed approach's colossal potential. In Table 5, the algorithm's performance in predicting power losses of magnetic particles has been made. The evaluation of the biological and mechanical behavior of the potential candidate for nanomaterials, i.e., silicates bioceramics-magnetite bio-nanocomposites, which can be applied to the magnetic hypothermia based on ANN has been made in [73]. In turn, the results presented by [71] show that ANN has better accuracy than genetic algorithms (GA) in predicting Young's modulus and ultimate tensile strength of nanocomposites, particularly polyethylene composites with multiple nanoparticles.

Table 5. The comparison of the algorithm's performance takes into account the prediction of power losses of magnetic particles.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Neural Network				
0.90	3963 records of simulated records	- temperature - vertex field - nanoparticles diameter - magnetic anisotropy - saturation magnetization - the identity of nanoparticles	- coercive field - magnetic remanence - hysteresis loop area	[5]
Algorithm Type: Random Forrest				
0.90	3963 records of simulated records	- temperature - vertex field - nanoparticles diameter - magnetic anisotropy - saturation magnetization - the identity of nanoparticles	- coercive field - magnetic remanence - hysteresis loop area	[5]

In [74], the application of the genetic algorithm for the optimization of agar nanospheres, which were used in the manufacturing process of drug loading, was proposed. The optimization problem was formulated to minimize the size of the particle, release efficiency, and PDI, as well as to maximize the absolute value of zeta potential and loading efficiency. It turned out that a genetics algorithm could successfully predict the parameters of Bupropion hydrochloride-loaded agar nanospheres. In turn, [75] the closed-loop optimization of the release process of the Poly (lactic-co-glycolic acid) (PLGA) biodegradable particles with ANN and genetic algorithms was described. As input data, particle size, and initial burst percent at the desired levels were chosen. It was postulated that the proposed algorithm can predict drug delivery.

In [76], the ANN was used to predict the optimal composition of two-dimensional graphene–Fe_3O_4 nanohybrids, which are dedicated to magnetic hyperthermia. It enables the prediction of the composition of the optimal nanohybrid, which can be applied to magnetic hypothermia in low dosage. The optimization based on multilayer perceptron neural networks of the experimental conditions of nanoparticles was described in [77]. The influence on nanoparticle characteristics factors like environmental conditions and type of precipitating agent was investigated. In turn, the mathematical framework for the magnetic drug delivery taking into account the ferrofluid flow was shown in [17].

Another critical issue in the manufacturing of nanoparticles is the synthesis process [78,79]. It should maintain precisely controlled characteristics. Since the synthesis of nanoparticles is a long-term and cost-consuming process due to the involvement of multiple chemical substances, the AI-based algorithm provides the opportunity to develop efficient experimental protocols. The following research describes the application of AI to the synthesis of semiconductor, metal, carbon-based and polymeric nanoparticles [80]. In [72], based on ultraviolet-visible (UV-vis) and PL spectrum data, the prediction of the optimal parameters of the synthesis of combinatorial CdSe nanoparticles was proposed. Thus, the heuristic and Bayesian optimization can be applied to the evaluation of the synthesis of the nanoparticles. Such an example is far from the magnetic hyperthermia application, while AI support can improve the experimental work also in the magnetic nanoparticles and magnetic hyperthermia field. In [81] the genetics algorithm particle swarm optimization (PSO) was used to predict the magnetic field generation. In [81], GA was used to optimize the Specific Absorption Rate in the case of hyperthermia treatment of the human head.

Recently, attempts were made to apply AI-based algorithms in the research of hydrogels. In reference [82], the Artificial Neural Network and Least Square Support Vector Machine were used to evaluate the swelling degree in the hydrogel, namely poly(NIPAAm-co-AAc) IPN. It turned out that Artificial Intelligence-based algorithms can, successfully and with high accuracy, predict the influence of pH and temperature on hydrogel deswelling behaviors. At the same time, the ANN model has higher computational efficiencies than the LS-SVM approach while maintaining this similar accuracy. Thus, in [83], ANN was used to evaluate the deswelling and heating behavior of the field-sensitive hydrogels, like poly(NIPAAm-co-VSA)/Fe_3O_4 IPN. The comparison of the algorithms for predicting deswelling behaviors is made in Table 6. It turned out that ANN achieved the highest efficiency in predicting deswelling degrees.

Table 6. The comparison of the algorithms for the prediction of deswelling behavior.

Accuracy	Application Field Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Artificial Neural Network				
0.99	1638 experimental data set	- time - temperature - pH	- swelling degree	[82]
0.99	438 experimental data set	- alternating magnetic field strength - time - temperature	- swelling degree - temperature	[83]
Algorithm Type: Least Square Support Vector Machine				
0.98	1638 experimental data set	- time - temperature - pH	- swelling degree	[82]

Magnetic nanoparticles are also used to remove various types of substances. The efficiency of the approach is strictly connected with the percent of compounds adsorbed onto modified magnetic nanoparticles [83–85]. Thus, AI-based algorithms can be applied to predict removal efficiency. In [85] the application of the Artificial Neural Network and adaptive neuro-fuzzy inference system for the prediction of the chromium removal efficiency was shown. In Table 7, the comparison of algorithms for the evaluation of the removal efficiency is presented. It turned out that the combination of the Artificial Neural Network with an adaptive neuro-fuzzy inference system provides higher prediction efficiency.

Table 7. The comparison of the algorithms for prediction of the removal efficiency.

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
Algorithm Type: Artificial Neural Network				
0.88	29 experimental data set	- initial dye concentration - initial pH - contact time - temperature	- maximum removal efficiency	[84]
0.97	experimental data set	- temperature - stirring rate - initial ethyl benzene - xylene (BTEX) concentration - contact time - pH - adsorbent dose	- removal efficiency	[49]

Table 7. *Cont.*

Accuracy	Database (Type and Size if Available)	Input Parameters	Output Parameters	Reference
0.98	18 experimental datasets from the literature	- pH - adsorbent dose - initial coupons concentration	- removal efficiency	[86]
0.98	experimental dataset	- pH - initial heptachlor concentration - contact time - stirring rate - adsorbent dose	- heptachlor removal efficiency	[87]
0.99	experimental dataset	- dose of photocatalyst - the power of visible light - initial concentration of tetracycline - radiation time - oxidant concentration	- removal percentage of tetracycline	[4]
Algorithm Type: genetic algorithm				
0.86	29 experimental data set	- initial dye concentration - initial pH - contact time - temperature	- maximum removal efficiency	[84]
Algorithm Type: adaptive neuro-fuzzy inference system				
0.94	18 experimental datasets from the literature	- pH - adsorbent dose - initial coupons concentration	- removal efficiency	[86]
0.98	experimental dataset	- pH - initial heptachlor concentration - contact time - stirring rate - adsorbent dose	- heptachlor removal efficiency	[87]
0.99	experimental data	- dose of photocatalyst - the power of visible light - initial concentration of tetracycline - radiation time - oxidant concentration	- removal percentage of tetracycline	[4]

6. Discussion and Conclusions

Recently, considerable effort has been made to apply AI to nanomedicine, including peptide synthesis, screening tests, prediction of drug toxicity, drug delivery, drug repositioning, polypharmacology, and physiochemical activity [88–90]. The prediction of the physicochemical properties of drugs requires the identification of the factors affecting the absorption, distribution, metabolism, and excretion of their compounds [90]. It is a promising direction; however, further research in drug delivery, biodistribution, and the long-term metabolism of nanomaterials in the human body is significant [91]. AI can help not only efficiently analyze large amounts of data but also predict the effects of further proceedings and has the potential to deliver targeted therapy, in particular, based on the application of magnetic hyperthermia that has been introduced clinically as an alternative approach for the tumor and cancer treatment [92–96]. AI-based algorithms provide the opportunity to optimize and accelerate nanofabrication's process of the materials. Prediction of the nanoparticle parameters, which impact the heat generation in MH, drug loading efficiency, biodistribution, or cytotoxicity might be crucial to propose more effective drug delivery systems [97]. AI algorithms have been applied to the analysis of the properties of the nanoparticles [98], nonlinear relationships, factors that have influenced the stability and size of nanoparticles [99], or prediction of the delivery processes [100]. It can also provide feedback regarding metabolic pathways and the subjects' responses to therapies [101]. Thus, AI has the potential to accelerate not only drug and nanognetics design [102] but also can boost progress in clinical trials.

To summarize, the comparison of Artificial Intelligence-based algorithms, which can be applied to the prediction of nanoparticle properties or magnetic hyperthermia parameters in terms of their types and accuracy, data availability taking into account their content, types, and quality has been performed in Tables 1–7. It resulted that the application of AI-based techniques to the prediction of magnetic nanomaterials contributes to their higher efficiency, as well as the development of new materials. The efficiency of algorithms is related to the type of input data, their high dimensionality, and their nonlinearity [103]. AI-based algorithms enable us to effectively predict parameters such as the size of nanoparticles, effective thermal conductivity, the ratio of thermal conductivity, toxicity, cell viability, Young's modulus, ultimate tensile strength, reaction yield, quantum yield, optimal composition, specific absorption rate, compressive strength, swelling degree, and porosity. In the case of the prediction of the size of the nanoparticles, the neural network, which is based on multilayer perceptron, provides higher efficiency than ANNs, Table 1. In the case of multilayer perceptron, the analysis was made with more input data (a kind of parameter). ANNs provide higher efficiency than multilayer perceptron, SVM, and feedforward neural networks in the case of evaluating thermal conductivity issues, Table 2. Methods like Random Forest, Least Absolute Shrinkage Selection Operator Regression, Ridge Regression, Elastic Net Regression, and Support Vector Machine cannot predict the core size and exposure dose with high accuracy. At the same time, Random Forest provides good accuracy in the prediction of cell viability, Table 3. The optimal properties of nanomaterial performance can be done with ANNs and multilayer perceptron, while Random Forrest is not efficient for this purpose, Table 4. In turn, the prediction of power losses of magnetic particles can be successfully performed with ANNs and Random Forrest, Table 5. Least Square Support Vector Machine and ANNenables predict, with high accuracy, the swelling degree, Table 6. The removal efficiency can be successfully evaluated with ANNS, and an adaptive neuro-fuzzy inference system, Table 7.

Since magnetic hyperthermia-based research are complex and often incorporates non-linear effects, the approach based on linear regression may need to provide higher prediction accuracy. Random Forest may give a higher accuracy as it enables non-linear learning effects, but this method tends to be instructive in the case of infinite single trees. In turn, SVM entails a high computational cost and needs to be better scalable for massive datasets. In contrast to regression and Random Forrest, SVM does not provide a probabilistic explanation for classification. Considering the computational cost, CNN minimizes this effort concerning regular neural networks. It also has a problem with the classification of images with different positions. The largest disadvantage of CNN is that it requires a considerable amount of good-quality data to be trained with high accuracy.

However, each case is different, requiring an individual approach. Here, a significant limitation of AI in nanomedicine is the lack of well-described, heterogeneous databases [104], experimental data error in training sets, and experimental validations [105]. Primarily, the dataset for prediction of the nanoparticle's properties and their synthesis were collected from already published papers and experiments. As a response to massive datasets, the need for platforms for storing and sharing nanomedicine data development began [106]. These data should be categorized and standardized [107,108]. The first attempts in this field have been made; for example, the database caNanoLab established by the National Cancer Institute (NCI) includes the design of 174 protocols for nanomaterials, which are coming from individual laboratories [109]. Other limitations are connected with converting diagnostic and therapeutic issues into measurable values [110]. It is also worth stressing the need to protect sensitive personal data, whose registration and storage involve personalized medicine [111]. Another important issue is connected with the security of confidential and sensitive data, including patients' medical information [94], which uses algorithms based on Artificial Intelligence. The data should be anonymized and subjected to the procedures of authorized information storage to avoid limitations of usage.

The integration of the properties of the nanoparticles with computational modeling is an issue in the delivery of efficient, targeted therapies. The mutual interaction of drug, plasma, vascular endothelium, and cellular membranes can be optimized with Artificial Intelligence-based algorithms [112]. Thus, they can be considered an effective IT support tool for magnetic hyperthermia-based research. It contributes to optimizing the properties of the nanomaterials, predicting interactions with drugs and human bodies, the behavior of nanocarriers in vitro and in vivo, and the drug delivery processes. The framework for applying AI-based algorithms for magnetic hyperthermia-based research can be adopted from other fields. The papers reviewed here clearly illustrate the effectiveness of the approach proposed. In addition to the need for more standardization of data protocols, very often available metadata does not contain annotations. Thus, future directions include predicting optimal experiments, for example [103], and data curation initiatives, for example [108]. Moreover, in the considered papers, it has been proven that Artificial Intelligence can facilitate, speed up, and contribute to increasing the effectiveness of magnetic hyperthermia-based research.

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