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REVIEW ARTICLE

Intelligent Healthcare Optimization Using Metaheuristic Algorithms: A Review of Emerging Methods and Applications

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ABSTRACT

Machine learning and optimization techniques have significantly changed the healthcare industry, especially in finding and managing essential and dangerous diseases like lung cancer, breast cancer, diabetes as well as heart disease. Lung cancer, which is among the common fatal cancers, requires proper subtyping before proper management is made. This has been achieved through machine learning alongside radiomics, where detailed imaging characteristics of the tumor from CT scans are retrieved without invasive procedures. In the same way, machine learning has provided much higher detection, diagnosis and treatment levels of breast cancer, diabetes and heart disease. This literature review sums up the priorities of studies showing the benefits of using machine learning and bio-inspired optimization methods to address the challenges posed by disease classification and prediction. Such complications have proved great potential in improving the diagnostic methods used for early intervention and, thereby, accurate and efficient diagnosis of a problem, developing an appropriate treatment plan and, thus, improving the patient caring methods and scenario, which has played an imperative role determining the future of modern-day health care.

Keywords: Machine learning ▪ Optimization ▪ Healthcare industry ▪ Metaheuristic algorithms

1. INTRODUCTION

Metaheuristic algorithms today constitute an incredibly significant aspect of solving optimization problems in many disciplines, including healthcare. Contemporary healthcare systems face many complex matters related to diagnostic accuracy, asset allocation, data storage, medical images, transport, and archiving. These systems' needs call for malleable approaches, which may scan through stochastic contexts and handle huge amounts of information to make nearly real-time decisions, which most traditional optimization techniques cannot do. Metaheuristics offers a broad, steady means for solving these problems, which are also able to avoid local optima and work within large-size complex spaces. Because they involve time, speed, and efficiency, even a minor improvement reduces the time spent. Wrong outcomes can significantly convert a patient's fate and the ambiance functionality of a venue.

Metaheuristics can also be applied in user authentication by keystroke dynamics, where metaheuristic algorithms have been used with other machine learning techniques to enhance the security of mobile health applications. The benefits of this method include boosting security while at the same time protecting the privacy and integrity of health information on smartphones [1]. The second example is applying adaptive mutation dipper-throated optimization with transfer learning to classify roads for self-driven cars. Notably, while this work mainly concerns itself with transport, the result has critical relevance in health care: improvement of the efficiency of the transport system of ambulances, for example, can save lives by serving more people in a shorter amount of time in the event of an emergency.

Energy optimization is another significant application that has benefitted a great deal from the use of metaheuristics. Energy efficiency is especially important for healthcare facilities, particularly those located in rural or difficult-to-serve regions. Metaheuristics have been applied to photovoltaic (PV) systems, improving energy extraction under varying environmental conditions and ensuring hospitals and clinics can maintain operations with minimal downtime, even in challenging settings. In diagnostics, feature selection and classification techniques, optimized through algorithms like Dipper-Throated Optimization, have enhanced the accuracy and speed of electrocardiogram (ECG) data analysis, allowing for more timely and reliable cardiac assessments. Other nature-inspired metaheuristics like Greylag Goose Optimization have also demonstrated their effectiveness in enhancing computational problem solving, which can notably cut the time taken and resources used for processing health care data.

Metaheuristic approaches have also been applied to energy management in healthcare systems' scarce or variable resource areas. For example, ensemble learning in cooperation with metaheuristics has enhanced predictions concerning sunshine duration in climate-sensitive zones. This is done to enhance the management of solar-powered health facilities, which are important where grid electricity is unreliable. Metaheuristics have also been used to solve the problem of imbalance and inequality in datasets in the health sector, including in the patient's record or research data. This algorithm enhances the efficiency of machine learning. It ensures that any skewed data distributions in health care applications, such as disease forecasts, patient surveillance, and treatment kits, work as intended.

Metaheuristics has helped in extraordinary developments in medical imaging, which is an important area in diagnostics and treatment planning. For instance, in the context of breast cancer detection, the application of optimized feature selection techniques has enhanced a means of categorizing tumors, thus enhancing early and accurate interventions. In the same manner, in designing biomedical devices like antennas used in telemedicine or wearable healthcare devices, these metaheuristic algorithms have become vital in optimizing parameters to achieve optimal performance yields, which could be endurance in practical applications.

Other key aspects of healthcare that have benefited from metaheuristic algorithms include logistics and supply chain management. Efficient supply chain management means that medical products, medicaments and equipment arrive at the healthcare organizations on time for general practice and crisis events. For example, metaheuristic-based dynamic voting classifiers have been applied to identify the disruption risk and increase the resilience of the healthcare supply chain system. Metaheuristic optimization in agriculture-associated healthcare has been implemented on weed detection in crop fields. It may have positive ripple effects for rural health care, as it would mean improved food supply and, therefore, improved health status of people in these areas. Hybrid models like Long Short-Term Memory (LSTM) combined with metaheuristics have been used to predict energy needs in hyper-arid regions, ensuring continuous power supply to critical healthcare operations in such areas.

Moreover, metaheuristic algorithms such as Chaotic Harris Hawks Optimization have also been useful when applied to non-linear objective function optimization tasks in healthcare scheduling and resource distribution and in increasing operational effectiveness. Other algorithms, for example, the Waterwheel Plant Algorithm, provide even more unique approaches to solving optimization problems, adding more possibilities to the potential of healthcare applications, including patient flow, hospital resource allocation, and treatment plans. The Al-Biruni Earth Radius Optimization algorithm has been used for medical data classification tasks concerning identifying diseases, including monkeypox, increasing the time and accuracy of detection and thereby designing efficient public health responses.

Metaheuristic has also proven useful in health cares that depend on agriculture, especially in the regions of semi-arid zones where water is essential. Accurate ensemble learning methods have been applied to estimate daily REWt and improve irrigation scheduling for agriculture-dependent regions to enhance the communities' well-being. Further, optimizing ensemble algorithms does not stop at basic applications. However, it embraces more sophisticated healthcare items, such as metamaterial antennas used in picture diagnostic imaging where parameter tuning to optimal value is paramount.

With increasing population densities in urban regions, efficient organization of patient traffic is crucial, given overcrowded and less effective bureaucratized health institutions. Metaheuristics have been applied to enhance traffic prediction, minimize traffic density and ensure that ambulances and fire brigades arrive at their destination without delay. Wireless sensor networks, which are finding application in patient monitoring systems and telemedicine, have also been advanced by metaheuristic optimization, enabling accurate acquisition of data and efficient energy utilization in such systems. In addition, the Waterwheel Plant Algorithm has been proven to improve energy consumption in healthcare facilities concerning operational costs for preserving functions like heating, ventilation and air conditioning.

Metaheuristic optimization has also greatly contributed to optimizing the performance of wireless sensor networks that are employed mostly in healthcare applications, patient monitoring in particular, and communication between medical instruments and systems. Metaheuristic algorithms have been used in student performance prediction models in education where healthcare professionals study; the information thus gained aids in enhancing the educational results with the aim of producing polished healthcare providers. Furthermore, satellite image classification, boosted by metaheuristics, has been employed to identify factors that adversely affect the environment, such as oil spillage, which remains a major threat to public health, especially in coastal regions. In transport, metaheuristics have been applied in the surveillance of road features like potholes to enhance safety and efficiency in the healthcare chain, especially in rural areas where roads are badly developed.

Overall, this paper shows how metaheuristic algorithms are useful in optimizing healthcare systems. These are still advancing techniques that have shown potential to upgrade diagnostic potential and energy control as well as logistics flow and medical device capability. For this reason, modern healthcare solutions cannot do without them; they are reliable, flexible solutions for improved outcomes and efficient usage of funds and resources in a mostly digital framework.

Statistical analysis plays a fundamental role in evaluating the effectiveness, reliability, and validity of machine learning and optimization-based healthcare models. In medical diagnosis and disease prediction, statistical measures are essential for determining how accurately a proposed model can distinguish between different disease classes, such as malignant and benign tumors, diabetic and non-diabetic cases, or normal and abnormal cardiac conditions. Therefore, the performance of the reviewed models is commonly assessed using several quantitative indicators, including accuracy, precision, recall, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC).

Accuracy is one of the most frequently used evaluation metrics, as it measures the overall proportion of correctly classified instances among all tested samples. However, in healthcare applications, accuracy alone may not be sufficient, especially when datasets are imbalanced. For example, in disease screening, the number of healthy cases may be much larger than the number of diseased cases, which can cause a model to appear accurate while failing to detect critical positive cases. For this reason, sensitivity and specificity are also important. Sensitivity measures the ability of the model to correctly identify patients with the disease, while specificity measures its ability to correctly identify healthy individuals. A high sensitivity value is particularly important in medical diagnosis because missing a diseased patient may delay treatment and lead to serious clinical consequences.

Precision and F1-score are also widely used to provide a more balanced evaluation of classification performance. Precision indicates the proportion of correctly predicted positive cases among all cases predicted as positive, which is important when false-positive results may lead to unnecessary medical procedures or additional clinical costs. The F1-score combines precision and recall into a single measure, making it useful when there is an imbalance between classes. In addition, the AUC metric provides a comprehensive evaluation of the model's ability to discriminate between classes across different decision thresholds. A higher AUC value indicates better classification capability and stronger diagnostic reliability.

Statistical validation methods such as cross-validation are commonly applied to ensure that the reported results are not dependent on a single data split. In k-fold cross-validation, the dataset is divided into k subsets, where the model is trained on $k-1$ subsets and tested on the remaining subset. This process is repeated until each subset has been used for testing. The average performance across all folds provides a more stable and reliable estimation of model performance. Such validation is especially important in medical studies, where datasets may be limited in size and model generalization is a major concern.

Furthermore, optimization techniques contribute significantly to improving statistical performance by selecting the most informative features and tuning model parameters. Feature selection reduces dimensionality, removes redundant or irrelevant variables, and improves computational efficiency. This is particularly useful in radiomics, gene expression analysis, ECG signal classification, and other high-dimensional healthcare datasets. By improving feature quality and model configuration, metaheuristic optimization algorithms can enhance accuracy, sensitivity, specificity, and overall predictive performance.

Overall, statistical analysis provides the quantitative foundation required to compare different machine learning and optimization models in healthcare. It enables researchers to determine whether a proposed model is clinically reliable, computationally efficient, and suitable for practical diagnostic applications. The use of multiple statistical indicators is therefore necessary to obtain a comprehensive evaluation of model performance and to ensure that intelligent healthcare systems can support accurate, early, and trustworthy clinical decision-making. The diseases discussed in this review, including lung cancer, breast cancer, diabetes, and cardiovascular diseases, represent a major global health burden. Their high incidence and mortality rates emphasize the importance of developing accurate, intelligent, and early diagnostic systems. Statistical evidence related to these diseases provides a strong justification for the use of machine learning and optimization techniques in healthcare, as these methods can support early detection, risk prediction, classification, treatment planning, and clinical decision-making.

Lung cancer is one of the most serious global health challenges and remains the leading cause of cancer-related mortality worldwide. According to recent global estimates, lung cancer accounted for approximately 2.5 million new cases and 1.8 million deaths in 2022. This high mortality rate is mainly associated with late-stage diagnosis, limited symptoms in early stages, and the aggressive nature of many lung cancer subtypes. Therefore, the application of machine learning models, particularly those based on radiomics and computed tomography (CT) imaging, is highly important for improving early detection and accurate subtype classification. By extracting quantitative imaging features from CT scans, intelligent models can assist clinicians in identifying tumor characteristics and supporting more personalized treatment strategies.

Breast cancer is also one of the most commonly diagnosed cancers worldwide and represents a major cause of cancer-related death among women. In 2022, approximately 2.3 million women were diagnosed with breast cancer globally, and nearly 670,000 deaths were reported. These statistics highlight the need for reliable screening, early diagnosis, and accurate classification between benign and malignant tumors. Machine learning techniques can contribute significantly to breast cancer diagnosis by analyzing mammography images, ultrasound data, histopathological features, and clinical records. In addition, optimization algorithms can improve the performance of diagnostic models by selecting the most relevant features and reducing the effect of redundant or noisy data.

Diabetes is a chronic metabolic disease that affects millions of people worldwide and is strongly associated with severe long-term complications. In 2021, diabetes was the direct cause of approximately 1.6 million deaths, and a large proportion of these deaths occurred before the age of 70. Diabetes can lead to cardiovascular disease, kidney failure, neuropathy, retinopathy, and other serious complications if it is not detected and controlled early. For this reason, predictive machine learning models are valuable tools for identifying individuals at high risk of developing diabetes. These models can use clinical variables such as glucose level, body mass index, blood pressure, insulin level, age, family history, and lifestyle factors to support preventive healthcare and early intervention.

Cardiovascular diseases remain the leading cause of death globally and represent the highest mortality burden among the diseases discussed in this review. Global estimates indicate that approximately 19.8 million people died from cardiovas-cular diseases in 2022, representing about 32% of all global deaths. Heart disease prediction is therefore a critical area for intelligent healthcare systems. Machine learning models can analyze electrocardiogram (ECG) signals, blood pressure, cholesterol levels, heart rate variability, and other clinical indicators to detect abnormal cardiac patterns and estimate disease risk. Optimization techniques further improve these models by enhancing feature selection, reducing computa-tional complexity, and improving classification accuracy.

Overall, the global burden of these diseases demonstrates the urgent need for advanced computational approaches in health-care. The large number of new cases and deaths associated with lung cancer, breast cancer, diabetes, and cardiovascular diseases confirms that early diagnosis and accurate prediction are essential for improving patient outcomes. Machine learn-ing and bio-inspired optimization methods can help address these challenges by improving diagnostic accuracy, support-ing personalized medicine, reducing clinical workload, and enabling more efficient healthcare decision-making. There-fore, disease burden statistics provide strong motivation for integrating intelligent optimization-based diagnostic systems into modern healthcare practice.

Figure 1 illustrates the global burden of the major diseases discussed in this review. Lung cancer and breast cancer show a high number of newly diagnosed cases, with lung cancer also presenting a particularly high mortality burden. Diabetes contributes substantially to global mortality, mainly through chronic metabolic complications and associated cardiovas-cular and renal disorders. Cardiovascular diseases represent the highest mortality burden among the reviewed conditions, emphasizing the urgent need for early prediction, continuous monitoring, and optimized clinical decision-support systems. These statistics support the importance of applying machine learning and bio-inspired optimization techniques to improve early detection, risk stratification, and personalized treatment planning.

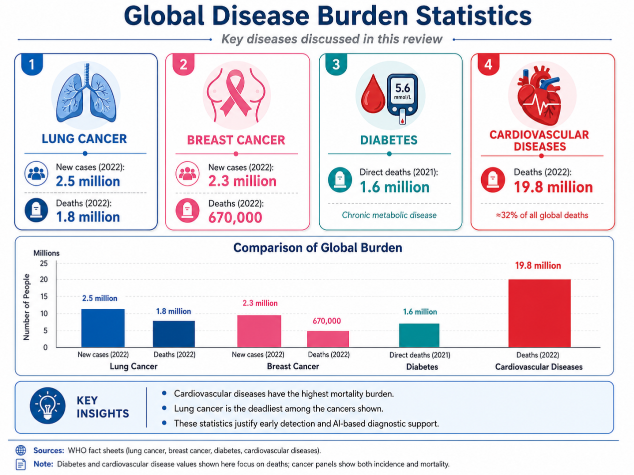

Figure 1. Global disease burden of the main diseases discussed in this review, including lung cancer, breast cancer, diabetes, and cardiovascular diseases. The figure compares the approximate number of new cases and deaths reported globally. Cancer statistics are based on 2022 global estimates, while diabetes mortality is based on 2021 estimates and cardiovascular disease mortality is based on 2022 estimates.

2. LITERATURE REVIEW

Even today, lung cancer is a leading cancer by mortality rates and creating a precise subtype is vital for therapeutic management. Innovations made within machine learning and the computational science of radiology have shifted the prospect of cancer diagnostics from tissue biopsy to non-invasive extraction of features from imaging modalities such as computed tomography (CT scans). Similarly, advancements have been made to other unique diseases that are essential to human life, including breast cancer, diabetes, and heart ailments, where the application of machine learning algorithm principles has been rather attractive in high accuracy and efficiency results. Such approaches contribute to a better understanding of the disease's profile, help to identify its features in the early stage and enhance the approaches to the individual's treatment. This literature review overviews important studies on the use of ML and optimization in solving classification problems in cancer diagnosis, diabetes prediction, and heart disease detection in order to understand the potential of these techniques in improving diagnostic systems and, therefore, patients' outcomes.

Lung cancer is still a problem in the modern world, and it falls within the top cancers by mortality rates. As noted in the work [2], it is demonstrated that precise differentiation of lung cancer subtypes is essential for the definition of its molecular profile, prognoses, and treatment strategies. Radiomics, an emerging discipline, plays a pivotal role in this process by enabling the extraction of quantitative imaging features from medical images, particularly computed tomography (CT) scans. This means that the tumor and its microenvironment can be characterized without invasive procedures, which is mandatory for identifying different subtypes of lung cancer and the prognosis of the response to the treatment. The research emphasizes using a Particle Swarm Optimization–Random Forest (PSO-RF) classifier to categorize lung cancer subtypes based on radiomic features, demonstrating its effectiveness in enhancing diagnostic accuracy. Enhancing feature selection and classifier parameters, the PSO-RF model significantly improves results compared to other traditional methods, exhibiting high accuracy to concentrations and small variation between measurements. This improvement in the current categorization of lung cancer based on radiomics underscores the possibility of using such methods in clinical practice, which would probably provide a better approach to treating patients depending on the peculiarities of their tumors.

The use of Artificial Intelligence in the early diagnosis of lung cancer has been well-received over the last few years because of significant improvement in patient outcomes. At the same time, feature extraction is still considered a topic of great research interest in this area, as detection models depend significantly on feature selection, while, as indicated in the paper [3], feature selection and effectiveness of the models directly depend on it. This study presents a hybrid feature extraction approach combining the Gray-level co-occurrence matrix (GLCM) with Haralick and autoencoder-derived features. It is important to note that the above features were then used as inputs for supervised machine learning classifiers. The Support Vector Machine (SVM) models, specifically SVM Radial Base Function (RBF) and SVM Gaussian, demonstrated near-perfect performance, with the SVM polynomial achieving an accuracy of 99.89% using the integrated feature set. In addition, the proposed SVM Gaussian model achieved a classification rate of 99.56%, and only SVM RBF attained 99.35% by using only the features of Haralick from GLCM. These results confirm the efficiency of the proposed feature extraction method and provide grounds for increasing the efficiency of diagnostic systems and the effectiveness of planning and decision-making stages in the case of lung cancer.

Breast cancer among women, which is one of the most common cancers, has been increasing in China, with the incidence rate increasing by 3% every year, and the age at first diagnosis is decreasing. A similar idea is noted in [4], where authors pointed out that examining the risk factors and prospective diagnosis with the help of historical data is critical. Modalities of modern computational intelligence, the discipline of data-driven statistical learning, presents pathways for breast cancer diagnosis. This study proposes an enhanced optimization algorithm (GSP_SVM), which integrates genetic algorithm, particle swarm optimization, and simulated annealing with a support vector machine (SVM) model. The results demonstrate that this hybrid approach achieves superior classification accuracy, Matthews correlation coefficient (MCC), and area under the curve (AUC) metrics. Compared to other optimizers, GSP_SVM holds a lot of potential in terms of containing informative data for diagnosing breast cancer, thus contributing to the effectiveness of diagnosis centers. Moreover, the paper examines its use in identifying and categorizing breast cancer at various levels and its ability to manage multi-classifications, supporting its adaptability in medical practice.

Cancer staging is incredibly useful in the medical field, and gene expression information is essential for determining cancer types. As mentioned in the work of [5], due to the huge number of genes expressed in any organism, gene expression pattern becomes a high-dimensional feature space for machine learning, often impairs classification models' capability. In order to overcome this, the study puts forward a new approach based on gene expression for cancer classification. The bio-inspired binary bat algorithm is used in feature selection, while the extreme learning machine is used for classification. The study also proposes that a new fitness function be adopted in order to improve the feature selection method in the binary bat algorithm. Simulation outcomes confirm the effectiveness of this new fitness function as compared to the existing one in the literature: the accuracy of cancer classification has been improved. This approach seems promising in enhancing the ability of the machine learning algorithm to diagnose cancer.

High-throughput pre-treatment imaging features can, in fact, be used to predict radiation treatment outcomes in radiotherapy and also serve to tailor the treatment regime. The studies described in [6] indicated that the small number of patients compared to the multitude of image features is an area of concern as it hampers biomarker discovery. This study was designed to solve this problem by creating powerful machine-learning techniques to assess the patient's survival based on quantitative features in pre-treated CT images in head-and-neck cancer patients. The research employed three neural network models: Back Propagation (BP), Genetic Algorithm–Back Propagation (GA-BP), and Probabilistic Genetic Algorithm–Back Propagation (PGA-BP) to model the relationship between radiomics data and patient survival. A novel t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm was utilized to eliminate irrelevant and redundant features before feeding the data into the models. The work involved 59 Head-Neck Cancer patients, of which 80% was used for training while 20% was used for testing. Of those, the PGA-BP model proved to provide the highest prediction accuracy, especially when applied in combination with the t-SNE algorithm for dimensionality. The PGA-BP model achieved much higher accuracy in estimating survival intervals, and thereby, the model might be useful in improving patient survival predictions in radiotherapy using quantitative imaging characteristics.

Breast cancer remains the second most prevalent cancer type and is second only to lung cancer in killing women. As discussed in [7], accurate diagnosis is critical for effective breast cancer treatment, and the use of machine learning methods has become increasingly popular for classifying malignant (cancerous) and benign (non-cancerous) breast tumors. This study applied three machine learning models—Support Vector Machine (SVM), Logistic Regression (LR), and Neural Network (NN)—to classify breast cancer using the Wisconsin Diagnostic Breast Cancer (BCWD) dataset. For each of the methods, several models with different parameters were tried. Concerning performance assessment, k-fold cross-validation and confusion matrices were applied. It demonstrated that the proposed method using SVM achieved higher classification accuracy, precision, recall, and specificity than the LR and NN methods when the cross-validation of k-fold was applied. However, when doing the train-test split to check on the models, the Neural Network performed much better than both SVM and LR with an accuracy rate of 99.4%. These results suggest integrating machine learning into breast cancer diagnosis and therapy management is possible.

According to [8], disease detection models are currently characterized by another important research limitation: low generalisability of the predictive models. This study fills that gap by providing a diabetes prediction model with a data preprocessing step for data quality. A comparative analysis was conducted on two ensemble learning techniques: Particle Swarm Optimization (PSO) integrated with AdaBoost and Ant Colony Optimization (ACO) integrated with XGBoost. These optimization techniques were used to improve these models' predictive capability by optimizing their parameters. Various performance criteria were computed and compared to identify the effectiveness of the developed models and to evaluate them systematically. The result highlights that the proposed PSO-AdaBoost ensemble model has shown superior accuracy compared to the ACO-XGBoost model in terms of accuracy, precision, F1 score, and AUC score. This has shown that PSO-AdaBoost outperforms the current system in predicting diabetes, thus providing direction for early identification.

Diabetes is a chronic disease that is already affecting millions of people across the globe. According to what has been published in [9], some of the most common causes of diabetes include age, obesity, loss of a significant amount of weight within a short period of time, and overall health. Diabetes patients are more susceptible to other illnesses like heart disease, renal failure, stroke, damage to nerves, and problems with vision. Screening for diabetes often can be difficult and expensive. In today's world, with COVID-19 stressing hospitals, it would be surreal if one could evaluate their risk of developing diabetes without visiting a physician. The rise of Artificial Intelligence (AI) offers potential solutions for disease prognosis. The primary objective of this study is to recognize diabetes using several classification models in machine learning. It proposes an improved diabetes classification model to improve the efficiency of the prediction. The algorithms that were benchmarked are Logistic Regression, Random Forest Classifier, Support Vector Machine, Decision Trees, K-Nearest Neighbors, Gaussian Process Classifier, AdaBoost Classifier, and Gaussian Naïve Bayes. These models were followed by evaluation measures regarding accuracy, precision, recall rate, F-measure, and error rate. By obtaining and analyzing the newest dataset from July 22, 2020, this work shows that actual data let researchers achieve better outcomes, which indicates the efficiency of AI approaches in early DM identification.

Diabetes is a long-term illness that affects the body's ability to regulate blood sugar levels adequately, and subsequently, the body can receive damage in its numerous organs, such as kidneys, eyes and the cardiovascular system. The study in [10] reveals that diabetes is among the most common causes of death and is controllable if it is detected timely and correctly. This research focuses on utilizing machine learning (ML) techniques to predict diabetes at an early stage, thereby helping to mitigate the severity of the disease. Several classification algorithms, including Random Forest, K-Nearest Neighbors (KNN), Decision Tree (DT), and Logistic Regression, were applied to the PIMA Indian Diabetes Dataset (PIDD) to predict diabetes. To assess the performance of these models, different measures like accuracy, precision, and F1-score were measured. In the models compared, the highest performance was achieved in Logistic Regression, which had an accuracy of 82.78%. From this result, we may conclude that Logistic Regression is the best-performing ML algorithm for diabetes prediction in this research, pointing to the possibility of using machine learning to boost early detection and record improvement.

Following the consideration of [11], two machine learning classifiers, as well as their interpretable versions, were used on the data of the Stockholm Diabetes Preventive Program that involved over 8,000 participants with normal glucose tolerance or prediabetes at baseline. The purpose was to determine which of the factors played a role in the additional progression of glucose tolerance over a follow-up period of 10 and 20 years. Such indexes as body mass index, waist-hip ratio and susceptible age, as well as systolic and diastolic blood pressure and history of diabetes among first-degree relatives, would seem to be the most dominant. The presence of these features, especially combined with increased genetic risk scores, was associated with an increased risk of type 2 diabetes. Instead, the machine learning model provided focused risk estimates, with information on how different features affected an individual's risk. The researchers noted that the use of this tool provided significant possibilities not only in predicting diabetes risk in patients without the diagnosed diabetes but also in providing strategies for individualized diabetic care. Since most of these risk factors also affect the metabolic status of diabetic patients, this model could be employed to develop better personalized and affordable models of patient care.

Diabetes is a comprehensive pathology resulting from multiple metabolic disturbances; it is an unceasing-growing disease. In the publication referred to as [12], the study was intended to try to build synergy between traditional model-based and novel feature-based data-driven approaches in order to develop new digital health technologies for better diabetes prevention and improving diagnostic and therapeutic approaches to this disease. The study developed several methodologies using two main sources of metabolic data: challenge data (from intravenous or oral glucose tolerance tests) and continuous glucose monitoring (CGM) data. For challenge data, three model-based approaches were developed to extract parameters that would provide a measure of performance of the key physiologic functions that underlie the pathophysiology of diabetes: insulin clearance rates and alpha cell insulin sensitivity. The study also sought to review the absence of modeling and data-driven approaches to create a new prevention model in gestational diabetes to distinguish the high-risk women for type 2 diabetes. The research was also useful in establishing that there was this increased risk and determining which features greatly contributed to this result. For CGM data, the study tried to adopt standardized parameters for calculating a range of characteristics, notably because guidelines in this area are not well developed. These metrics were then used in feature-based machine learning methods to develop an online Diabetes mellitus preventive and management system. This tool has potential applications in innovative diagnosis, early complication detection, such as diabetic retinopathy, and predicting hypoglycemic events from causes such as hemodialysis or physical exercise. In the latter case, an actual metric called HIKE was created to fit the situation. Furthermore, the work responded to the question of how to measure exogenous insulin bioavailability using in-silico dynamic modeling that may have applications for the optimization of pharmacological treatment.

Heart disease (HD) is the leading cause of death worldwide, and early detection remains a significant challenge in healthcare. According to the work in [13], the objective was to employ a deep learning approach to increase the precision and speed of heart disease diagnosis. The research proposed a new hybrid optimization deep learning ensemble classification model to detect heart disease. This was followed by the steps of data collection and data cleansing of data from an appropriate database. Finally, the preprocessed data underwent a feature fusion technique by using a congruence coefficient and overlap coefficient based on the deep belief network. The feature fusion output was subsequently used for classification, achieved through the proposed Social Water Cycle Driving Training Optimization (SWCDTO) ensemble classifier. The base classifier of this work is developed from the driver training optimization algorithm and the social water cycle algorithm, which can train multiple classifiers efficiently with the aim of enhancing performance. Finally, after using the classifiers on the feature set, predictions were made by combining the results from each of the classifiers. The study compared the SWCDTO-based ensemble classifier with other heart disease prediction algorithms, demonstrating superior performance in terms of specificity (95.84%), accuracy (94.80%), and sensitivity (95.36%). Also, the proposed method improved time complexity and, thus, the time complexity of heart disease detection.

Risk assessment for heart disease based on a clustering model with numerical data and ECG signals can be considered to be one of the most powerful solutions for increasing the accuracy of diagnosis. In the research presented in [14], a combination of Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) was employed to preprocess ECG signals and reduce data dimensionality. Following this, a hybrid meta-heuristic method combining the Jaya Algorithm and the Red Deer Algorithm (J-RDA) was utilized to optimize feature extraction. Once feature optimization was complete, the model integrated optimized Density-based Spatial Clustering of Applications with Noise (DBSCAN) and K-Means Clustering (KMC), with J-RDA fine-tuning key parameters for improved clustering performance. The proposed multiobjective model was intended to improve the prediction of heart disease by handling difficulties relevant to numerical and ECG formats. The findings revealed that the proposed model was useful in increasing accuracy and performance levels in heart disease prediction as a solid solution to verification for the multi-dual data inputs.

Cardiovascular disease is still the number one death cause worldwide, including in Iran; thus, early detection is instrumental in lowering the death rate. In the analysis made in [15], the study concentrated on constructing diagnostic models to detect heart disease by applying machine learning, neural networks and deep learning algorithms. The research utilized the Cleveland heart disease dataset from the University of California Irvine (UCI) repository, where the data underwent extensive preprocessing, including outlier detection, normalization, discretization, feature selection, and feature extraction. This changed the dataset about the same into the normalized and continuous form that can fit the different demands in the algorithms. Randomized search with cross-validation and grid search with the Talos scan were used in model tuning. Among the machine learning models tested—such as decision tree, random forest, support vector machine (SVM), and XGBoost—SVM achieved the highest accuracy at 92.9%. In contrast, among neural network models, the multilayer perceptron (MLP) attained the highest accuracy of 94.6%. From these predictions, authors conclude that machine learning and neural network models can be conveniently applied to diagnose heart disease.

In fact, it has been established that the performance of the machine learning algorithm depends on the data fed to it. The study specified in the publication of [16] relates to the issue that big datasets involve ambiguity, noise, granularity and the presence of unlabeled data where pattern recognition and outcome visualization are minimized. To overcome these challenges, the researchers proposed a model utilizing unsupervised learning, specifically clustering algorithms such as Expectation Maximization (EM) and Make Density Based Analysis (MDBC), along with K-means, EM, and GenClust++. The data employed in this study is survey data concerning the healthcare problems, such as chronic illness and routine checkups, of India's various states and districts. This data is collected from the Open Data Government Platform India Portal and has ordinal values. It is used here as an example of exploratory data analysis. The study also applied particle swarm optimization (PSO) to optimize the dataset's attributes before training it with clustering algorithms, which resulted in improved log-likelihood values compared to using simple clustering methods alone. Furthermore, the research aims to compare the performance speeds of this algorithm to know how each of these handles each of the attributes.

Data mining has gained significant popularity in healthcare and medical research, particularly due to its ability to handle complex, multidimensional data with the use of various machine learning (ML) algorithms. According to the study [17], this research was to give an estimate of the probability of a cesarean section at birth; it involved using machine learning algorithms on selected important health indicators concerning the pregnant female. To deal with data skewness in the cesarean data, several data balancing techniques were applied later on for both balanced and base cesarean samples by using several classifiers. A success rate of over 95% was attained by the study after using the ML classifiers, which were particularly pertinent to accurately predict the cesarean sections.

In recent years, advancements in information technology have significantly contributed to the development of medical cyber-physical systems (MCPS), particularly within digital healthcare. As discussed in [18], medical edge devices powered by CPU-GPU cooperative multiprocessor system-on-chips (MPSoCs) offer great potential for processing large volumes of health-related data. However, current methods of CPU-GPU cooperative MPSoCs do not include accurate workload estimations because of the utilization of worst-case scenario cycles, the exclusion of essential specifications of certain healthcare applications, and the reliability constraints expected from CPU-GPU cores. This can lead to reduced functionality of medical edge devices and a decline in the quality of services (QoS) in digital healthcare applications. In response to these challenges, this study proposes a machine learning and swarm intelligence solution for enhancing the QoS of context-aware and personalized digital healthcare applications on reliability-guaranteed edge devices. The researchers developed two predictors. They also proposed two models: one for the estimation of ML models for application workloads and another for QoS estimation with features analysis. These predictors were integrated into a swarm intelligence-driven application scheduling scheme, utilizing a cooperative dual-population evolutionary algorithm (c-DPEA) to optimize application mapping and partitioning. Algorithms proposed in this work showed that this approach enhanced the overall average of QoS by 15.7% or balanced the deviation of each application's QoS by 64.3% to provide a better solution for digital healthcare.

It is always the dream of every healthcare administrator to tap into the most limited resources to cater to the world's increasing population during crises like pandemics. In line with this assertion, I found in the literature to support the following statement in [19] that early and timely access to resources determines the quality of healthcare services and can present patients with life-saving options. This task becomes even more difficult with the rising population of patients with chronic diseases. Machine learning algorithms present a number of possible solutions because they help healthcare administrators to make timely decisions. Such algorithms can estimate the tendency of the pandemic, categorize patients by symptoms, and predict the further number of admissions. Examining the application of machine learning to potential solutions for some major healthcare issues with a focus on the period of the COVID-19 pandemic. This honed the relevance of various features that are part of the process of designing more efficient and accurate machine learning models and ended with two examples. The first case describes a model that estimates the number of diabetic patients likely to seek care in hospitals in the future years in particular regions, while the second case involves data from the health records of COVID-19, highlighting the future of the application of machine learning for optimized utilization of resources and healthcare management decision.

This paper seeks to solve the transportation problem of biological sample tubes from draw centers, which are key components of health systems, to the main hospital in Bologna, Italy. According to [20], blood and other biological samples are taken in the morning and then delivered to the hospital for analysis. Every sample has a short lifespan; in other words, the samples must get to the hospital before a certain time is up. If a sample cannot meet this deadline, it either must be discarded or taken to stabilization centers called Spoke Centres to receive a new delivery deadline. Inter-vehicle transfers are allowed at these centers, making it possible for one car to drop off the sample for stabilization and the other to take it to the hospital. In order to enhance this convoluted transportation operation, the study has formulated and implemented an Adaptive Large Neighborhood Search Algorithm. The effectiveness of this algorithm was tested by computational experiments based on real-life data and successful management of biological sample transportation.

The exponential growth of data generated by telemedicine systems, the Internet of Things (IoT), and wearable devices enhances the need for efficient data transmission, processing, and storage. Yet, as acknowledged in [21], utilization of the cloud to manage this data causes latencies, and prior studies have indicated that energy cost and distance strongly correlate; transmitting the data from wearables consumes much more energy than sensing or computation. Thus, continuous healthcare monitoring in telemedicine requires energy-efficient clustering techniques, particularly those employing metaheuristic algorithms. This chapter introduces a novel multiobjective water wave optimization (MOWWO) algorithm combined with a support vector machine (SVM), referred to as the MOWWO-SVM model, designed for cluster-based healthcare monitoring using wearable devices. The model functions in two stages: these two categories include clustering and classification. The MOWWO algorithm determines cluster heads (CHs), which collect data from wearables and transmit it to the cloud via fog devices. Disease diagnosis is done using the SVM model, which has been trained, and its parameters are optimized by MOWWO. MOWWO-SVM model showed proof of concept with sensitivity, specificity, and accuracy of 95.354%, 93.324%, and 93.868%, respectively, indicating the applicability of the proposed schema in telemedicine systems.

The Internet of Things (IoT) technology enables seamless communication between connected devices, offering significant potential in healthcare applications. To create a healthcare application that will reduce costs, increase efficiency, upgrade data analysis, and improve patients' outcomes, metaheuristic and mining algorithms, two branches of artificial intelligence are used in the article designated as [22]. Metaheuristic algorithms have proven to be effective tools for modeling and optimization, and this study proposes a hybrid approach combining Grey Wolf Optimization (GWO) and Genetic Algorithm (GA). Diversity and convergence are guaranteed using the spiral-shaped path of GWO, but the GA is incorporated to strengthen the convergence. Additionally, Support Vector Machine (SVM) and Naïve Bayes classifiers were used to extract and analyze heart-related data collected from sensors. The framework's goal is to establish an Electronic Healthcare (E-Health) system, connecting patients with healthcare providers for continuous monitoring, diagnosis, and information storage. The results show that the proposed hybrid of GWO and GA is more efficient than the individual use of GWO and GA and that the mining algorithms provide higher accuracy when integrated with this hybrid work framework to indicate the potential of the framework toward effective and reliable healthcare monitoring.

Using machine learning in the diagnosis and treatment of severe diseases like lung cancer, breast cancer, diabetes, and cardiac diseases has, therefore, shown a lot of potential. Research has indicated that this is true, as models such as the PSO-RF for lung cancer, a hybrid SVM for breast cancer, and optimized algorithms for diabetes and heart disease offer greater precision and time response than traditional methods. Results from the application of radiomics, new feature extraction techniques, and bio-inspired algorithms have improved the chances of early diagnosis of these conditions and prior determination of the prognosis and responses to personalized treatment options. With the advancement of machine learning, medical diagnosis and overcoming health problems with the help of your personal health assistant will be even more effective, thereby allowing the creation of better solutions to enhance the quality of life for patients with various diseases around the world. The Figure 2 illustrates the integration of artificial intelligence, radiomics, and machine learning in cancer diagnosis, particularly for lung and breast cancer. It presents a complete diagnostic workflow that begins with medical imaging modalities such as CT scans, MRI, PET, and mammography, followed by tumor segmentation, radiomic feature extraction, model training, classification, and clinical decision support. The lung CT scan and breast mammography panels demonstrate how suspicious regions can be segmented and transformed into quantitative imaging features, including shape, intensity, and texture descriptors. These extracted features are then processed through a machine learning pipeline involving preprocessing, feature selection, model optimization, validation, and prediction. The risk stratification panel further shows how the trained model can estimate malignancy probability and support clinical decision-making. Overall, the figure emphasizes the importance of AI-based radiomics in improving diagnostic accuracy, reducing subjectivity, and assisting physicians in personalized treatment planning.

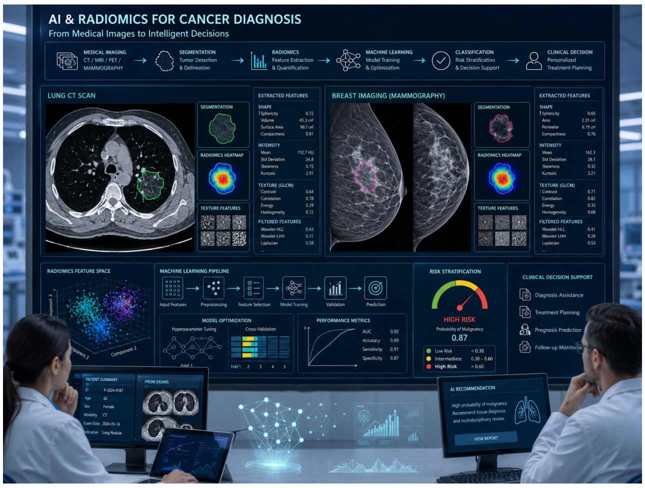

Figure 2. AI- and radiomics-based workflow for cancer diagnosis. The figure illustrates the diagnostic process from medical image acquisition, tumor segmentation, and radiomic feature extraction to machine learning model training, risk stratification, and clinical decision support. It highlights how CT scans and mammography images can be converted into quantitative features that support accurate classification, malignancy prediction, and personalized treatment planning.

The Figure 3 presents a predictive healthcare framework for diabetes and heart disease based on machine learning, remote patient monitoring, and clinical decision support. It illustrates how real-time patient data can be collected from wearable devices, glucose monitors, ECG patches, activity trackers, blood pressure sensors, and sleep monitors. These heterogeneous data sources are integrated with electronic health records, laboratory results, and lifestyle information to create a comprehensive patient profile. The central dashboard demonstrates key health indicators, including glucose trends, ECG signals, blood pressure, heart rate variability, oxygen saturation, diabetes risk, and cardiovascular risk. By analyzing these variables, machine learning models can identify hidden patterns, estimate future disease risk, and support early intervention.

The figure also highlights the role of optimization in improving healthcare decision-making. The optimization engine supports feature selection, risk stratification, treatment recommendation, and care plan optimization. This process allows clinicians to focus on the most relevant patient-specific indicators and generate personalized recommendations related to medication, nutrition, exercise, sleep, and stress management. In addition, the workflow emphasizes continuous feedback, where patient outcomes are monitored and used to refine predictive models over time. Overall, the figure demonstrates how intelligent healthcare systems can combine machine learning, wearable monitoring, telemedicine, and personalized care planning to improve early detection, reduce disease complications, and enhance long-term patient outcomes.

Figure 3. Predictive modeling framework for diabetes and heart disease. The figure illustrates how remote patient monitoring, wearable sensors, glucose trends, ECG signals, clinical indicators, and electronic health records can be integrated into a machine learning-based decision-support system. The framework supports risk prediction, pattern recognition, treatment recommendation, personalized care planning, and continuous feedback to improve early detection and long-term patient outcomes.

3. CONCLUSION

This review emphasizes the substantial role of machine learning and optimization techniques in the diagnosis, prediction, and management of critical diseases, particularly lung cancer, breast cancer, diabetes, and heart disease. The reviewed studies demonstrate that intelligent computational models can provide more accurate, faster, and more reliable diagnostic support than many conventional approaches. Advanced models, including Particle Swarm Optimization–Random Forest, support vector machines, ensemble learning methods, neural networks, and hybrid metaheuristic classifiers, have shown strong potential in improving diagnostic accuracy, reducing classification errors, and enabling earlier disease detection.

In cancer diagnosis, radiomics and advanced feature extraction techniques have expanded the ability to analyze medical images and extract meaningful quantitative information from tumors. These techniques are especially important in lung and breast cancer applications, where early detection and accurate subtype classification can significantly influence treatment planning and patient survival. By combining image-derived features with optimized machine learning classifiers, diagnostic systems can better distinguish between malignant and benign cases, identify disease patterns, and support clinicians in making more informed decisions. Furthermore, feature selection methods help reduce the complexity of high-dimensional medical data, allowing models to focus on the most relevant clinical and biological indicators.

Bio-inspired optimization algorithms, such as the binary bat algorithm, Particle Swarm Optimization, Genetic Algorithm, Grey Wolf Optimization, and other enhanced metaheuristic approaches, further strengthen predictive modeling by improving feature selection, parameter tuning, and classification performance. These algorithms are particularly valuable because medical datasets often include noise, imbalance, missing values, and a large number of features. Through optimization, machine learning models can become more stable, interpretable, and efficient, which is essential for real-world healthcare applications where accuracy and computational speed are both important.

The reviewed literature also highlights the importance of machine learning in diabetes and heart disease prediction. In these applications, optimized classifiers can help identify high-risk patients at earlier stages, support preventive care, and reduce the burden on healthcare systems. Since diabetes and cardiovascular diseases are strongly associated with long-term complications, early prediction can contribute to better patient monitoring, timely intervention, and improved treatment planning. Similarly, the use of ECG signals, clinical variables, and optimized feature extraction methods in heart disease detection shows that hybrid computational systems can enhance diagnostic confidence and support decision-making in clinical environments.

Beyond disease diagnosis, metaheuristic optimization has demonstrated broader relevance in healthcare systems, including medical resource allocation, healthcare logistics, energy management, wireless sensor networks, telemedicine, wearable monitoring systems, and medical device optimization. These applications show that optimization techniques are not limited to classification tasks but can also improve the operational efficiency and sustainability of healthcare services. For example, optimizing energy consumption in healthcare facilities, improving biological sample transportation, enhancing IoT-based patient monitoring, and supporting healthcare supply chain resilience can all contribute to more effective and reliable healthcare delivery.

Overall, the integration of machine learning and metaheuristic optimization represents a promising direction for modern healthcare. These technologies can support personalized medicine by adapting diagnostic and treatment strategies to individual patient characteristics. They can also improve patient outcomes by enabling early detection, accurate classification, efficient monitoring, and optimized healthcare resource utilization. However, further research is still needed to improve model generalizability, validate algorithms on larger and more diverse datasets, enhance interpretability, and ensure practical deployment in clinical settings. As healthcare continues to move toward data-driven and intelligent systems, machine learning and optimization techniques are expected to play an increasingly important role in addressing complex medical challenges and improving the quality, efficiency, and accessibility of healthcare services.

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