# Multiple Diseases Forecast Through AI and IoMT Techniques: Systematic Literature Review

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**Abstract.** Over the past few years, researchers and developers have managed to overcome several challenges in order to provide informative, interactive and effective healthcare solutions. In particular, the recent developments in Artificial Intelligence (AI) field, more specifically ML and DL techniques, have contributed significantly to making Clinical Decision Support Systems (CDSS) more effective in healthcare processes by improving diagnostics, therapy, and prognosis. On another side, the Internet of Medical Things (IoMT), which has evolved into a tool to next-generation bioanalysis., combines networked biomedical devices with software applications to efficiently support healthcare tasks. Practically speaking, persons are susceptible to suffer from one or more chronic or non-chronic diseases under several conditions. This is why AI and IoMT are believed to enable the early identification of potential threats to human health that require effective health actions. In this paper, we accomplish an SLR of AI-based CDSS and IoMT techniques for multi-disease forecasting by making analysis and discussions according to various aspects. The aim is to help researchers in this field of interest to open up future prospects, especially since the existing literature reviews on medical decision support systems mainly focus on the prediction of a single disease rather than multiple diseases.

**Keywords:** Clinical Support System · Machine Learning · Deep Learning · IoMT · Systematic literature review

## 1 Introduction

Healthcare systems have been majorly revolutionized over the last years due to the tremendous progress in digital health technologies such as artificial intelligence (AI), robotics, IoMT, etc. This advancement has noticeably reduced the medical diagnostic and monitoring errors made by humans due to tiredness,


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work overload, and massive generated data [1], Consequently clinical outcomes can be improved, and data can be tracked over time through digital health. Artificial Intelligence (AI) and IoMT technologies are increasingly being used in the Healthcare sector, especially in advanced clinical decision support systems (CDSS) applications. It provides solutions that would assist in accelerating the decision-making processes within healthcare systems for precisely, earlier, and more reliably focused medical treatments [2]. IoMT has a significant impact on data collection with patient data monitoring, whereas AI is expected to analyze the increasing amounts of data and make decisions according to what it learns from the data. The most important factor in the treatment of any disease is to predict or recognize early diseases. According to [2], in the United States, it is predicted that there will be 1.9 million new cancer diagnoses and 609,360 cancer deaths in 2023. Through early identification of a patient's risk of cancer, along with other clinically relevant information, predictive models with AI using routinely performed blood tests have the potential to help physicians diagnose and deliver effective treatment to cancer patients earlier [3]. DL and ML are the areas that can be used to support the prediction of data-driven diagnosis systems. Researchers have introduced several ML and DL models to tackle the problem of huge and various data in promoting intelligent disease diagnosis to diagnose various diseases. Such models may predict the early diagnosis of the disease and provide solutions. Early diagnosis and efficient treatment are the best solutions to minimize the mortality rates caused by any disease. Consequently, the majority of medical experts become attracted to the new predictive models for disease prediction built around machine learning algorithms and deep learning. [4]. With the occurrence and emergence of telemedicine and intelligent health care came a major problem of restricted data access and limited data access. Therefore the IoMT is attracting the interest of the healthcare research community, where its potential to generate disruptive healthcare innovations may play a key role in reducing the pressure within health systems. Besides, combining IoMT with AI may deliver tailored health services that participate directly in enhancing the patient's life quality [5]. Our principal research aim is to address The following questions using SLR guidelines.

1. How effective is Artificial Intelligence in medical decision support systems ?
2. Which diseases were treated using Machine Learning and Deep Learning ?
3. How did the researchers implement the IoMT to predict disease?
4. What motivates using artificial intelligence in medical decision-supporting systems ?

This paper presents an SLR of approaches and techniques for AI-based medical decision support systems. The main contributions of this SLR include Multiple diseases predictions using machine learning, deep learning, and IoMT. The rest of the paper is structured as follows: Sect. 1 presents a Background about the used technologies, Sect. 2 presents Material and Methods. The Sect. 3 is for Results and Interpretation, and we conclude the paper with general discussion and perspectives.

## 2 Background

### 2.1 Machine Learning

According to Arthur Samuel [6], ML is the area of study that enables computers to learn autonomously, without requiring explicit programming. It is used for training machines to handle data more efficiently [6]. ML implements complex algorithms to recognize patterns in large amounts of data and predict outcomes independently of specific codes. We can classify ML into three classes: unsupervised, supervised, semi-supervised, and reinforcement learning. Supervised learning is where ML algorithms are trained on labeled data. Semi-supervised learning techniques have the ability to train machine learning models using both labeled and unlabeled data. Meanwhile, unsupervised learning algorithms aim to identify natural connections and patterns within unlabelled data. Reinforcement learning, on the other hand, is a general concept for ML approaches that include both prediction and decision-making. Such ML technology has an iterative approach to learning and can adapt based on initial feedback [7]. The Table 1 presents the ML algorithms used in this systematic review:

### 2.2 Deep Learning

A DL architecture is an artificial neural network (ANN) having two or more hidden layers to achieve higher prediction accuracy [10]. Deep learning applications in health care cover various problems, such as cancer detection, disease monitoring, and individual treatment advice. Deep learning works through learning models in data structures with neural networks of multiple convolution nodes of artificial neurons [11].

### 2.3 Internet of Medical Things (IoMT)

The term IoMT is used to describe the interconnection of medical devices. Devices that communicate effectively with one another and integrate into larger-scale healthcare systems to improve patient health [12]. IoMT devices allow for healthcare monitoring without the need for human intervention through the integration of automation, interfacing sensors. IoMT technology enables patients to remotely connect with clinicians, granting them access to medical care from a distance and transfer medical data over a secure network [13].

## 3 Material and Methods

### 3.1 Search Strategy

A systematic literature review defines the available technologies and approaches applied to evaluate the clinical efficacy of CDS systems in disease detection and prediction. The references used in the review study were found through searches of papers in Google Scholar, IEEE Xplore Digital Library, Springer,

**Table 1.** ML Algorithms Summary.

| ML Algorithm | Type | Description | References: |
|---|---|---|---|
| K Nearest Neighbors | supervised | It is mainly used in classification problems. KNN ranks the objects according to the nearest distance, i.e., the proximity between the item and all the other items in the learning data | [20] |
| Support Vector Machine | supervised | The support vector machine is mainly used for regression and classification. It finds the optimal hyperplane for data classification. | [7] |
| Decision Tree | supervised | Decision trees are used to predict the dependent variable values by learning from simple decision rules derived from the data. It is formed with criteria defined as "entropy" | [19] |
| Random Forest | Unsupervised | The RF classifier is composed of multiple decision trees of the individual items in the given data set, it picks the average of the sub-set of each tree. Each node decision tree executes a query about the data. | [20] |
| Logistic Regression (LR) | Unsupervised | The LR models are acquired from the statistics branch for binary classification. The model LR chooses the class's likelihood of given data instances to predict as 0 or 1. | [20] |
| K-means | Unsupervised | In this approach, the dataset is partitioned into K clusters, where each cluster is represented by the mean value of its constituent samples. This mean value is commonly referred to as the "centroid." | [7] |
| Naive Bayes | Unsupervised | Naïve Bayes is a robust machine-learning algorithm to predict outcomes. We use it to choose the best hypothesis (h) that fits the given data (d). | [8] |
| Artificial Neural Network | Supervised | The ANNs have neurons interconnected to each other. They are connected within the layers of the network. It can solve problems that were impossible by human or statistical standards. The ANN contains input hidden, and output layers. | [21] |
| C5.0 | Supervised | C5.0 is an example of a decision tree algorithm used in ML. It build a model by using the tree structure based on relationship between features and potential outcomes. It can manage both nominal and numerical features. C5.0 is a ML algorithm that is based on C4.5, a classification algorithm which uses the concept of entropy of the information to find the feature impurity. | [9] |

and Elsevier, including a combination of ML keywords (Artificial Intelligence, Disease Prediction, machine learning, IoMT, Deep learning, and medical decision support systems). The articles used in this research consist of papers from 2018.

### 3.2 Identify the Research Questions

The Table 2 the motivations of our research:

**Table 2.** Description of the motivations behind the different research questions.

| Research Question | Motivation |
|---|---|
| 1. How effective is Artificial Intelligence in medical decision support systems? | 1. There are many research types to predict several diseases using AI algorithms. AI is important for healthcare as it can be associated with other technologies such as IoMT, cloud, and big data to achieve better results. |
| 2. Which diseases were treated using ML and DL ? | 2. Heart disease, diabetes, brain tumor, COVID19, Alzheimer |
| 3. How did the researchers implement the IoMT to predict disease? | 3. As data is the most crucial part of improving disease prediction models, some researchers used sensors to gather data to test the IoMT-based model. |
| 4. What motivates using artificial intelligence in medical decision-supporting systems? | 4. Artificial intelligence provides doctors with a quick and efficient pre-treatment and disease prediction decision-making process |

### 3.3 Study Selection and Data Used in the Articles

Researchers demonstrated the effectiveness of the new technologies; they applied innovative systems built on machine learning and deep learning, in addition to IoMT. They used different algorithms to demonstrate the benefit of artificial intelligence along with their methodologies. To apply the different algorithms, they have used various data gathered from The Cleveland heart disease dataset 2016 which is publicly available from the University of California, Slides of human cancer tissue from the NCT biobank and the UMM pathology, (the Genomic Data Commons Data Portal (TCGA Pan-Cancer Clinical Data Resource), (Shandong Provincial Hospital dataset), (the Radiological Society of North America (RSNA)), Some researchers have encountered a few data sets, joined them, and built new one to work on (the Cleveland, Hungary, Switzerland, VA Long Beach, and Starlog heart disease dataset).

## 4 Results and Interpretation:

We divided this section into 2 parts, First, we presents researches applying Machine Learning algorithms to diagnose diseases with IoMT. The second part includes and discusses studies using deep learning and IoMT to predict diseases.

### 4.1 Machine Learning and IoMT-Based Diagnostic Applications

ML is increasingly used across various fields, including diagnosing diseases in healthcare. Many researchers have offered decision support systems for diagnosis based on machine learning [15]. In [14] researchers proposed a smart medical

decision support system for the detection of heart disease, through several models such as LR, KNN, ANN, to classify individuals with cardiac diseases and individuals in a normal state. The proposal in [14] reached a 91.10% classification accuracy [14]. Other researchers used effective collection, pre-processing of data and data transformation methods to generate precise information for the training model for heart disease prediction. They used KNN for the missing data and Relief and LASSO for features extraction. The accuracy achieved is 99.05% [16]. Another study about heart disease prediction discussed in [17], researchers implemented the model prediction with 5 Active learning methods (MMC, Random, Adaptive, QUIRE, and AUDI). The experiments consist of using hyperparameter optimization by the grid search technique. [17]. Morshedul Bari Ant, at [18], focused on Alzheimer's disease. He applied ML algorithms to detect dementia. This system was created with the OASIS (Open Access series of imaging studies) dataset which trained by SVM, logistic regression, decision tree, and random forest models [18]. The study in [19] suggested ML approaches used with blood test data to forecast the likelihood of COVID-19-related death. A robust combination of five features predicts mortality with 96% accuracy. [19]. The main goal of the research in [20] was to explore the potential applications of big data analytics and machine learning-based techniques in diabetes. The proposed work achieves an accuracy of 83% [20]. Chronic Kidney Disease prediction was covered in the study [21], The researchers used the CKD dataset extracted from the UCI repository. Their major aim was the feature optimization. The developed model implemented 6 ML algorithms for training: ANN, C5.0, LR, LSVM, KNN, and random tree. The model's most significant accuracy in SMOTE with all features was 98.86% [21]. Shahadat Uddin compared the performances of the K-nearest neighbor (KNN) algorithm and its variants (Classic one, Adaptive, Locally adaptive, k-means clustering, Fuzzy, Mutual, Ensemble, Hassanat, and Generalised mean distance) for forecasting eight diseases [22]. A further interesting disease to explore in [36] about skin cancer, Researchers presented a machine learning (ML) classification-based automated image-based system for the recognition, extraction, processing, and categorization of the skin. The proposed method extracts the most valuable features from the skin images with an accuracy of 87% [36]. In [23], The researchers proposed ML and IoMT-based model to provide clinical decision support to reduce doctors' workload and decrease the death rate within the COVID-19 pandemic. The research described in [24] provided an ML model for a dataset of fundamental medical health that predicts what foods should be offered to particular patients according to their medical condition. The medical dataset consisted of 30 patient records with 13 features associated with various illnesses and 1000 items obtained from hospitals and the Internet. Andrei Velichk in [3] proposed a model for determining the presence of COVID-19 based on typical blood results. It applied 13 classifiers for examination and used the HGB approach for feature selection. The researchers used advanced Arduino computing and the IoMT cloud service [3]. The Table 3 summarizes researchers' studies of medical decision-making systems with machine learning and IoMT:

### 4.2 Deep Learning and IoMT-Based Diagnostic Applications

The study in [25] presented a DL architecture to detect tumor and non tumor tissue in histological images of CRC. the model achieved a nine-class accuracy of 94% [25]. An end-to-end deep learning system (DLS) was proposed by the researchers In [26] to predict Survival for patients with various forms of cancer [26]. Researchers have proposed a global architecture of pathological type identification of lung cancer during the early stage by CT images. From the experimental outcomes, VGG16-T with boost has an accuracy rate of 86.58% [27]. In [28] the research presented A Novel Method to detect COVID-19 through AI in Chest X-ray Images. The researchers proposed two approaches: The first one for COVID-19 classification and evaluation. The second one, for the feature extraction [28]. Other researchers proposed a new automated DL method for multiclass brain tumor classification [29]. In [30] researchers proposed a decision support system through physicians' knowledge that applied a fuzzy inference system (FIS). The reason for proposing such a system was that during the COVID-19 period, the datasets were not available. Therefore the solution was to benifit from the researchers' knowledge. Marwa EL-Geneedy in [31] developed a learning-based pipeline to recognize Alzheimer's multi-class disease with brain MRI images. The suggested approach provided both a local and a global categorization (i.e., normal vs. Mild Cognitive Impairment (MCI) vs. AD). The model reached 99.68% accuracy [31]. In [32], authors benefited from the advance of IoMT, and they proposed an IoMT-based fog calculation model to diagnose patients who suffered from type 2 diabetes [32]. Another study [33], consisted of a clinical decision support system with cloud-based IoMT for CKD prediction with DNN. The System gathers patient data through IoMT devices, and stored them in the cloud with their associated medical records from the UCI repository. The DNN classifier achieves a maximum classifier accuracy of 98.25% [33]. To extract precise characteristics from an MRI image, the researchers in [34] established a neural network model with a VGG16 feature extractor, with an accuracy of 90.40% for dataset 1 and 71.1% for dataset 2 [34]. The work [35] presented a new light-weight "Reduced-FireNet" deep learning based model for histopathology image self-classification [35].

Researchers [37] proposed a new approach to predict heart disease. They applied a pre-trained Deep Neural Network to extract feature, Principal Component Analysis (PCA) to reduce dimensionality, and Logistic Regression (LR) for prediction. The model suggested achieved an accuracy of 91.79% [37]. Roseline in [38] and other authors proposed an IoMT diagnosis system to identify breast cancer. The system consists of classifying the tissue into malignant and benign classes. The proposed model achieved a classification accuracy of 98.5% with CNN and 99.2% with ANN [38]. Oher research interest was about analyzing medical images using Deep Learning in real-time. The proposed system contains two parts: the first one aims to define the regions of interest (RoIs) where capillaries might exist, and the second part is to predict if the RoIs contain capillaries or not using CNN [39]. The study described in [40] focused on applying deep learning techniques to detect COVID-19. The proposed work used CNN architec-

**Table 3.** Machine learning and IoMT-based diagnostic applications

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [14] | a machine learning-based diagnostic approach to identifying heart disease | 2018 | Decision Tree Classifier, KNN, ANN, Naive Bayes, SVM, Logistic Regression | 7 ML algorithms, 3 feature selection algorithms, the cross validation and 2 classifiers performance | Certain irrelevant features reduce the diagnostic system's performance and increase the calculation time | Multivariate (the Cleveland heart disease) |
| [32] | IoMT-based fog computing model to Diagnose Patients with Type 2 Diabetes | 2019 | Cloud Computing, fog computing, IoMT | The smart wearable served as both the measurement's tool and platform. The accuracy of the blood glucose measurement was assessed using 100-1000 large-scale simulations. They employed a hybrid procedure that combined the VIKOR method with type-2 neutrosphic technology. | a low accuracy prediction | Multivariate dataset |
| [16] | Prediction system for heart disease | 2021 | AdaBoost (AB), Decision Tree (DT), Gradient Boosting (GB), K-Nearest Neighbors (KNN), and Random Forest (RF), Relief, LASSO | Using 5 classifiers for prediction and 2 feature selection methods | The dependency on a specific Feature Selection technique and the missing values in the dataset | Multivariate (the Cleveland, Hungary, Switzerland, VA Long Beach Statlog heart disease |

**Table 3.** *(contniued)*

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [23] | ML and IoMT model for COVID-19 prediction in smart healthcare environments based on lab results. | 2021 | IoMT Random Forest, SVM | Combining the IoMT and ML (smart hospital environments), Various ML approaches were applied. | Large variations in the scales of the character-istics, excluded to just three ML models | multivariate dataset |
| [19] | A Clinical Decision Support System for Early COVID-19 Mortality Prediction Based on Machine Learning | 2021 | neural networks, logistic regression, XGBoost, random forests, SVM, and decision trees | The proposed model is based on blood tests data which make it more performance | They need more data from diverse resources | multivariate dataset |
| [18] | Predict Alzheimer's disease using ML Algorithms | 2021 | Support vector machine, logistic regression, decision tree, and random forest | Using multiple ML Algorithms to compare the results | Train small datasets | longitudinal Magnetic Resonance Imaging (MRI) |
| [21] | An examination of machine learning for the prediction of chronic kidney disease | 2021 | ANN, KNN, LSVM, C5.0, Chi-square, Logistic Regression, Filter method, Wrapper method, Embedded method | Using SMOTE class balancer | small dataset with many attributes | Multivariate |
| [3] | Routine Blood Values and Machine Learning Sensors for COVID-19 Disease Diagnosis for Internet of Things Application | 2022 | histogram-based gradient boosting, linear discriminant analysis, KNN, LSVM, NLSVM, passive-aggressive, multilayer perceptron, decision tree (DT) | Using the HGB approach for feature selection and 13 classifiers for disease prediction | The data represent mainly a unique institution the data set excludes patient comorbidity | Multivariate (SARS-CoV-2-RBV1) |

**Table 3.** *(contniued)*

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [22] | Comparative performance analysis of KNN algorithm with its different variants for disease prediction | 2022 | Hassanat distance KNN (H-KNN), Generalised mean distance KNN, Mutual KNN, Ensemble approach KNN | applying the KNN algorithms with its variants | researchers didn't preprocess datasets a low model accuracy (high accuracy 86%) It ignores minority classes, which can affect its performance Inconsistent output for noisy data sets | Multivariate |
| [17] | Multi-Label Active Learning-Based Machine Learning Model for Heart Disease Prediction | 2022 | MMC, Random, Adaptive, QUIRE, and AUDI | using active learning methods for multi-label data | few labelled examples were used to train the initial classifier. Memorization still must to adapt | Multivariate |
| [24] | IoMT-Assisted Patient Diet Recommendation System Through ML Model | 2020 | RNN, GRU LSTM | combining IoMT with machine learning and deep learning to give a high prediction | low quality of IoMT used devices | Multivariate (Categorical and Numerical) |

tures like VGG16, DeseNet121, MobileNet, NASNet, Xception, and EfficientNet [40]. The Table 4 summarizes researchers' studies of medical decision-making systems with Deep learning and IoMT: [h]

## 5 Discussion

This systematic review is interested in the recent proposed approaches of IoT and AI that are used in healthcare, while addressing their benefits and weaknesses. This review demonstrates that there is a significant increase in the number of the proposed works in this research area. The adoption of AI in medical field can speed up the process of tumor diagnosis without the need to the histological examination that can take a lot of time. This is due to the progress in CPU computing power, the efficiency of recent ML and DL algorithms and the accessibility

**Table 4.** Deep learning and IoMT-based diagnostic applications

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [25] | a model to recognize the different tissue types which are prevalent in the histological images of CRC (non-tumor tissue types). | 2019 | VGG16, GoogleNet, Alexnet, Squeezenet, Resnet50 | The data is trained with CNN by transfer learning and reach a 9 classes | Before being used consistently in the clinic, this study needs to be prospectively validated. The technique of manually extracting tumor areas from whole slide histology images could be completely automated | Medical Images |
| [26] | An approach to provide significant prognostic information in several cancer types at specific pathological stages. | 2022 | CNN | Models were used to classify individual patients according to cancer stage (stage II). The CNN consisted of depth-separable convolution layers, identical to the MobileNet architecture, with adjusted size and number of layers to accelerate training and reduce the risk of overfitting | The approaches and outcomes can only be applied to datasets from TCGA (There are limited image) | histopathology images |
| [28] | A novel method CoVIRNet (COVID Inception-ResNet model) to identify the COVID-19 patients automatically using x-ray images. | 2021 | GAN, Deep Transfer Learning | The proposed deep training building blocks utilized different regularization techniques for minimizing overfitting due to the small COVID-19 | The proposed technique's performance was tested on a small dataset of publically available chest radiographic images of different cases of pneumonia and COVID-19 | X-ray Images |

**Table 4.** *(contniued)*

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [27] | A CT image classification approach for advanced lung cancer based on the VGG16 convolutional neural network | 2020 | VGG16 | The researchers built their own dataset containing 2219 CT-images and trained it with VGG16 and applied the boosting strategy to aggregate multiple classification outcomes to enhance the performance of classification methods. | More contextual tumor information, such as connections to surrounding blood vessels, and patient information, such as a medical history report, can be merged | CT images |
| [29] | An innovative automated deep learning approach for detecting multiple-class brain tumors. | 2021 | Densenet201 CNN | A pre-trained model (the Densenet201) for multiclass brain tumor classification. The use of MGA and Entropy-Kurtosis-based methods to choose the best features. The fusion of the optimal features | the reduction of certain important features | MRI Images (BRATS2018 and BRATS2019) |
| [30] | A decision support system based on doctor knowledge to decrease stress in the community, to disrupt the chain of propagation of COVID-19 | 2020 | Fuzzy inference system (FIS) | The system based on expert's knowledge | The system is based on only 3 criteria: fever, fatigue and dry cough | Textual Dataset |

**Table 4.** *(contniued)*

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [33] | An ioMT with cloud-based clinical decision support system for CKD prediction and adherence with severity level | 2019 | DNN IoMT | they used a feature selection method based on Particle Swarm Optimization (PSO) | poor CDS security | Multivariate |
| [34] | A deep learning based convolutional neural network model with VGG16 feature extractor to identify Alzheimer Disease through MRI scans | 2022 | VGG16 CNN | Using the VGG16 for feature extraction and use two datasets for evaluation | Small datasets | MRI Images |
| [31] | An MRI-based deep learning method for precise Alzheimer's disease identification | 2022 | CNN, Transfer Learning | Employing the augmentation approach to produce new images (to solve the problems of data lack) | prediction for only one stage of Alzheimer's disease | MRI Scans |
| [35] | A noval Lightweight Deep Learning Model for Classifying Histopathological Images for IoMT | 2021 | CNN, SqueezeNet | Using the IoMT for disease identification in real time with deep learning model. A new model with small size to capture medical images and process information protect the medical images of patient | IoMT Devices have limited computational power and memory space | Multivariate dataset |

**Table 4.** *(contniued)*

| Ref. | Study aim | Year | Technologies used | Strength | Weakness | Data Type |
|---|---|---|---|---|---|---|
| [36] | Classifier for predict 6 skin disease | 2023 | CNN SVM | Classifier for predict 6 skin disease | low accuracy | CT images |
| [24] | IoMT-Assisted Patient Diet Recommendation System Through Machine Learning Model | 2020 | RNN, GRU and LSTM | combining IoMT with machine learning and deep learning to give a high prediction | IoMT Devices have limited computational power and memory space | Multivariate dataset |
| [37] | A heart disease prediction with deep learning | 2023 | PCA Logistic Regression DNN | A number of DNN structures for prediction evaluation. Apply the PCA | Researchers didn't use Feature Extraction Algorithms | multivariate dataset |
| [38] | IoMT and Deep learning based model for breast cancer prediction | 2022 | SVM, ANN, CNN, PSO | Employing the PSO as feature selection approach Integrate the medical devices (IoMT) | Researchers need large data | multivariate dataset |
| [39] | A Software Design Pattern for Deep Learning-Based Real-Time Medical Image Analysis | 2022 | Cloud, DNN, Hadoop Distributed File System | detect the callipers in heart disease and COVID-19 in real time Use 3 metrics to evaluate the proposed model | a low hardware capacities | Medical Images |
| [40] | CNN architecture to detect COVID-19 through lung CT Scan. | 2022 | VGG16, DeseNet121, MobileNet, NASNet, Xception, and EfficientNet | Using Multiple pre-trained models for predicting Using Lung CT scan | A small datastes and few number of epochs. | CT scan Images |

of huge amounts of data (big data) collected from electronic health monitors and medical health records. The presented work in this paper covered the involvement of machine and DL models along with IoMT in the diagnosis of cancer, diabetes, chronic diseases, heart, Alzheimer, and COVID. The machine learning models

used include random forest classifier, logistic regression, decision tree, K-nearest neighbor (KNN), and support vector machines (SVM). Moreover, the deep learning models used include convolutional neural networks (CNN) have often been used for disease diagnosis and pre-trained models: VGG16, GoogleNet, Alexnet, Squeezenet, Resnet50. Despite the significant advantages of AI and IoT-based techniques in diagnosing diseases, many challenges remain to be overcome such as:

1. The small size of the pre-processed datasets that can be used to evaluate the proposed approaches efficiency.
2. The lack of efficient feature selection techniques to clean medical data while generating high precision in disease prediction.
3. The problems of data security during the collection phase.
4. The absence of models validation phase by medical experts.

## 6 Conclusion and Future Perspectives

AI is a broad field of approaches that combines data mining and analytics, machine learning and deep learning, data collection, and pattern recognition that is regularly evolving and growing to fit the criteria needed of the Healthcare sector and its Patients. This article explores the potential impact of technologies such as IoMT and AI in healthcare and the clinical support system through a systematic literature review of 27 published papers. To clarify the performance of AI and IoMT in clinical support systems, This current study was divided into three sections covering applications for machine learning- and deep learning-based diagnostics, and IoMT-based applications. The main conclusions build across this paper state that the approaches of AI and IoMT in the clinical support system for disease detection, prediction, and patient monitoring are an avoidable path to migrate toward precision medicine. However, problems like lack of data, ethical and data security, and non-practical accuracy represent the major research challenges that need to be addressed. Therefore, in future work, we aim to elaborate and introduce technical and research solutions for aiding intelligent medical support systems to provide secure and robust models. Due to the continuous progress in artificial intelligence and IoMT fields, there are many opportunities for extending the research presented in this work. Although our SLR has highlighted the potential of AI and IoMT technologies to predict and prevent the onset of various diseases, it still needs improvement to be suitable for the medical field. In our future works, we will focus on the potential of innovative deep learning and machine learning methods. Furthermore, to improve the predictive performance of these models, researchers need to integrate other data sources such as genetic and environmental factors. To determine the most effective fusion among data sources and modeling approaches for various illness types, additional investigation is also needed. Real-time illness forecasting systems which can be implemented to support medical decision making is another research area in our further studies.

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