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A REVIEW ON HEALTHCARE DISEASES DIAGNOSIS MODEL WITH AID OF ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

The diagnosis of diseases such as Non-Communicable Diseases (NCDs) and Cancer is decisive for planning proper treatment and ensuring the well-being of patient. Human error hinders accurate diagnostics, as interpreting medical information is a complex and cognitively challenging task. The application of Artificial Intelligence (AI) can improve the level of diagnostic accuracy and efficiency in healthcare fields. While the current literature has examined various approaches for diagnosing various diseases, an overview of fields in which AI has been applied, including their performance aiming to identify emergent digitalized healthcare services, has not yet been adequately realized in extant research. By conducting a critical review, the paper portrayed the AI techniques in diagnostics of NCDs and cancer and provide a snapshot to guide future research. This study observed that Deep Learning (DL) approaches have been mostly used for solving issues of NCDs and cancer disease detection in terms of different metrics. However, several issues need to be addressed before the successful application of DL in disease diagnostics can be achieved. Therefore, to end this, an enhanced DL-based system will be proposed in the future study for effective detection of NCDs and Cancer.

Keywords: Non-Communicable Diseases (NCDs), heart disease, kidney disease, and diabetes, Lung and Breast cancer, Detection, Machine learning (ML) and Deep Learning (DL)

1. INTRODUCTION

Due to the modern lifestyle of the inhabitants, there arises a risk of mortality and morbidity by NCDs such as heart disease, kidney disease, and diabetes. The World Health Organization identified NCDs, such as diabetes mellitus or cardiovascular diseases to be a major threat to economies and societies **[1]**. Also, globally, NCDs are the leading cause of death and are rising at an alarming rate, particularly in low- and middle-income countries **[2]**. Moreover, NCDs are implicated in 73% of all global deaths in 2017, with 28.8 million deaths attributed to risk factors like high blood pressure, high blood glucose, or high Body Mass Index (BMI) **[3]**. Furthermore, NCDs are forecasted to account for 81% of all global deaths in 2040 **[4]**. Also, Diabetes is a chronic disease characterized by high blood sugar. It may cause many complicated diseases like stroke, kidney failure, heart attack, etc. The term heart disease indicates the abnormalities that affect the heart.

Besides, cancer is one of the major diseases that cause a high number of deaths globally **[5]**. According to estimates from the World Health Organization (WHO) in 2019, cancer is the first or second leading cause of death before the age of 70 years in 112 of 183 countries and ranks third or fourth in a further 23 countries **[6]**. As shown in **Figure 1**, Breast cancer is the second most prevalent cancer in women and is so far the top reason for cancer death across the world **[7, 8]**. Additionally, in the world, lung cancer is the one of most cancer for men in second and women in fourth. Lung cancer-related diseases have been one of the most common causes of death worldwide **[9]**. Cancer's rising prominence as a leading cause of death partly reflects marked declines in mortality rates of stroke and coronary heart disease, relative to cancer, in many countries **[10]**. Since the symptoms of cancer normally appear only in the advanced stages, so it is very hard to detect resulting in a high mortality rate among the other types of cancers.

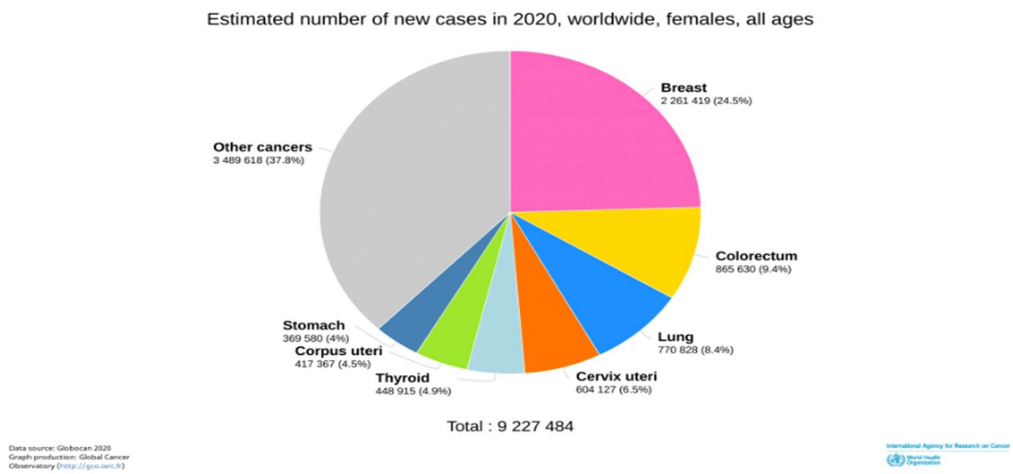

Figure 1: The new estimates on the global cancer burden for women of all ages, indicating that it has risen to 19.3 million cases and 10 million cancer deaths in 2020, Data source: IARC released on 14th December the updated Globocan 2020 report [8]

Based on the above discussion, there is a need for early prediction of diseases for the purpose of diagnosing and this can result in better chances of it being able to be treated successfully **[11]**. Also, the early identification of the diseases improves the chances of cure as well as reduces other related diseases. Consequently, it leads to higher survival rates. However, it is difficult to identify NCDs because of several contributory risk factors such as diabetes, high blood pressure, high cholesterol, abnormal pulse rate, and many other factors. Similarly, cancer detection is difficult to process. Therefore, to identify the diseases, over the few decades, several techniques have been used. Manual diagnosis of cancer and NCDs is tedious and time-consuming; thus, there arises a need for automatic diagnosis. The current healthcare systems have proven to be helpful, but they are prone to errors. To overcome these issues, Artificial Intelligence (AI) provides advantages pertaining to the diagnosis of diseases. Also, in the case of medical images, the medical image classification using CAD has emerged as an efficient tool that can help doctors classify medical images in different categories, leading to early diagnosis and treatment. In this context, AI techniques such as Machine Learning (ML) and Deep Learning (DL) have come up with algorithms capable of diagnosing, more accurately, the disease at an earlier stage and thus diminishing the number of readmissions in hospitals and clinics. AI techniques can thus boost the procurement of new fidelity protocols in medicine and reduce healthcare costs due to misdiagnosis **[12, 13]**.

Therefore, this survey focuses on recent research developments for the early diagnosis of diseases such as NCDs, breast, and lung cancers using ML & DL techniques. It highlights the strengths and weaknesses of various research methods distinguishing this survey paper. Finally, the future direction of this research is discussed. The rest of the paper is organized as follows: Section 2 is reviews the related research articles which is mainly focus on ML and DL techniques for detection of the NCDs and Cancer. Section 3 reviews the comparative analysis of the research. The challenges and future directions are illustrated in Section 4. Finally the paper concludes in Section 5.

2. Literature Review

This survey explores relevant papers related to diagnosing NCDs and cancers using classification algorithms of Machine Learning while the rest implements Deep Learning techniques in this section.

2.1 Heart Diseases

Narayan, Subhashini, and E. Sathiyamoorthy (2019) **[14]** had proposed an efficient medical recommendation system namely Fourier Transformation-based Heart Disease Prediction System (FTHDPS) by using Fourier Transformation and ML technique to predict chronic heart diseases effectively. Here, the input sequences rely on the patient's time series details or data, which were crumbled by Fourier Transformation for extracting the frequency information. In FTHDPS, a bagging model was utilized for predicting the conditions of the patients in advance to produce the absolute recommendation. In FTHDPS, three classifiers were used, namely Artificial Neural Network (ANN), Naive Bayes and Support Vector Machine (SVM), and real-life time series chronic heart disease data were used to evaluate the proposed model. The experimental results demonstrated that FTHDPS is much efficient to provide a reliable and accurate recommendation to heart patients.

Dwivedi, Ashok Kumar (2018) **[15]** had proposed six machine learning techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Logistic Regression, k-Nearest Neighbor (kNN), Classification Tree, and Naive Bayes based prediction models for prediction of heart disease. These methods were validated using tenfold cross-validation and evaluated in terms of various performance measurements. The recital of these methods was assessed on eight diverse classification performance indices. In addition, these methods were assessed on the receiver operative characteristic curve. The highest classification accuracy of 85 % was reported using Logistic Regression (LR) with sensitivity and specificity of 89 and 81 %, respectively.

Cherian *et al*, (2020) **[16]** had proposed an enhanced neural network based heart disease prediction model with the inclusion of specific processes like Feature Extraction, Record, Attribute minimization, and Classification. Initially, both statistical and higher-order statistical features were extracted under feature extraction. Subsequently, the record and attribute minimization were carried out, where Principal Component Analysis (PCA) plays its major role in solving the "curse of dimensionality." Here, it was planned to influence the utility of meta-heuristic algorithms for the weight optimization of NN. This paper introduced a hybrid algorithm termed Particle Swarm Optimization (PSO) merged LA (Lion Algorithm) update (PM-LU) algorithm that solves the above-mentioned optimization crisis. Finally, the efficiency of the proposed work was compared over other conventional approaches and its superiority was proven with respect to certain performance measures. From the analysis, the presented PM-LU-NN scheme with regards to accuracy is 3.85%, 12.5%, 12.5%, 3.85%, and 7.41% better than LM-NN, WOA-NN, FF-NN, PSO-NN and LA-NN algorithms.

Priyanga *et al*, (2021) **[17]** had proposed a hybrid Recurrent Neural Network (RNN)-Logistic Chaos-Based Whale Optimization (LCBWO) structured hybrid framework for predicting heart disease within 5 years using EHR data. Meanwhile, in the hybrid model established multilayer bidirectional Long Term Short Term (LSTM) was used for feature selection, LCBWO algorithm for structural improvement and fast convergence, and LSTM for disease prediction. This research used 10 cross-validations to obtain generalized accuracy and error values. The findings and observations provided here were focused on the knowledge obtained from the EHR report. The results show that the proposed new hybrid RNN-LCBWO framework achieves a higher accuracy of 98%, a specificity of 99%, precision of 96%, Mathew's correlation coefficient of 91%, F-measure of 0.9892, an Area Under the Curve (AUC) value of 98%, and a prediction time of 9.23 seconds. The accurate predictions obtained from the comparative analysis show the significant performance of the proposed framework.

2.2 Diabetes

Maniruzzaman *et al*. (2020) **[18]** had presented a ML based system for predicting diabetic patients. Logistic Regression (LR) was used to identify the risk factors for diabetes disease based on p-value and Odds Ratio (OR). The paper had adopted our classifiers like Naïve Bayes (NB), Decision Tree (DT), Adaboost (AB), and Random Forest (RF) to predict the diabetic patients. LR model demonstrates that 7 factors out of 14 as age, education, BMI, systolic BP, diastolic BP, direct cholesterol, and total cholesterol are the risk factors for diabetes. The overall accuracy (ACC) of the ML-based system is 90.62%. The combination of LR-based feature selection and RF-based classifier gives 94.25% ACC and 0.95% AUC for the K10 protocol. The authors claimed that the proposed technique would be very helpful for predicting diabetic patients.

Mosquera-Lopez *et al*, (2019) **[19]** had proposed Glucop30, a robust data-driven glucose prediction model that is trained on a big dataset (27,466 days) to forecast glucose concentration along a short-term prediction horizon of 30 minutes. The proposed prediction method was composed of (i) an RNN with LSTM units that predicts the general trend of future glucose levels, followed by (ii) a patient-specific smoothing error correction step that accounts for inter-patient and intra-patient glucose variability. In addition, they report on the accuracy of the proposed method when both CGM and insulin data were used for prediction; however, they discovered that adding insulin as an additional input feature improves prediction accuracy by only 1%. Glucop30 achieved leading performance as measured by the RMSE of 7.55 (SD = 2.20 mg/dL) and MAE of 4.89 (SD = 1.43 mg/dL) for an effective prediction horizon of 27.50 (SD = 2.64) minutes.

Samant *et al*. (2018) **[20]** had proposed a RF Classifier based model for medical diagnosis of diabetes using iris images. The investigation was performed over a close group of total 338 subjects (180 diabetic and 158 non-diabetic). Infra-red images of both eyes were captured simultaneously. The region of interest from the iris image was cropped as zone corresponds to the position of the pancreas organ according to the iridology chart. Statistical, texture, and discrete wavelength transformation features were extracted from the region of interest. The results show the best classification accuracy of 89.63% calculated from the RF classifier. Maximum specificity and sensitivity were absorbed as 0.9687 and 0.988, respectively. Results had revealed the effectiveness and diagnostic significance of the proposed model for non-invasive and automatic diabetes diagnosis.

Health care systems are merely designed to meet the needs of increasing population globally. People around the globe are affected with different types of deadliest diseases. Among the different types of commonly existing diseases, diabetes is a major cause of blindness, kidney failure, heart attacks, etc. Yuvaraj, N., and K. R. SriPreethaa (2019) **[21]** had proposed various ML algorithms on the Hadoop clusters such as the Decision Tree algorithm, Naïve Bayes algorithm, and Random Forest for the diabetes prediction in healthcare systems. The results show that the Random Forest algorithm could able to produce highly accurate diabetes predictive healthcare systems. Pima Indians Diabetes

Database from the National Institute of Diabetes and Digestive Diseases was used to evaluate the working of the algorithm.

2.3 Kidney Diseases

Khamparia *et al*. (2020) **[22]** had presented a deep learning framework for chronic kidney disease classification using a stacked autoencoder model utilizing multimedia data with a softmax classifier. The stacked autoencoder helps to extract the useful features from the dataset and then a softmax classifier was used to predict the final class. It has experimented on UCI dataset which contains the early stages of 400 CKD patients with 25 attributes, which is a binary classification problem. Precision, recall, specificity and F1-score were used as evaluation metrics for the assessment of the proposed network. It was observed that this multimodal model outperformed the other conventional classifiers used for chronic kidney disease with a classification accuracy of 100%.

Belur Nagaraj *et al*. (2020) **[23]** had introduced a Feed-Forward Neural Network model to predict End-Stage Renal Disease (ESRD) in patients with type 2 diabetes using multiple baseline demographic and clinical characteristics. Eighteen baseline demographic and clinical characteristics were used as predictors to train ML models to predict ESRD (doubling of serum creatinine and/or ESRD). The Feed Forward Neural Network (FFNN) model predicted ESRD with an AUC of 0.82 (0.76-0.87), 0.81 (0.75-0.86) and 0.84 (0.79-0.90) in the RENAAL, IDNT, and ALTITUDE trials, respectively. The proposed model selected urinary albumin to creatinine ratio, serum albumin, uric acid, and serum creatinine as important predictors and obtained a state-of-the-art performance for predicting long-term ESRD.

Ren *et al*, (2019) **[24]** had proposed to study the problem of kidney disease prediction in hypertension patients by using a NN model. Specifically, the first model the prediction problem as a binary classification task. Then they propose a hybrid neural network which incorporates Bidirectional Long Short-Term Memory (BiLSTM) and Autoencoder networks to fully capture the information in EHR. They construct a dataset based on a large number of raw EHR data. The dataset consists of totally 35,332 records from hypertension patients. Experimental results show that the proposed neural model achieves 89.7% accuracy for the task. A hybrid neural network model was presented. Based on the constructed dataset, the comparison results of different models demonstrated the effectiveness of the proposed neural model. The proposed model outperformed traditional statistical models with discrete features and neural baseline systems

Jerlin Rubini *et al*, (2020) **[25]** had proposed an efficient Multi-Kernel Support Vector

Machine (MKSVM) and Fruit Fly Optimization Algorithm (FFOA) for disease classification. Initially, FFOA was employed to choose the finest features from the available set of features. The selected features from the medical dataset were processed and provided to the MKSVM for medical data classification purposes. Next, testing of the dataset takes place using the own benchmark Chornic Kidney Dataset (CKD) dataset from UCI machine learning repositories such as Kidney chronic, Cleveland, Hungarian, and Switzerland. The performance of the proposed CKD classification method was elected by accuracy, sensitivity, specificity, positive predictive value, negative predictive value, false positive rate, and false negative rate. The investigational outcome specifies that the proposed CKD classification method achieves a maximum classification precision value of 98.5% for CKD, 90.42904% for Cleveland, 89.11565% for Hungarian, and 86.17886% for Switzerland dataset than existing hybrid kernel SVM, fuzzy min-max GSO neural network, and SVM methods.

2.4 Lung cancer

Early detection of lung cancer is the only possible way to improve a patient's chance for survival. A Computed Tomography (CT) scan is used to find the position of the tumor and identify the level of cancer in the body. Lakshmanaprabhu *et al*. (2019) **[26]** had presented an innovative automated diagnosis classification method for Computed Tomography (CT) images of lungs. In this paper, the CT scan of lung images was analyzed with the assistance of Optimal Deep Neural Network (ODNN) and Linear Discriminate Analysis (LDA). The deep features extracted from a CT lung images and then dimensionality of feature was reduced using LDR to classify lung nodules as either malignant or benign. The ODNN was applied to CT images and then, optimized using Modified Gravitational Search Algorithm (MGSA) for identify the lung cancer classification The comparative results show that the proposed classifier gives the sensitivity of 96.2%, specificity of 94.2% and accuracy of 94.56%.

Shakeel *et al*. (2019) **[27]** had proposed an improved profuse clustering and deep learning instantaneously trained neural networks to lung cancer detection. This paper dealt with the improvement of the quality of lung image and diagnosis of lung cancer by reducing misclassification. The lung CT images were collected from Cancer Imaging Archive (CIA) dataset, noise present in the images were eliminated by applying weighted mean histogram equalization approach which successfully removes noise from image, also enhancing the quality of the image, using improved profuse clustering technique (IPCT) for segmenting the affected region. Various spectral features were derived from the affected region. These are examined by applying DL instantaneously trained neural networks for predicting lung cancer. Eventually, the system was examined by the efficiency of the system using MATLAB-based simulation results. The system ensured 98.42% of accuracy with a minimum classification error of 0.038.

Shanthi, S., and N. Rajkumar (2021) **[28]** had presented a lung cancer prediction using stochastic diffusion search (SDS) based feature selection and machine learning methods. In this work, a modified SDS-based algorithm was used to identify optimal feature subsets. The neural network, Naïve Bayes, and the decision tree have been used for classification. The results of the experiment proven that the proposed method is capable of achieving better levels of performance compared to existing methods like minimum redundancy maximum relevance, and correlation-based feature selection.

Gu *et al*. (2019) **[29]** had presented a machine learning-based radiomics strategy for the prediction of cell proliferation in non-small cell lung cancer (NSCLC).A lesion volume of interest (VOI) was manually delineated and radiomics features were extracted by MaZda software from CT images. A random forest feature selection algorithm (RFFS) was used to reduce features. Six kinds of ML methods were used to establish radiomics classifiers, subjective imaging feature classifiers, and combined classifiers, respectively. The performance of these classifiers was evaluated by the Receiver Operating characteristic Curve (ROC) and compared with Delong test. Among the radiomics classifiers, the random forest-based radiomics classifier achieved the best performance (AUC = 0.776) in predicting the Ki-67 expression level with sensitivity and specificity of 0.726 and 0.661, which was better than that of subjective imaging classifiers (AUC = 0.625, $P < 0.05$).

2.5 Breast cancer

Deep learning (DL) is an approach being utilized and requested by radiologists that assist them in making an accurate diagnosis and help to improve outcome predictions. Kaur *et al*. (2019) **[30]** had presented a deep neural network and Multiclass Support Vector Machine (MSVM) for intellectual detection and validation of automated mammogram breast cancer images. The paper employed the pre-processing method and inbuilt feature extraction using K-means clustering for Speed-Up Robust Features (SURF) selection. The results demonstrated that the accuracy rate of the proposed automated DL method using K-means clustering with MSVM was better than using a decision tree model. Experimental results show that the average accuracy (ACC) rates of the three classes, i.e., normal, benign, and malignant cancer, using the proposed method are 95%, 94%, and 98%, respectively. The increased sensitivity rate is 3%, specificity is 2%, and ROC area is 0.99 using SVM compared to the Multi-Layer Perception (MLP) and J48+K-mean clustering WEKA manual approach.

Kyono *et al*. (2020) **[31]** had presented a DL technique to correctly identify normal mammograms and select the uncertain and abnormal examinations for radiological interpretation and improve workflow efficiency. A Convolutional Neural Network (CNN) in conjunction with multitask learning was used to extract imaging features from mammograms that mimic the radiological assessment provided by a radiologist, the patient's non-imaging features, and pathology outcomes. A deep neural network was then used to concatenate and fuse multiple mammogram views to predict both a diagnosis and a recommendation of whether or not additional radiological assessment was needed. The proposed model was able to identify 34% (95% confidence interval, 25%-43%) and 91% (95% confidence interval: 88%-94%) of the negative mammograms for test sets with a cancer prevalence of 15% and 1%, respectively. Finally, ML was leveraged to successfully reduce the number of normal mammograms that radiologists need to read without degrading diagnostic accuracy.

Moreover, Kavitha *et al*. (2022) **[32]** had proposed an Optimal Multi-Level Thresholding-based Segmentation with DL enabled Capsule Network (OMLTS-DLCN) breast cancer diagnosis model utilizing digital mammograms. The OMLTS-DLCN model involves an Adaptive Fuzzy based median filtering (AFF) technique as a pre-processing step to eradicate the noise that exists in the mammogram images. Besides, Optimal Kapur's based Multilevel Thresholding with Shell Game Optimization (SGO) algorithm (OKMT-SGO) was applied for breast cancer segmentation. In addition, the proposed model involves a CapsNet-based feature extractor and Back-Propagation Neural Network (BPNN) classification model was employed to detect the existence of breast cancer. The diagnostic outcomes of the presented OMLTS-DLCN technique were examined by means of the benchmark Mini-MIAS dataset and DDSM dataset. The experimental values obtained highlight the superior performance of the OMLTS-DLCN model with higher accuracy of 98.50 and 97.55% on the Mini-MIAS dataset and DDSM dataset, respectively.

Arefan *et al*. (2020) **[33]** had presented an end-to-end deep learning model and a GoogLeNet-LDA model for predicting breast cancer risk using normal mammograms. A total of 452 normal images (226 MLO view images and 226 CC view images) of this case-control cohort were analyzed to predict the outcome, i.e., developing breast cancer (cancer cases) or remaining breast cancer-free (controls) within the follow-up period. The paper implemented proposed models and compared its effects in several experimental settings using two mammographic view images and inputting two different sub-regions of the images to the models. The proposed models were also compared to logistic regression modelling of mammographic breast density. The area under the receiver operating characteristic curve (AUC) was used as the model performance metric. Both models exhibited superior performance than the percent breast density (AUC = 0.54; 95% CI: 0.49–0.59). The proposed deep learning modelling approach can predict short-term breast cancer risk using normal screening mammogram images.

Toğaçar *et al*. (2020) **[34]** had presented a convolutional neural network-based model namely BreastNet for the diagnosis of breast cancer through histopathological images. The general structure of the BreastNet model is a residual architecture built on attention modules. Each image data is processed by the augmentation techniques before applying it as input to the model. The proposed model performed the classification of breast cancer through histopathological images. As a result, 98.80% classification success was achieved with the proposed model. The success rate of the proposed model was better than the success rates of AlexNet, VGG-16 and VGG-19 models performed on the same data set. In addition, the results obtained in this study yielded better results than the other studies that use the current BreakHis dataset.

3. Comparison Analysis

This paper reviews totally 34 recent articles in different journals such as Elsevier, Springer, IEEE, Willey, and others. Among them, 21 articles analysed the prediction of NCDs and cancer diseases using different ML and DL as well as soft computing techniques. The NCDs and cancer prediction using various techniques are presented in **Table 1**. This Table illustrates the purpose of NCDs and cancer prediction by exploring various performances of different algorithms presented by different authors on different parameters which may include the data set, different diseases, classifier used, and the results obtained by each author as well as limitations.

Table 1: Comparative analysis of the states of arts for detection of diseases such as NCD and Cancers

Ref. No	Types of diseases	Types of techniques	Dataset adopted	Method adopted	Performance Metrics	Remarks
[14]	Heart disease	Machine learning	UCI datasets	artificial neural network, Naive Bayes and support vector machine	Accuracy-76.5%	1.SVM does not perform very well when the data set has more noise i.e. target classes are overlapping 2.It requires much computational power as well as resources as it builds numerous trees to combine their outputs. 3.Accuracy and other performance must be improved
[15]	Heart disease	Machine learning	UCI datasets	artificial neural network, (ANN), support vector machine (SVM), logistic regression, k-nearest neighbor (kNN), classification tree, and Naive Bayes	Accuracy- 85 % Sensitivity-89% Specificity-81 %,	Accuracy and other performance must be improved
[16]	Heart disease	Machine learning and soft computing techniques		ANN ,Particle Swarm Optimization (PSO) merged LA (Lion Algorithm) update (PM-LU) algorithm	Accuracy is good	Accuracy and other performance must be improved
[17]	Heart disease	Deep learning	EHR dataset	hybrid recurrent neural network (RNN)-logistic chaos-based whale optimization (LCBWO)	Accuracy-98%, Specificity-99%, Precision-96%, Correlation coefficient-91%,	The performance must be improved
[18]	Diabetes	Machine learning	UCI datasets	naïve Bayes (NB), decision tree (DT), Adaboost (AB), and random forest (RF)	Accuracy-90.62%	Accuracy and other performance must be improved
[19]	Diabetes	Deep learning	Glucop30 dataset	recurrent neural network with long-short-term-memory (LSTM)	Accuracy-1%	1. It requires a very large amount of data in order to perform better than other techniques.
[20]	Diabetes	Machine learning	Diabetes dataset	Random Forest (RF) Classifier based model	Accuracy -89.63%	The performance must be improved
[21]	Diabetes	Machine learning	Diabetes dataset	Decision Tree algorithm, Naïve Bayes algorithm, and Random Forest	Accuracy-94%	The performance must be improved
[22]	Kidney Diseases	Deep learning	UCI dataset	Deep learning framework	Accuracy-100%	1. It requires a very large amount of data in order to perform better than other techniques.
[23]	Kidney Diseases	Machine learning	ESRD dataset	Feed-forward neural network	Accuracy is 0.84	The performance must be improved

[24]	**Kidney disease**	**deep learning**	**EHR data**	**Bidirectional Long Short-Term Memory (BiLSTM) and Autoencoder networks**	**Accuracy-89.7%**	**The performance must be improved**
[25]	**Kidney disease**	**Machine learning and soft computing techniques**	**CKD data**	**Multi-kernel support vector machine (MKSVM) and fruit fly optimization algorithm (FFOA)**	**Precision value of 98.5% for chronic kidney dataset, 90.42904% for Cleveland, 89.11565% for Hungarian, and 86.17886% Accuracy-98.5%**	**The performance must be improved**
[26]	**Lung cancer**	**Deep learning**	**CT image**	**Optimal Deep Neural Network (ODNN) and Linear Discriminate Analysis (LDA)**	**Sensitivity-96.2%, Specificity-94.2% Accuracy-94.56%**	**The performance must be improved**
[27]	**Lung cancer**	**deep learning**	**Cancer imaging Archive (CIA) dataset**	**improved profuse clustering technique (IPCT), DNN**	**Accuracy-98.42%**	**1. It requires a very large amount of data in order to perform better than other techniques.**
[28]	**Lung cancer**	**Machine learning**	**TCGA dataset**	**neural network, Naïve Bayes, and the decision tree**	**Sensitivity-94.66%, specificity-95.14% and Accuracy-94.78%**	**The performance must be improved**
[29]	**Lung cancer**	**Machine learning**	**CT images dataset**	**Random forest feature selection algorithm (RFFS)**	**AUC = 0.776**	**The performance must be improved**
[30]	**Breast cancer**	**deep learning**	**Mini –MIAS dataset**	**Deep neural network and Multiclass Support Vector Machine (MSVM)**	**Accuracy-normal, benign, and malignant cancer, using the proposed method are 95%, 94%, and 98%, Sensitivity-3%, Specificity-2%,**	**The performance must be improved**
[31]	**Breast cancer**	**deep learning**	**Mammograms dataset**	**Convolutional neural network**	**Accuracy-95%**	**The performance must be improved**
[32]	**Breast cancer**	**deep learning**	**Mini –MIAS dataset**	**CapsNet based feature extractor and Back-Propagation Neural Network (BPNN)**	**Accuracy is 98.50**	**1. It requires a very large amount of data in order to perform better than other techniques. 2. The performance must be improved**
[33]	**Breast cancer**	**deep learning**	**Mammograms dataset**	**deep learning model and a GoogLeNet-LDA model**	**AUC = 0.54; 95% CI: 0.49–0.59**	**The performance must be improved**
[34]	**Breast cancer**	**deep learning**	**BreakHis Dataset**	**Convolutional neural network-based model**	**Accuracy-98.80%**	**1. It requires a very large amount of data in order to perform better than other techniques.**

4.3 Challenges to Deep Learning

Experimental results from studies by different authors have proven that NCDs and cancer diagnosis are better using deep learning than conventional machine learning. Deep learning is beneficial for handling complex, heterogeneous, unstructured, and poorly annotated data, but it needs improvement in data integration, interpretability, temporal modelling and incorporating expert knowledge. Despite its advantages, the following are some crucial challenges that need to be addressed when using deep learning for NCDs and cancer diagnosis:

- A Convolutional neural network is significantly slower due to an operation such as max pool **[31, 34]**
- Also, deep learning is extremely expensive to train due to complex data models. Moreover, deep learning requires expensive GPUs and hundreds of machines **[17, 19, 26, 30, 32 and 33]**

4.4 Other Challenges

- Most of the studies analyzed used different datasets privately obtained by Clinics or cancer research agencies for evaluating and analyzing these. The chief drawbacks of this argument are that the performance of such models across different studies is difficult to compare with.
- Another limitation in some publications is the use of data expansion approaches rather than transferring learning to prevent over fitting.
- The lack of benchmarks was seen as a challenge and a lack of flexibility.

4.5 Future Directions

This sub-section describes the potential future direction of the process of NCDs and Cancer disease classification techniques used in medical image detection. According to the challenges discussed, such a process could face a multi-complex attribute problem; like that, all the DL techniques are considered available alternatives to be a suitable techniques. Therefore, adapting candid and structured techniques for decisions using multiple criteria could boost the decision-making quality.

4.5.1 Dataset and pre-processing

In this step, three main portions should be defined, namely, the target dataset required pre-processing technique for the dataset and the most suitable features for the classification task. Different datasets can be found in the literature to diagnose NCDs and Cancer. Each dataset has some limitations. For example, the number of training samples is small, the provided images are of low quality, and the size of the images is not equal. Thus, pre-processing steps (e.g. using data augmentation techniques **[34]** to generate more medical image samples in order to provide comprehensive training) are needed to tackle such issues. The pre-processing of images **[30, 32]** and features extracted **[17, 18, 26]** from images have a great impact on classification in terms of improving accuracy. Also, it revealed that the dimensionality reduction approach decreased the complex problem as well as time consumption. Therefore, steps of pre-processing and future extraction are considered in future research. Thus, all mentioned scenarios will have a great impact on the results of the evaluation and benchmarking for disease classification techniques. Accordingly, these steps should be provided to achieve an efficient evaluation and benchmarking process for NCDs and cancer classification over ML techniques. To train and test NCDs and Cancer classification techniques, the dataset will be separated into two parts. The first part will be used towards training the set, whereas the second part will be used for testing the set.

4.5.2 Generalizability of deeply learned models

Some of the studies discussed in the survey have used small training datasets. Moreover, trained models were not being exposed to meticulous validation on massive testing data that may increase false positives and false negatives due to over fitting and memorizing training data. Data augmentation reduces the risk of over fitting due to small training set by introducing variations or jittering to the original data, thus improving generalizability. But augmenting the training set is not equivalent to independent training samples of comparable size. Therefore, many such models' generalizability to unseen data of new patients is still unknown and is an important parameter to be considered.

4.5.3 Training deep models using smaller datasets in medical applications

Some studies utilize pre-trained models on large image datasets in recent years, but none uses these models on a smaller dataset. As medical datasets are not abundant in numbers, thus, new algorithms should be developed to train deep models on smaller medical image datasets.

4.5.4 Performance of Deep Learning

From this survey, accuracy is very important to the detection of diseases. Also, DL has outperformed ML techniques for the detection of diseases **[17, 19, 22, 25, 27, 32, and 34]**. Therefore, future research will be proposed DL techniques-based detection systems for NCDs and Cancer. Moreover, the performance of the DL must be improved in the future for effective detection of NCDs and Cancer.

4.5.5 Performance of Optimization Techniques

Based on the survey, soft-computing techniques such as PSO and LA **[16]**, LCBWO **[17]**, and FFOA **[25]** are employed in literature to improve the performance of the techniques for accurately detecting NCDs and cancer. Since, optimization techniques have minimized error, cost, or loss of ML and DL techniques and improved the performances of DL and ML. Therefore, in the future, the performance of the DL will be improved by soft computing techniques.

4.5.6 Using of multiple modalities for breast and lung classification.

Based on the survey, accuracy of the breast and lung classification is improved by multi-modalities. Therefore, in the future, to enhance the accuracy and performance of breast and lung classification, the multiple modalities will be employed.

4.5.7. Performance Metrics

According to survey, most of the articles discussed different performance evaluation metrics to evaluate the performance of the presented methods. For example, Accuracy, sensitivity, precision, F-measure, AUC (Area under the curve). These metrics are considered in future works

5. CONCLUSION

In this study, we review the latest studies focused on the detection and classification of NCDs and cancer, using various machine learning and deep learning techniques in different data and image modalities. This review divides machine learning and deep learning applications into five categories according to the diseases described in Section 2. Five different popular machine learning techniques are the strengths of the review, including SVM, DT, KNN, and Naive Bayesian Network, and ANN. The review also focused on the Convolutional Neural Network and its Deep Learning architectures used to detect and classify NCDs and cancer from different image modalities. This review provides a description of the medical imaging as well; Mammograms, Histological, and CT images. Also, the review provides NCDs datasets.

This survey also highlights research challenges and future recommendations for new researchers in this field. DL methods also exhibited an outstanding performance for varied evaluation parameters such as accuracy, sensitivity, specificity, F-measure, etc. High-level and low-level features can be learned automatically from the input image using DCNN. Training deep learning models from scratch is time-consuming and requires extensive resources. As a result, many studies have utilized pre-trained models and attained remarkable performance. Results have proven that deep learning outperforms conventional machine learning in diagnosing diseases when the dataset is broad. Research gaps from the recent studies depict that practical and scientific research is an urgent necessity for improving healthcare in the long run. In future work, enhanced DL classifiers for NCDs and cancer prediction can be applied.

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