Global Journal of Computer and Engineering Technology (GJCET)

Vol. 3, No. 1, January, 2023 ISSN: 2767-1933

MACHINE LEARNING APPROACH FOR CLINICAL DECISION SUPPORT SYSTEM (CDSS): A CRITICAL REVIEW

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ABSTRACT

Clinical Decision Support Systems (CDSS) aid in disease diagnosis and prediction process, which can enhance accuracy and can help in critical decisions making processes. The study attempts to assess the state-of-the-art of CDSS at the moment, to identify recent hybrid machine learning (ML) techniques, as well as evaluate the strengths and weaknesses of various ML models. It also explores various CDSS, and the finding of this study suggests that systems developed using integrated ML techniques have been proven better than any particular technique. This study reinforces CDSS's importance in disease diagnosis.

Keywords: Machine Learning (ML), Healthcare, Clinical Decision Support System (CDSS)

1. INTRODUCTION

Several chronic diseases are curable via a timely diagnosis. Despite noticeable growth, the healthcare industry is nevertheless confronted with several difficulties., which result in the delay of proper diagnosis and ultimately affect prognosis that may be fatal. Presently, unanticipated crises like COVID-19 cause extra pressure on the system. An interactive decision support system, or CDSS, can help healthcare institutions make decisions about diagnosis and prognosis. ML can process massive, multi-dimensional datasets in a dynamic environment. It can detect patterns of disease and anomalies in a patient's medical records. It has the potential to handle numerous disease-related variables for the diagnosis and prognosis of diseases. Thus, integrating ML with the healthcare system can help to utilize scarce resources and a massive variety of data for management plans, screening patients at different stages, contact tracing, and accelerating clinical trials (van der Schaar et al., 2020). It can improve medical care services, treatment plans, and training of patients (Kaplan, 2001). ML is giving better results in image classification, and it can help medical professionals detect, diagnose, and treat diseases like COVID-19. Many Researchers are working on implementing ML techniques in developing suitable CDSS. Most researchers are using methods as shown in Figure 1 for developing CDSS:

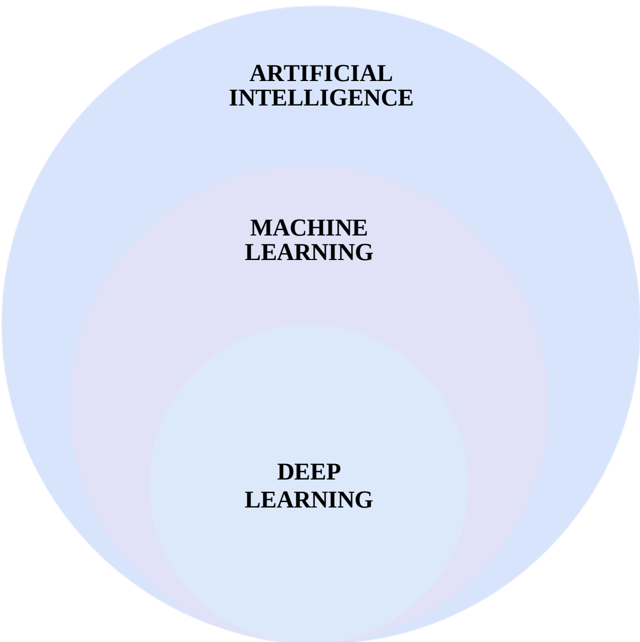


Figure 1: Approaches used in designing CDSS

Artificial Intelligence (AI) is the technique that gives a machine power to perceive, learn and take decisions. Computers learn through experience using ML. Computers are taught to learn from examples using DL which is a subset of ML. Models are trained using large, labeled data sets on neural networks of many therefore it requires high computing power. The most popular deep neural network is the convolutional neural network also known as ConvNet, which can extract features directly.

2. MACHINE LEARNING

Machine learning can be supervised, unsupervised, and reinforced (Figure 2)

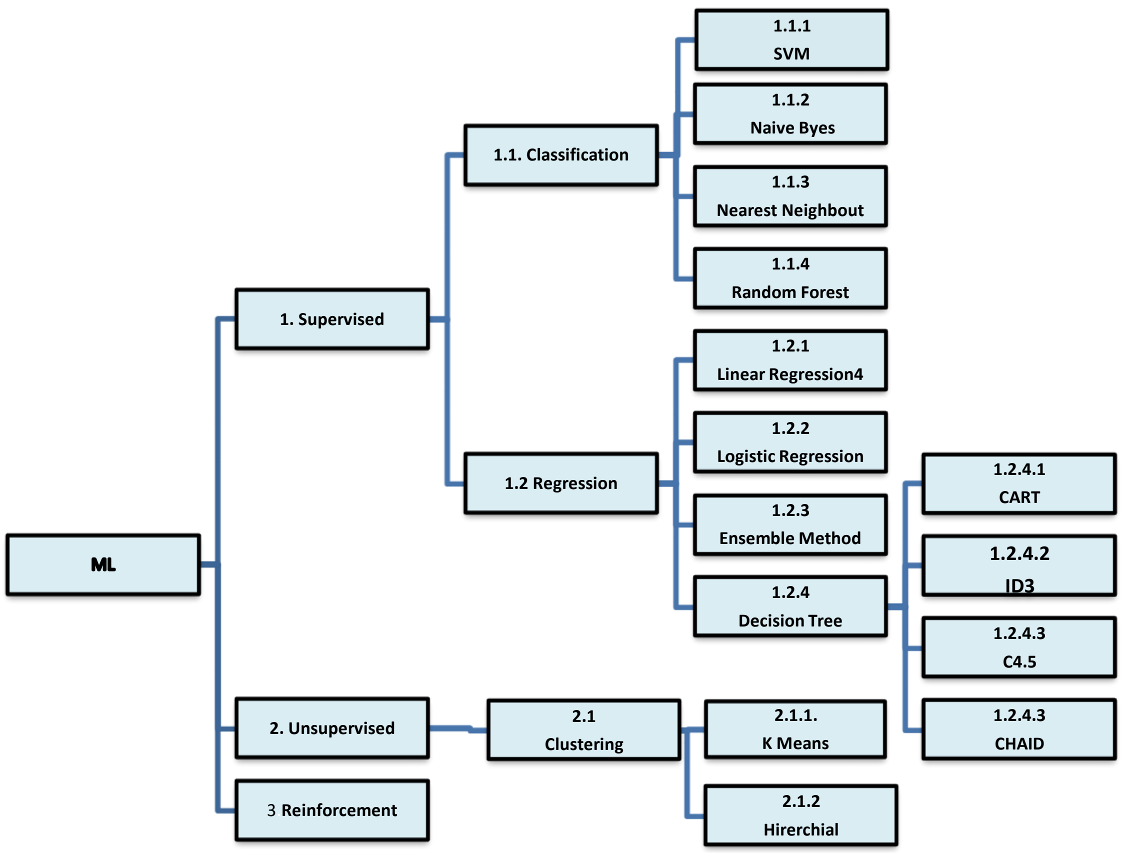


Figure 2: Types of machine learning

(i) Supervised Learning: It uses known input and output data to make predictions and classification models. Supervised learning can be implemented for:

(a) Classification: This technique is used for classifying the data into different categories. Popular algorithms of this category are SVM, Discriminant Analysis, Naïve Bayes, KNN.

Support vector machines(SVM) classify data by selecting a hyperplane with largest margin.

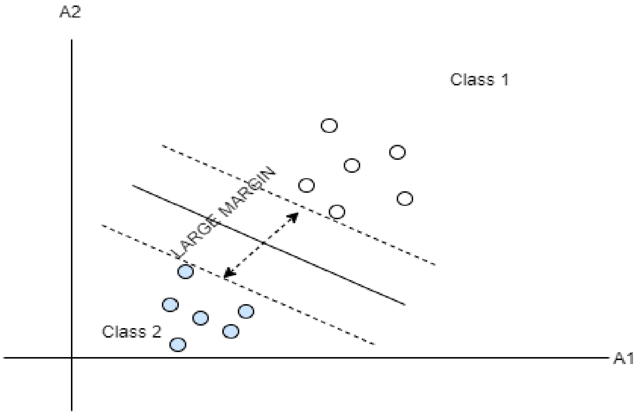
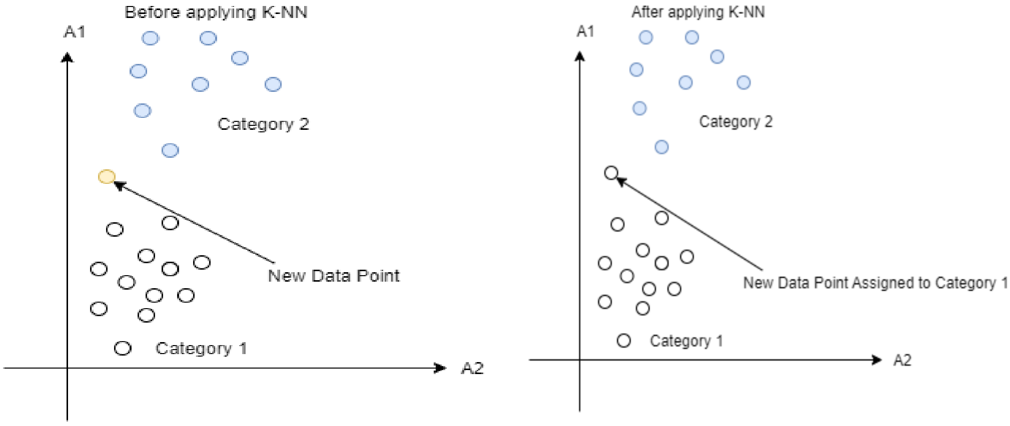


Figure 3: Support vector machines (Han et al., 2012)

Naive-Bayes(NB) is based on the Bayes theorem and requires minimal training data.
K Nearest Neighbor (KNN) works by finding the K number of nearest neighbors to an unlabeled item in the feature vector space. The class to this item is then assigned as the class of the majority of its K nearest neighbors.



(a) **(b)**

Figure 4: K-Nearest Neighbour

Random Forest (RF) is used when there are large input variables and training datasets.
Regression: This technique is used for the prediction of continuous values. Neural Networks, Linear Regression, Decision Trees and Ensemble Methods have commonly used algorithms in this category.
Linear regression is a statistical method for predicting continuous variables.
Logistic regression figures out how a dependent binary variable is related to one or more independent variables.
Ensemble Methods combine weak classifiers to form a model that commonly provides better results than the individual models. The most common ensemble methods used are Bagging (Bootstrap averaging) and boosting. Bagging creates subsets of the dataset and makes models; all models are then aggregated using the average. In boosting, a weight is given to each item to be classified by the models. Models are then sequentially trained on the weighted items. The misclassified items are updated so that they get more weight. Finally, the predictions of all models are combined, usually by adding the weighted predictions made by the models.
A decision tree is a type of classification tree that is created by applying a set of rules to a dataset in order to model the relationships between classes. We have splitting attributes as tree nodes, whose values impact data set partitioning when this node is extended. The nodes are expanded based on a criterion called the splitting criterion. Decision tree construction involves Construction Phase, Pruning Phase, and processing pruned tree

Classification And Regression Tree (CART) uses the gini index for finding the best split. Initially, two nodes are created, each of which is then split in the same manner. By analyzing the input fields candidates' splitters are found. If no further split is possible that node becomes the leaf node. The leaf nodes are assigned classes and error rates.

Iterative Dichotomiser(ID3) uses each node to correspond to a splitting attribute and each arc is a possible value of that attribute. For measuring the informativeness of a node Entropy is used.

C4.5 is an extension of C4.5 and accounts for unavailable values. It creates trees with variable branches per node. For each value of the attribute, one branch is created.

Chi-square automatic interaction detection (CHAID) stops growing the tree before overfitting. It is derived from AID (Automatic Interaction Detection).

(ii) Unsupervised Learning: It uses only input data. It is used to learn more about data and is used for pattern recognition.

(a) Clustering is the most common unsupervised learning technique, applied for pattern recognition based on identifying characteristics of input data. K-Means, Hierarchical Method, Neural N/w, and Hidden Markov Model are algorithms under the category of unsupervised learning.

K Means Clustering in which K groups are made from unlabeled items. It solves the problem of clustering by grouping similar items together

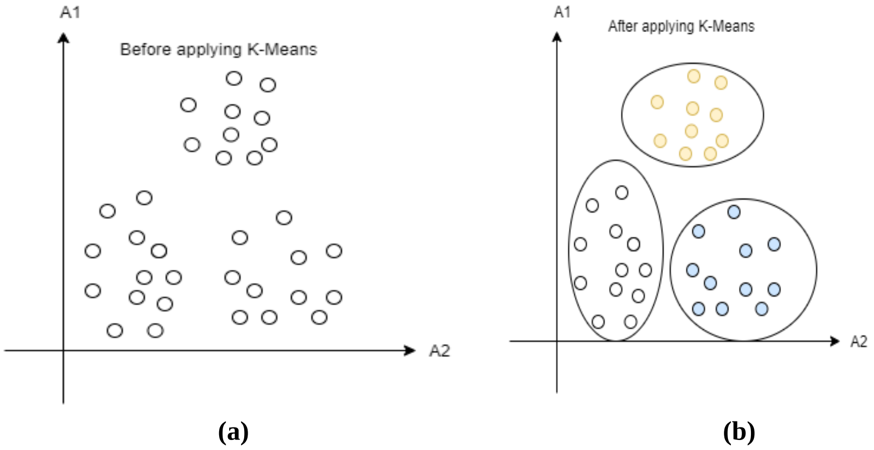


Figure 5: K-Means Clustering

Hierarchical groups similar data in clusters. Data from different clusters differ but data from the same cluster are similar.

(iii) Reinforced Learning: is a form of supervised learning but in this method, the network receives some feedback. (Sivanandam, & Deepa, 2011)

Artificial Neural Network (ANN) is used to give a better presentation of data. This technique is inspired by human brain architecture made of brain cells or neurons (Figure 3). Neuron(nodes) is a processing element(Rajasekaran & Pai, 2003). The neurons of ANN are interconnected with each other constituting a structure in which the weight of these connections is adjusted to train the network. It is usually a layered structure.

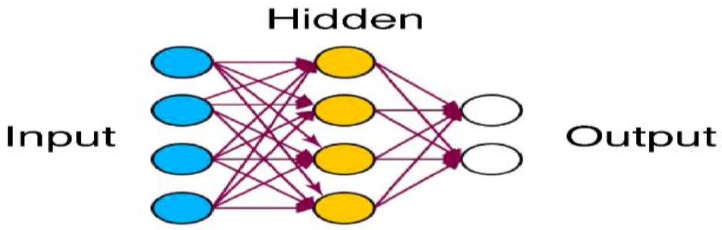


Figure 6 : ANN(Chen et al., 2018)

The ANN models are described based on the following specifications (Sivanandam, & Deepa, 2011):

Model's synaptic interconnections: The network architecture of the neural network is formed by interconnections between neurons and arranging the neurons in different layers. Feed

Forward neural networks are made up of neurons from one layer that is connected to neurons from the next layer, whereas feedback neural networks are made up of neurons from the same or previous layer that is directed back as inputs to the same or previous layer. ANN is classified as Supervised, Unsupervised, and Reinforced.

Deep learning is the technique through which a computer model directly learns to carry out classification and may attain perfect accuracy. Here, models are trained to utilize a vast collection of labeled data and multi-layered neural network architectures.

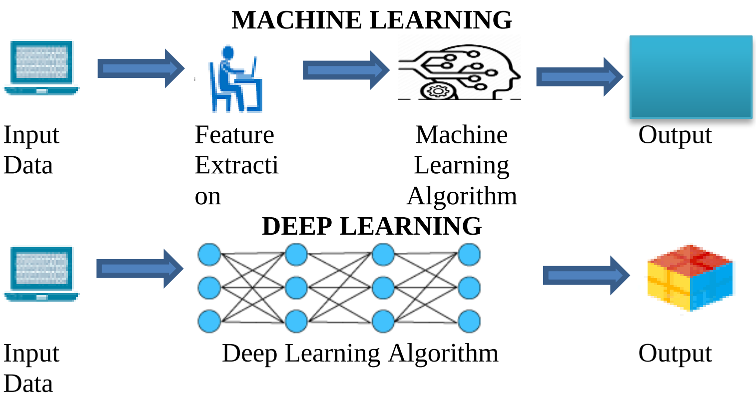


Figure 7: Deep Learning Vs. Machine Learning

3. LITERATURE REVIEW

A CDSS is built upon accurate data and an inferencing mechanism that joins knowledge and data to help physicians in decision-making. CDSS can be used to analyze and treat life-threatening diseases like cancer. It can be implemented in the diagnosis of cardiovascular disease and in locating infected regions. It can work independently or be used as a complement to the health record system. It can improve patient security, giving, for example, caution to reduce error (Zikos & DeLellis, 2018).

The literature reviewed for this research work has been collected from various reputed indexed databases like ScienceDirect, Shodhganaga, IEEE Xplore, and Springer Nature. Details of reviewed research papers and findings is as Table 1.

Table 1: Research Papers reviewed

S.no.	Author	Technique	Dataset Used	Outcome
1.	Saboor et al., 2022	XGB, SVM, Random Forest, LDA, AB, CART, ET, LR, MNB.	Z-Alizadeh Sani dataset	SVM has shown 96.72% accuracy.
2.	G et al., 2021	LR, NB, MLP, DT, SVM, RF, HDPM, Hybrid Linear stacking model, and Xgboost algorithm	UCI	Accuracy was 96% with the HLS-XGBoost model.
3.	Cherradi et al., 2021	KNN and ANN	Z-Alizadeh Sani, Cleveland datasets	An average accuracy of 96.78% with training accuracy of 100%
4.	Kanwal et al., 2022	SVM, logistic regression, Optimized Artificial Immune Networks, CNN	GitHub	Accuracy upto 98-99% was achieved for SVM proposed hybrid approaches, which was found to be 70.85% for CNN and 96-97% for DNN.
5.	Nagavelli et al., 2022	Naive Bayes, SVM, XGBoost	PhysioNet database, Cleveland and Statlog	XGBoost Accuracy of the algorithm was 95.9, precision 97.1, and recall 94.67.

6.	Liu et al., 2022	SVM, Gradient Boosting Algorithm, DT, RF	Shanghai Ninth People's Hospital	Achieved high accuracy.
7.	Vijayan & Anjali, (2015)	NB, SVM, DT , Adaboost	UCI	With decision stump serving as the base classifier, the Adaboost method was able to achieve an accuracy of 80.72%.
8.	Wang et al., 2018	Deep Neural Network	Collected from Ophthalmologist & Neonatologist	shown improved performance when identifying ROP.
9.	Talo et al., 2019	Convolutional neural network	Harvard Medical School database	Among five pre-trained models, ResNet-50 attained the best accuracy of 95.23%
10.	Bi et al., 2020.	CNN and K-Means.	Alzheimer's Disease Neuroimaging Initiative (ADNI)	This method attained 92.5% average prediction accuracy.
11.	Alakus & Turkoglu, (2020)	Deep Learning (CNN, LSTM, ANN, RNN, CNNLSTM, CNNRNN)	Israelita Albert Einstein Hospital,	For identification of COVID positive patients yielded 99.42% recall, 91.86% F1-Score, 86.66% accuracy and 86.75% precision,
12.	Grover et al., (2018)	DNN	UCI	DNN has shown better accuracy in comparison to others with classification accuracy was 94.4422% and 62.7335 for train and test datasets.
13.	Xu et al., 2020	Deep learning, ResNet(for feature extraction), Noisy-OR Bayesian function	CT Samples from hospitals in Zhejiang, China.	An accuracy of 86.7% while screening for COVID-19 was shown by the Deep learning model.
14.	S. Gambhir et al., 2017	NB, PSO optimized ANN	From different hospitals in Delhi	The PSO-ANN-based diagnostic model has the best level of accuracy (87.27%) for detecting dengue early, followed by ANN (79.09%), then Naïve-Bayes (77.2%), then PSO (76.3%) and lastly by Decision Tree (73.63%). The highest sensitivity was achieved in the case of the PSO-ANN (68%) algorithm. followed by ANN (55.55%), then PSO (48%), and then by Naive-Bayes (44%), and lastly by Decision Tree (41.66%).
15.	Behnood et al., 2020	ANFIS, Virus optimization algorithm (VOA)	COVID-19 dataset of U.S. counties.	ML Models showed superior performance compared to linear regression.
16.	Basu & Campbell, 2020	Long Short-Term Memory Networks (LSTMs)	John Hopkins University Repository	Analyses provided by the model can help in deciding on mitigation.
17.	Doupe et al., 2019	Deep Learning, Decision Trees, Ensemble Methods	Simulated Insurance Claim	Emerging Machine Learning tools can be potentially useful for healthcare.

18.	Ichikawa et al., (2016)	Gradient-boosting decision tree, LR and RF.	Annual health check-ups, Japan	The best performance was shown by RF and GBDT in terms of sensitivity and specificity datasets.
19.	Jamshidi et al., 2020	LSTM, GAN, and Extreme Learning Machine	Collected from Checkups	ML algorithm can give better results while understanding spread patterns and can improve the accuracy of diagnosis.
20.	Gao et al., (2020)	LR, DT, SVM and Gradient Boosted DT	Medical College of Tongji	Mortality risk of Covid 19 patients was more accurately categorized.
21.	Roy et al., (2020)	DNN derived from Spatial Transformer Networks	Dataset of Lung Ultra Sonography Image Collected from several Italian hospitals	Produced better results.
22.	Rustam et al., 2020	LASSO, ES, LR and SVM	GitHub	When compared to LASSO and LR, ES produced the best performance when forecasting the number of newly confirmed cases.
23.	E. Gambhir et al.,(2020)	Polynomial Regression Algorithm and SVM	Health and Family Welfare Ministry of India	Polynomial Regression Algorithm achieved 93% accuracy.
24.	Lalmuana wma et al., (2020)	ML and DL	Datasets in articles	Medicine, screening & prediction, forecasting, and contact tracking can all be made better using AI and ML, but Deep Learning algorithms have the most potential.
26.	Zhong et al., (2012)	Multi Level SVM	Project for Cost Utilization and National Healthcare	MLSVM is superior to CVM (Core Vector Machine), and ACSVM (Adaptive clustering based SVM).
27.	Nahar et al., (2013)	Rule mining algorithms (Tertius, Apriori and Predictive Apriori)	UCI cardio diseases dataset	Rule mining yields the greatest results.
28.	Shrivas et al., (2018)	RF, CART, SVM, FST Proposed FST based on the union of the four existing ranking-based FST.	UCI	With 9 features UBFST achieved 98.50% and with 14 features it achieved 99.25% accuracy.
29.	Khan & Shamsi, 2018	Deep Neural Networks and NLP	PhysioNet (Physionet,2017)	With 77% accuracy, it can spot the first ailment, compared to 34% for the second.
30.	Soufi et al., (2018)	Fuzzy Logic Classifier (FLC), Rule-Based Reasoning (RBR)	Imam Reza Hospital (Tabriz-Iran)	CDSS with test data produced an accuracy of 99.44%.
31.	H. S. Hota, (2014)	Statistical and decision tree-based classification,	UCI repository site	An ensemble model is better than individual models,

		unsupervised and supervised ANN, Ranking-based feature selection technique		
32.	H. S. Hota & Dewangan, (2016)	Classification and Regression Technique (CART), BFTREE: Best First Tree (BFTREE), C4.5, Feature Selection Technique	UCI	Even after using FST with only four features and 84.82% accuracy, CART outperforms the other two DTs.
33.	H. S. Hota, (2013)	SVM, C5.0, Rank-based feature selection technique.	UCI repository	Accuracy of 92.59% was attained by using SVM in conjunction with the C5.0 decision tree.
34.	H. Hota & Shrivas, (2014)	C4.5, Info Gain, Correlation	NSL-KDD	With info gain feature selection, C4.5 achieved the highest accuracy.
35.	H. S. Hota et al., (2013)	ANN and DT	UCI	Using C5.0 with SVM as an ensemble, the accuracy was 94.35%.

Sacchi et al.,(2015) used two repositories, PubMed and Web of Science, and discovered that cancer (12%) is the most researched medical field, followed by diabetes and cardiovascular disorders, HIV, chronic diseases, and mental health. They further observed the 66% treatment selection, 6% treatment, 19% diagnostic support and 9% preventative goals of the support system. Their investigation revealed that healthcare decision support systems still prioritise constructing inference engines on top of conventional data models and are not patient-centric.Doupe et al., (2019) applied Deep Learning, Decision Trees, and Ensemble Methods and discovered that researchers looking to improve the prediction of a healthcare result can benefit greatly from Machine Level. CNNs were developed by Talo et al., (2019), to identify brain disorders using MRI scans. Authors classified brain MRI images into five using ResNet-50, ResNet-34, AlexNet, Vgg-16, and ResNet-18pre-trained models. ResNet-50 gave the best accuracy(95.23%) and can be used by clinicians to validate their findings. Bi et al., (2020) utilized CNN based on feature extraction to predict Alzheimer's disease from MRI scans. They proposed a fully unsupervised deep learning technology that gave 92.5% average prediction accuracy. Authors found methods very efficient in predicting AD and need further verification with a larger scale database. In their work on Alzheimer, authors Chaves et al., (2013) (Grover et al., 2018)utilized SVM for classification along with PCA and Partial Least Squares(PLS) for feature extraction. With SPECT (single photon emission computed tomography) and PET (positron emission tomography), this led to accuracy results of 91.75% and 90%, respectively. In their study, Grover et al., (2018) predicted the prevalence of Parkinson's disease using a deep neural network (DNN). This was done in order to determine the prognosis for patients with Parkinson's disease.They noticed that accuracy can be improved further by using a larger dataset. Gave better accuracy in comparison to others with classification accuracy was 94.4422% and 62.7335 for train and test datasets.

Alakus & Turkoglu, (2020), utilized laboratory data and DL for clinical predictive models of COVID-19 infection. The models gave 86.66% accuracy, 86.75% precision, an F1-score of 91.89%, and an AUC of 62.50%. The objective of the research work carried out by authors Xu et al., (2020) was to distinguish cases of COVID-19 from influenza and normal cases. They employed Deep Learning and CT images. 3D deep learning models were used to segment infection regions from pulmonary CT images. They observed that the DNN successfully screened COVID 19.Using Computed Tomography Scan, it can classify IAVP, healthy cases, and COVID-19 with an accuracy of 86.7%. Behnood et al., (2020) applied the combination of virus optimization algorithm (VOA) and Adaptive Network Based Fuzzy Interference System (ANFIS) to examine the impact of weather and population density upon COVID 19 infection rate in the U.S. They found that in predicting infection rates machine learning models could be proven successful. Authors Jamshidi et al., (2020) utilized Generative Adversarial Network(GAN), Extreme Learning Machines(ELM) and Long Short Term Memory(LSTM) in their research on DL Strategies for the management and diagnosis of COVID 19. They concluded that viral spread pattern of a large dataset can be better predicted using advanced ML techniques. Rustam et al., (2020) used Exponential Smoothing(ES), SVM, LASSO, and LR for forecasting COVID-19. They concluded that in comparison to LR and LASSO, ES gave the best results. Basu & Campbell, (2020), found that LSTM can help in deciding on mitigation. Gao et al., (2020) implemented an ensemble model using four machine learning methods Neural Network, Gradient Boosted Decision Tree, SVM, and LR. He arrived at the opinion that the model enables a reactive health

service that is favorable to COVID-19 patients at high risk.Roy et al., (2020) utilized DNN to classify and localise COVID-19 markers in ling Ultrasonography and found that experiments demonstrate satisfactory results. E. Gambhir et al., (2020) employed SVM and polynomial regression algorithm for COVID-19 spread. They demonstrated that the polynomial regression algorithm gave an accuracy of 93%. Lalmuanawma et al., (2020) reviewed DL and ML methods used in several research articles and concluded that DL algorithms have more potential in comparison to other learning algorithms.
Ramana et al., (2012) utilized SVM, C4.5, BPNN, and NB. The outcomes revealed that AP liver dataset outstripped the UCLA dataset in all four measures of performance. Wang et al., (2018) proposed an automated approach for the early-onset retinal disease identification. For identity and grading, they used two DNN models, Gr-Net and Id-Net. They discovered that the developed system was very efficient and effective while identifying ROP but the outcome of grading was not so good. Keleş & Keleş, (2008) used Neuro-fuzzy classification algorithm. They developed Expert System for Thyroid Diseases Diagnosis (ESTDD) and found that it gave 95.335 accuracies. In their work on chronic kidney disease classification, Shrivas et al., (2018) used RF, CART, SVM, FST. They Proposed FST based on the union of the four existing ranking based FST (Chi-Squared, Gain Ratio, Symmetric Uncertainty and Info Gain) known as UBFST, authors found that with 9 features UBFST achieved 98.50% and with 14 features it achieved 99.25% accuracy.

Keleş et al., (2011) used Neuro-fuzzy rules and the Expert system Ex-DBC to diagnose breast cancer. They achieved 81% negative and 96% positive predictive values. H. S. Hota, (2013) utilized Statistical and decision tree-based classification, unsupervised and supervised ANN to diagnose breast cancer. Author discovered ensemble model better than any model, whereas the accuracy of counter propagation network(CPN) is very close to ensemble model. H. S. Hota, (2014) used SVM, C5.0, Rank-based feature selection technique for the identification of breast cancer and found that with a reduced feature subset an ensemble of C5.0 decision tree and SVM yielded 92.59% accuracy.

Gupta et al., (2011) utilized SVM, CART, KNN, NB, DT, ID3, and MLP to analyze the efficiency of several data mining classification strategies applied to healthcare data. With the PIMA Indian Diabetes dataset and the Stat Log Heart Disease Dataset, the scientists discovered that SVM offered the most promising results, with accuracies of 96.74% and 99.25%, respectively.

Saboor et al., (2022) implemented nine machine learning classifiers ET, CART, XGB, LDA, MNB, AB, LR, SVM and RF. To train and to validate algorithms, the authors used a standard method of k-fold cross validation. Their findings demonstrated that classifier accuracy might be enhanced through the use of hyperparameter tuning and data standardization. Overall, ET and XGB classifiers performed well, while SVM attained an accuracy of 96.72%.

G et al., (2021) came up with a revolutionary method that they called HLS-XGboost i.e. Hybrid Linear Staking mode and Xgboost algorithm for classification of cardio disorder. Their method provided an enhanced performance level and had an accuracy of 96%. Cherradi et al.(2021) put forth a model based on KNN and ANN. They split database by applying K-fold cross-validation. The experimental work yielded 96.78% accuracy along with 100% training accuracy. As evident from the table maximum authors have used UCI Repositories, Github, and Kaggle for datasets and most of them have used Machine Learning in their work.

Waring et al., (2020) observed that despite demand of Automated ML(AutoML) , these strategies in the healthcare industry has received very little attention. In any machine learning project, developing an excellent, representative, and varied dataset is a significant challenge. The ML algorithm should ideally be trained on data that is of the same format and quality as the data that will be utilized in the end. EHR data, which is unreliable and prone to inconsistency, is extensively used in clinical settings. Nonetheless, there is a chance that undesirable outcomes will arise from training models based on ML on this noisy data source. A significant problem is that these black-box AutoML systems do not provide sufficient levels of transparency.

Kuo et al., (2019) automated estimated CKD and glomerular filtration rate (eGFR) status determination using deep learning. For the purpose of predicting kidney function using 4,505 renal ultrasound images, they used the transfer learning (TL) and embedded robust Resnet model pre-trained on Imagenet. To prevent the model from overfitting and to enhance its ability to generalize, bootstrap aggregation was also utilized. Also, they exploited properties of the deep neural network to detect CKD, which is indicated by an eGFR of less than 60 ml/min/1.73 m2. A significant link between forecasts of creatinine-based GFR and artificial intelligence (AI) was demonstrated by Pearson A Pearson correlation coefficient of 0.741 demonstrated the significant link between forecasts of creatinine-based GFR and artificial intelligence (AI). A Pearson correlation coefficient of 0.741 demonstrated the significant link between forecasts of creatinine-based GFR and artificial intelligence (AI). coefficient of 0.741. Their methodology classified CKD state 85.6% more accurately than expert nephrologists (60.3%–80.1%).

According to Kanda et al., (2022), a higher risk of death from CKD and heart failure was reported among individuals with early-stage type 2 diabetes mellitus (T2DM). It is still necessary to design effective screening and risk valuation methods to identify T2DM who have a high likelihood of developing heart failure or chronic kidney disease. The purpose of this research was to construct a unique model based on ML, that might forecast the probability of developing HF or CKD in early-stage T2DM patients. The models were developed using a retroactive dataset of 217,054 T2DM patients without cardiac or renal disease from a Japanese claims database. After internal validation, Xgboost demonstrated perfect outcome in terms of hospitalization and diagnosis for HF or CKD. It was further confirmed using a different dataset containing 16,822 patients. The 5-year prediction area under the ROC curves for heart failure and CKD treatment and hospitalosation in the external validation was 0.718 and 0.837, respectively. When related to individuals expected to be at low risk, those anticipated to be at high risk had a significantly higher rate of heart failure or CKD, according to an analysis of Kaplan-Meier curves. Consequently, the generated model, in the extrenal validation, accurately foretold the likelihood of emerging heart failure or chronic kidney disease in T2DM patients. The researchers noticed that Early detection and treatment of T2DM patients at high risk of CKD/HF using ML models may improve prognosis.

Abdeltawab et al.(2019) developed a DL based computeraided diagnostic(CAD) system to predict acute renal transplant rejection early. The suggested CAD system combines imaging signals and clinical biomarkers. The CAD system is evaluated using Diffusion weighted(DW) MRI scans of 56 individuals from geographically diverse populations and various scanner image collection techniques. The suggested system's overall accuracy in differentiating between non-rejected and rejected kidney transplants is 92.9%, with 93.3% sensitivity and 92.3% specificity. These findings show the possibility of the suggested approach to provide a trustworthy diagnosis of the status of a renal transplant in a non-invasive manner for any DW-MRI scans, irrespective of imaging technique or distance.

Bai et al., (2022) sought to determine whether machine learning (ML) might be used in patients with CKD, to predict the end stage kidney disease. They collected data based on information collected from a long-term CKD cohort. The baseline features of the patients and the outcomes of routine blood tests were major predictors. ESKD status at five years was the outcome of interest. Fivefold cross-validation evaluated NB, DT, LR, KNN and RF. The effectiveness of each model was assessed in comparison to that of the Kidney Failure Risk Equation (KFRE). 748 CKD patients enrolled between April 2006 and March 2008 were followed for 6.3 ± 2.3 years. Among 70 individuals (or 9.4%), ESKD was noted. The KFRE is unparalleled in its sensitivity, precision and accuracy. LR,RF and NB all showed a level of predictability that was comparable to that of the KFRE. Furthermore, the sensitivity scores of these ML models were higher, which may be useful for patient screening. The study demonstrated the feasibility of using ML to predict the prognosis of CKD based on readily available data.

Zhang et al., (2021) mentioned that routine screening for the early diagnosis of prevalent chronic diseases would benefit from the adoption of algorithms based on DL, especially in remote or resource-limited areas. They have shown that deep learning models can be used to diagnose type 2 diabetes and chronic kidney disease solely from fundus images or in conjunction with clinical metadata. Patients can be stratified according to their risk of the disease progressing based on their estimated glomerular filtration rates and blood-glucose levels, with mean absolute errors of 11.1-13.4 ml min1 per 1.73 m2 and 0.65-1.1 mmol l1, respectively. The models were trained and validated using 115,344 retinal fundus images from 57,672 patients.

Sabanayagam et al., (2020) made use of information gathered from three cross-sectional, population-based investigations conducted in China and Singapore. The DL-based algorithms were created (5188 patients) and validated (1297 patients) using data from the Singapore Epidemiology of Eye Disorders (SEED) project, which included participants under the age of 40. External testing was performed on two separate datasets: Singapore Prospective Study Program and Beijing Eye Study. Chronic renal disease was identified as an estimated glomerular filtration rate of 60 mL/min per 173m2. Image Deep Learning Algorithm, the risk factors (RF), as well as the hybrid Deep Learning Algorithm integrating the two, were all trained. Using the area under the ROC curve, model performances were assessed (AUC). The AUC was 0911 for image DLA (95% CI 0886 0936), 0916 for RF (0891-0941), and 0938 for hybrid DLA (0917-0959) in the SEED validation dataset. They concluded that retinal photography could be used as an additional or opportunistic screening technique for chronic kidney disease in community groups since it performs well in estimating the disease.

Qian et al., (2021) found that there was a lot of variation between different raters, a lot of false positives, and that deep learning models weren't being used that followed the Breast Imaging Reporting and Data System guidelines

(BI-RADS) standards, and have not undergone prospective testing have all hindered the clinical application of breast ultrasound for the assessment of cancer risk and deep learning for the classification of breast-ultrasound images. They have demonstrated that an explainable deep-learning system predicts BI-RADS scores for breast cancer as accurately as seasoned radiologists. Furthermore, they discovered that ultrasound imaging may be useful in screening mammography procedures when combined with multimodal, multiview breast ultrasound pictures that include heatmaps for deep learning-predicted malignancy risk.

Kermany et al., (2018) have demonstrated that machine learning classifiers can query electronic health records in a manner like doctors and discover relationships that earlier statistical techniques have missed. Deep learning techniques are used in their methodology to retrieve clinically relevant data from EHRs using an automated natural language processing system. A total of 101.6 million data points from 1,362,559 paediatric patient visits presented to a major referral centre were examined to train and validate the framework. Their model displays good diagnostic accuracy across a wide variety of organ systems, and its performance in diagnosing common childhood disorders is on par with that of experienced doctors. This work serves as a proof of concept for the use of an AI-based system to assist clinicians in managing massive volumes of data and supplement diagnostic evaluations in situations of diagnostic uncertainty or complexity.

4. CONCLUSION

This research work was an attempt to bring substantial insight into CDSS. After studying almost 120 articles, it was discovered that, since the last decade, much work had been done in designing CDSS. From the literature review, it is concluded that developing CDSS for early disease prediction and diagnosis is challenging, and there is a vast scope of research in this area. The above literature survey also points out that deep learning tools are becoming popular and have already been applied by various authors for using medical image data for a specific disease. However, feature selection is also an essential component of the CDSS model. Most CDSS models have utilized Deep Learning and Machine Learning (Especially SVM, RF, LR, and Decision Tree). The implementation of Machine Learning and Deep Learning in CDSS has been fruitful, however, most models still require patient-centric results. Future research may employ other algorithms that consider different attributes and datasets, allowing for predicting the severity or stage of the disease rather than merely whether the patient has the condition. Additionally, forecasts if a cure is likely to be found.

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