Review Article

International Journal of Advanced Technology and Engineering Exploration, Vol 10(106)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2023.10101219

Impact of machine and deep learning techniques on diseases classification and prediction: a systematic review

Animesh Kumar Dubey[1*], Amit Kumar Sinhal[2] and Richa Sharma[3]
Research Scholar, Department of Computer Science and Engineering, JK Lakshmipat University, Jaipur, India[1]
Professor, Department of Computer Science and Engineering, JK Lakshmipat University, Jaipur, India[2]
Associate Professor, Department of Science and Liberal Arts, JK Lakshmipat University, Jaipur, India[3]

Received: 03-March-2023; Revised: 23-September-2023; Accepted: 25-September-2023

Abstract
A substantial amount of data related to various diseases was collected every year from different medical universities and hospitals worldwide, which was utilized to assess disease rates manually. However, it had not been adequately harnessed to establish connections between symptoms and disease risk. Machine learning (ML) and deep learning (DL) had become popular as technologies that were considered more precise and efficient in a variety of medical issues, including diagnosis, prognosis, and intervention. These were representational learning techniques that were used to nonlinearly transform the data, revealing hierarchical connections and patterns. To create effective methods for reducing the various risk factors of different diseases, it was necessary to properly understand and critically analyze the current ML and DL models. This work provided a cogent assessment of the shortcomings of the existing systems and covered the growing corpus of recent literature on ML and DL models for predicting various diseases. For an assessment of the state-of-the-art, the taxonomic structure of the available literature on predicting various diseases was examined, broken down into the techniques employed, projected outcomes, factors involved, types of datasets used, and corresponding goals.

Keywords
Disease prediction, Machine learning, Deep learning, Healthcare, Data analysis.

1.Introduction
Over the past few years, various researchers have applied machine and deep learning (DL) techniques to predict several diseases, including cancer, heart disease, Parkinson's disease, diabetes, asthma, brain tumors, obesity, skin conditions, COVID-19, Alzheimer's disease, pneumonia, and crop diseases.

According to the World Health Organization (WHO) statistics, heart or cardiovascular diseases are responsible for more deaths worldwide than any other disease, accounting for 31% of all deaths. In the United States (US), this disease is the cause of one in every four deaths, with one person dying from it every 36 seconds [1–3]. In India, the number of deaths due to heart diseases reached approximately 4.8 million in 2020, a significant increase from the 2.26 million recorded in 1990. Recent projections indicate that India is on track to become the leader in the incidence of heart diseases [1–3].

It's worth noting that advancements in machine and DL techniques have played a crucial role in early detection, risk assessment, and treatment planning for various diseases, including heart disease.

Presently, one death out of five in India is due to this disease and in upcoming years, this ratio is expected to reach up to every third death, majority will belong to the younger age groups [1]. Due to expensive diagnosis, about 75% of deaths occur in low- and middle-income countries. According to National Center for Biotechnology Information (NCBI), in every 10 years, mortality rates due to cardiovascular diseases increased about 60% in the US [2]. Deaths-related to this disease is higher in developing countries as comparison to developed countries [3]. Obesity or overweight are the abnormal or excessive fat accumulation that presents a risk to health. Childhood and teenage obesity are one of the most serious health problems over the globe. It has spread to every country and is now a worldwide crisis in public health. All around the world, childhood and

*Author for correspondence

adolescent obesity is becoming more common. Around forty-one million young children under the age of five were overweight worldwide. Asian children below the age of five made up half of this total, and African children made up nearly a quarter. If childhood obesity remains untreated, there is a higher likelihood that it will continue into adulthood. Adults who are obese, are more likely to have heart disease and diabetes [4]. In last few decades, algorithms based on machine learning (ML) and DL plays an important role in the field of crops related diseases prediction. As one of the major sources of food, agriculture is one of the most pressing societal issues. Currently, several countries still struggle with hunger as a result of a lack of food and an increasing population. The combined effects of a growing population, erratic weather patterns, soil erosion, and a changing climate call for strategies to guarantee timely and reliable crop development and output. Additionally, it must support to increase agricultural output. These needs suggest that a keen observation should be placed on crop yield forecast, crop protection, and land evaluation in order to increase global food production. An accurate crop diseases prediction can play the important role in the overall growth of any nation [5].

In last two decades, researchers have been used various ML and DL algorithms for prediction of brain related diseases like Parkinson, Alzheimer, brain tumor and epilepsy. It has always been challenging to identify neuro-degenerative disorders because of the intricate architecture of the brain, which varies with age and clinical background. It is crucial to make a diagnosis of these illnesses as soon as possible. In contrast to traditional manual methods, computer-aided processes are more effective at detecting various brain related diseases [6]. The most severe but prevalent neurodegenerative disorder is Alzheimer's. It kills the cells in the area of the brain that controls language and memory, leaving the patient with blurred memory and diminished capacity to carry out daily tasks. As the illness worsens, the affected person begins to lose control over physiological functions, which eventually results in death [7]. A brain tumor consists of basically an aberrant cell proliferation. Brain tumors come in two form, benign and malignant. It might be difficult to distinguish between a brain tumor and normal brain tissues because there are many distinct types of brain tumors. Epilepsy is a brain function problem that results in generalized seizures, occasionally even unconsciousness. People of various ages have been observed to be affected by it, and it typically has no severe symptoms. After stroke, it is the second most common neurological condition in people, and it affects over fifty million individuals worldwide. After Alzheimer's, Parkinson's disease has the most prevalent neurological condition. Early detection of this diseases, involves keeping an eye out for several signs and symptoms, such as bradykinesia (slowness of movement), rigidity (stiffness of muscles that prevents proper stretching), tremor at rest (shaking of body parts, especially the hands), and voice impairment (losing control over speech) [8].

Globally, COVID-19 caused an unheard-of societal and financial influence. More than thirteen million people infected worldwide. There are no signs that the pandemic is about to stop [9]. Kidneys in the body are damaged and are not properly purifying your blood, it means you have kidney related disease. The main function of the kidneys is to remove surplus water and waste from the blood in order to generate urine, therefore if someone has this disease, it signifies that impurities have accumulated in the body. Diabetes and high blood pressure plays key role for occurring of this disease. Therefore, preventing this disease is achieved by the management of these two disorders. Typically, this disease does not show any symptoms until the kidney is severely damaged. According to studies, hospitalization cases are rising six percent every year, but the worldwide death rate is staying the same [10]. Skin lesions, scales, plaques, pigmentation are the common symptoms, which are frequently brought by skin illnesses. Pain and deformity are the long-term effects of such diseases. According to a study conducted in 2010, world's most prevalent diseases were skin disorders, making them the fourth greatest cause of nonfatal disease burden. Both high-income and low-income nations have experienced significant economic costs as a result of skin disorders. Each person's skin issues may negatively impact all facets of life, including interpersonal connections, employment, social interaction, physical exercise, and mental wellness [11].

The main source of sugar is blood glucose, which is obtained through the food we eat. The pancreas produces a hormone called insulin, which aids in obtaining glucose for our use for energy. Insufficient insulin production causes glucose to accumulate in bloodstreams and prevent it from entering our cells. The buildup of glucose will eventually affect our health. The body's organs can be impacted by elevated blood sugar levels. Disruption to both large and small blood arteries, which can result in cardio disease, stroke, and problems affecting the kidneys, eyes, mouth, legs, and nerves [12]. Pneumonia is a lung disease brought on by bacteria, viruses, or fungus and is one of the most prevalent respiratory disorders. Pneumonia poses a life-threatening risk to young children, elderly people, hospitalized individuals using ventilators, and asthmatic patients. Additionally, pneumonia is a high-risk condition, particularly in developing nations where millions of people live in poverty and lacking to access the healthcare. In each year, pneumonia infects over 150 million individuals, mostly children under the age of five [13]. A report from the WHO, cancer is an international health problem that kills people all over the world. A category of cells known as cancer are those that originate from body parts and frequently migrate quickly to other metastatic regions. The intricate relationship between surroundings and the genes results in abnormal proliferation of cells [14, 15]. *Figure 1* shows the various disease, which were taken by various researchers for detection and prediction through ML and DL techniques. In this study, heart and brain related diseases have been considered for analysis.

Figure 1 Diseases were taken for prediction through ML and DL in previous literatures

1.1About ML and DL technology

As per *Figure 2*, ML and DL methodologies is the part of artificial intelligence and DL is the branch of ML. ML involves the technique of developing an automated machine by using its prior knowledge and to address a problem that has been presented to it. Due to the present accessibility of inexpensive computational resources and memory, the idea of applying ML to several domains for resolving problems quicker than humans, has attracted a lot of attention. It enables the processing and analysis of extraordinarily vast amounts of data in order to find discoveries and relationships between the data that are not immediately apparent by the naked eyes [16, 17]. Its intelligence depends on numerous computations that allow the computer to create relevant assessments by abstracting from experience. However, DL is an advanced technique that allows systems for extraction, assess, and comprehend the appropriate details from the initial data set by modelling how the people learn and think. Most DL methods use the deep neural network (DNN) approach, which consists of two or more hidden layers between the input and output layers [18]. It attempts to collectively acquire useful features that span progressively more abstract and sophisticated layers, culminating in the ultimate prediction. The emergence of big datasets, faster parallel computers, and a wealth of ML concepts related to sparsity, regularization, and optimization have recently helped deep architectures achieve state-of-the-art performance. DL models require more data because they train from unprocessed inputs and do not use manual feature engineering. In today's scenario, large amounts of data can be easily collected from various researchers and organizations to train DL models with different parameters.

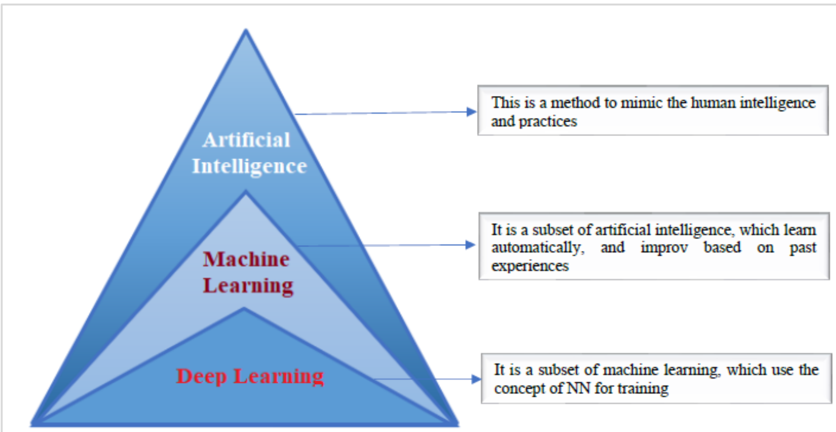

Figure 2 Hierarchies of learning technology

1.2Methods of ML and DL

In the realm of ML and DL, the classification technique plays a pivotal role in determining the success of an assessment. Over time, various approaches to classification have been developed within the field of ML, and their success rates are commendable. These techniques were purpose-built for the task of categorization. Despite the consistent performance of ML, DL has emerged as the primary choice for numerous categorization tasks in recent times. The key distinction between these two lies in the method used to extract attributes for the classification algorithm. DL, which extracts attributes from multiple intricate hidden layers, demonstrates significantly superior categorization accuracy compared to ML [19]. *Figure 3* shows a concise overview of the diverse ML and DL techniques utilized.

1.3 Evaluation criteria of ML and DL techniques

Effectiveness of any ML and DL algorithms are totally based on the performance parameters such as, accuracy (ACR), precision (PRS), recall (RCL), F-score (FSC), Matthew's correlation coefficients (MCCS), Area under receiver operating characteristic curve (AURC). Performance parameters are calculated by using the concept of confusion matrix (CMX). It is a two-dimensional table, which maps the value between actual and predicted output. It contains four parameters true positive (T+), true negative (T-), false positive (F+), and false negative (F-). These parameters help to evaluate the performance of any classifier. In CMX, column represents the real class value and row act for predicted class [20]. For the detection method, various indicators of performance reflect various interpretations. A model may produce excellent results with respect to ACR, but it may produce extremely subpar outcomes in respect of PRS. ACR is the fundamental criterion for any categorization process. It is as straightforward as comparing the proportion of precise forecasts to all projections made. It addresses both favorable and unfavorable outcomes. Exactness of the diagnosis evaluates through PRS. The ACR of any model is the harmonic mean of its RCL and PRS. The graph between RCL and false positive rate (FPRT) is frequently used to evaluate the potential of binary categorization methods. The capability of any predictive algorithm to differentiate between two distinct options under several discrimination thresholds is defined by AURC. Mathematical formulation of performance parameters is summarized in *Figure 4.*

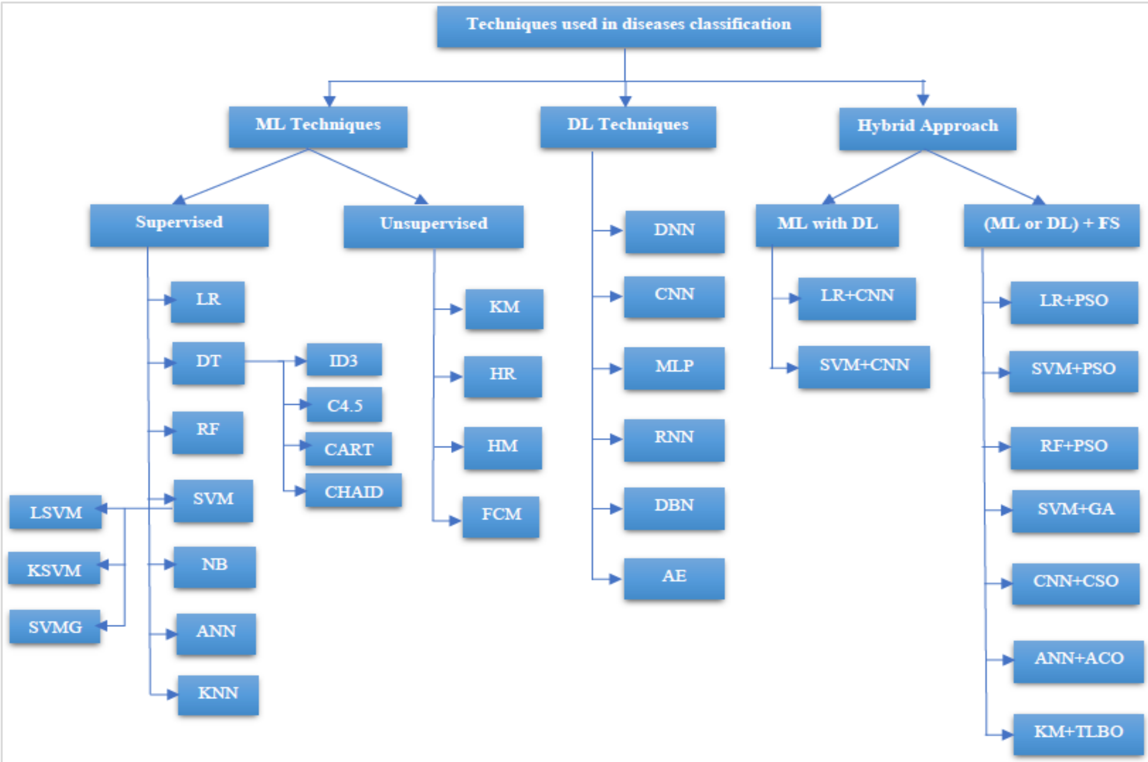

Figure 3 Various techniques of ML and DL used in diseases classification

(Support vector machine with grid search (SVMG), kernel-SVM (KSVM), Linear-SVM (LSVM), k-nearest neighbors (KNN), artificial neural networks(ANN), naive Bayes (NB), support vector machine (SVM), random forest (RF), decision tree (DT), logistic regression (LR), iterative Dichotomiser 3(ID3), classification and regression tree (CART), Chi-square automatic interaction detection (CHAID), fuzzy c-means (FCM), hidden Markov (HM), hierarchical (HR) clustering, k-Means (KM), Autoencoders (AE), deep belief network (DBN), recurrent neural network (RNN), multilayer perceptron (MLP), convolutional neural network (CNN), deep neural network (DNN), particle swarm optimization (PSO), genetic algorithm (GA), cat swarm optimization (CSO), ant colony optimization (ACO), teaching learning based optimization(TLBO))

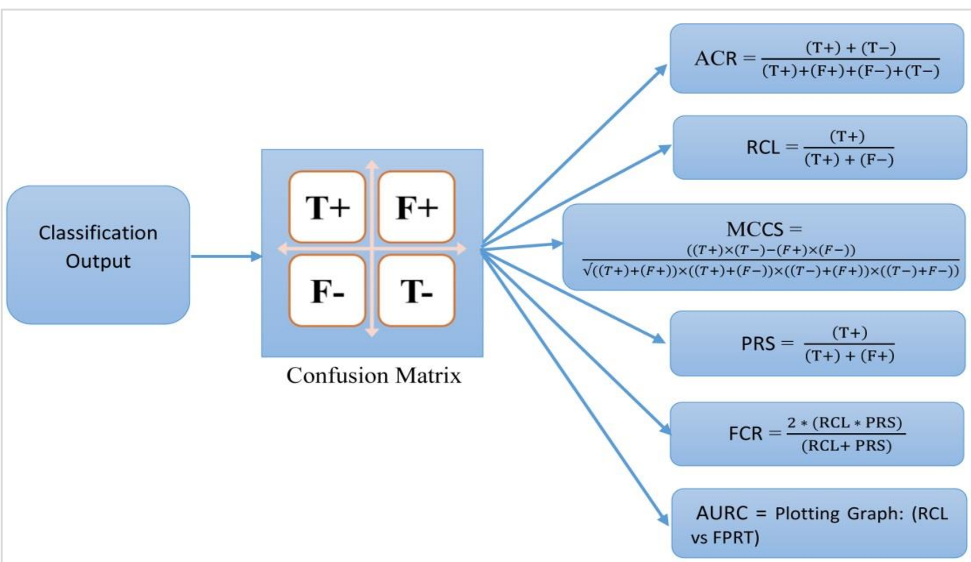

Figure 4 Details of performance parameters used in ML and DL

1.4 Contributions

The key contributions of this survey are to gather and analyze the recent research on prediction of several diseases related to heart and various brain diseases like Parkinson, Alzheimer's, brain tumor and epilepsy prediction by using ML and DL techniques. Also analyzed the effectiveness of combined approach like as, ML and DL with some feature engineering techniques, on different performance parameters. Finally, the main findings from the examined articles are then briefly discussed. Moreover, several open problems and potential future research directions are offered. Inclusion flow of this review work is shown in *Figure 5* and year wise selection percentage of article has been indicated in *Figure 6*.

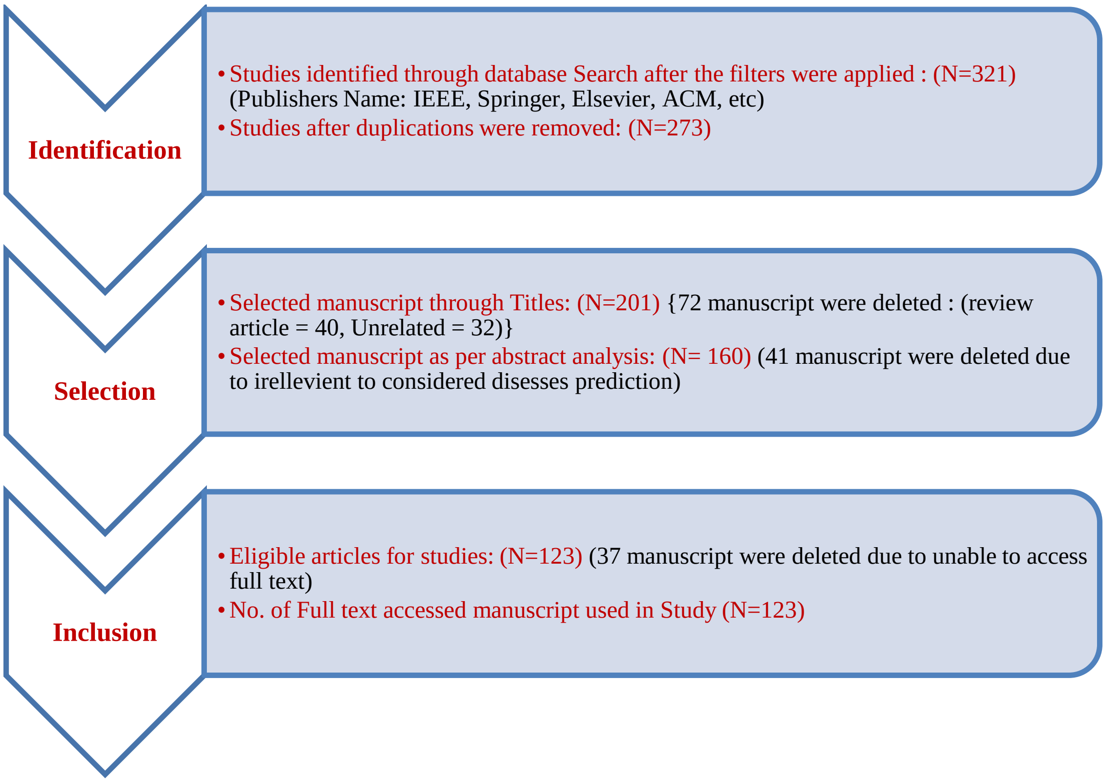

Figure 5 Inclusion flow of the systematic review

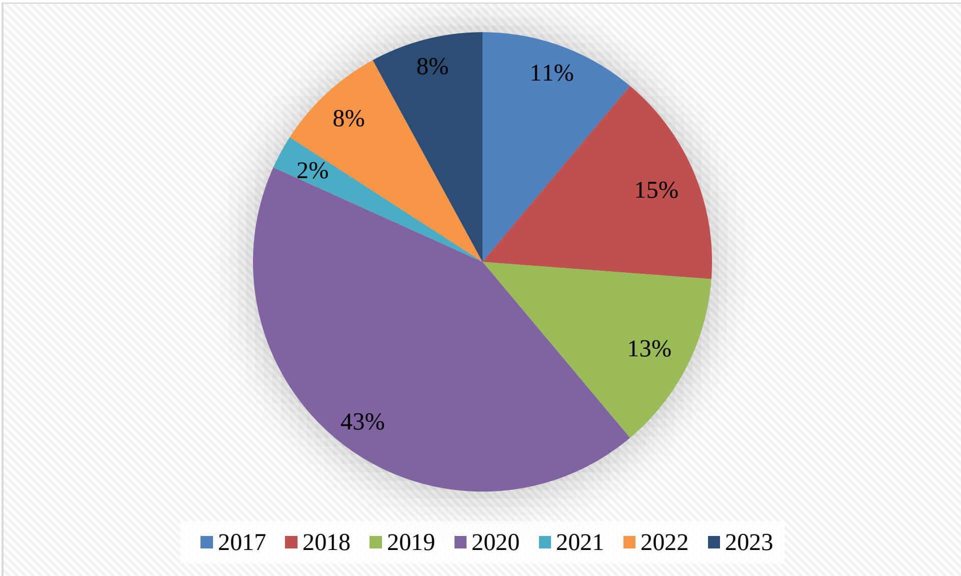

Figure 6 Year wise percentage of article selection for the study

The subsequent sections of this article are organized as follows: Section 2 provides a review and analysis of several ML techniques, Section 3 explores the DL methods, and Section 4 discusses a combined approach. In Section 5, an analysis of various key findings is presented. Lastly, Section 6 offers the conclusion of this study, along with directions for future research.

2.ML Techniques

In this section, an overview has been provided of latest developments in ML techniques to detect and predict different types of diseases. For the prediction of diseases, researchers have been utilized the ML methods in different ways as per their datasets and objectives, which is shown in *Figure 7*.

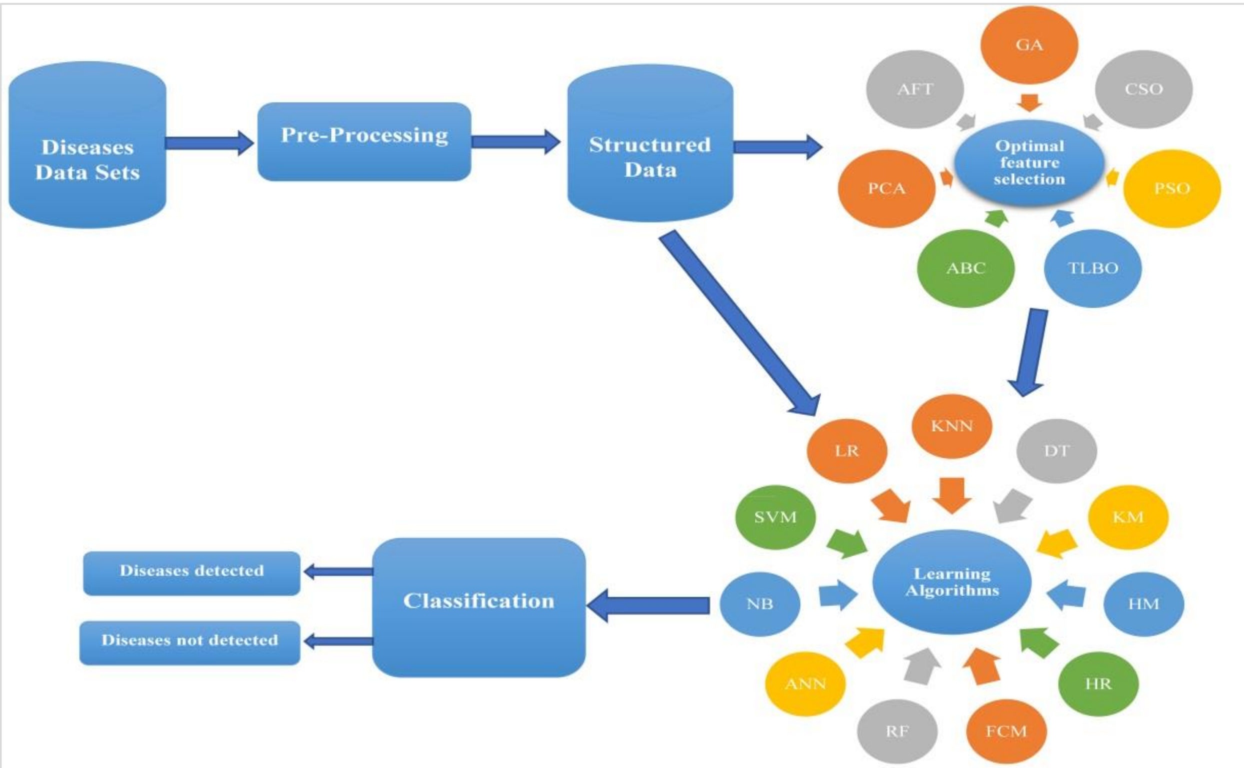

Figure 7 Process of ML techniques used in diseases classification

2.1Brain related diseases

In last two decades, researchers have been used various ML algorithms for prediction of brain related diseases like Parkinson, Alzheimer's, brain tumor and epilepsy. It has always been challenging to identify neuro-degenerative disorders because of the intricate architecture of the brain, which varies with age and clinical background [21]. Radiologists used manual detection procedures in the past to determine the development of various stages of Alzheimer's. Such manual procedures could lead to mistakes in results that had major consequences for the patients. Recent methods based on ML techniques can automatically diagnose Alzheimer's in its early phases [22]. In order to make an early prediction of Alzheimer's, an automated technique adopting SVM approach of ML was proposed in [23], whereas gene-protein sequence was utilized as a potential source of data. It had been recommended that ML-based technique can be an effective way for anticipating Alzheimer's by using the sequence data of gene-coding proteins based on the results of categorization. The authors of [24] looked into a forecasting approach of ML for early Alzheimer's diagnosis based on patient-specific neuropathological abnormalities. In this case, medical manifestations were seen as less precise and definite than post-mortem examination abnormalities. With 77% ACR, the authors noted that the presented model was possibly not suitable for use in clinical practice, but it could be a step towards better therapy in Alzheimer's. In [25], an ML model for early Alzheimer's diagnosis was put up by utilizing KNN for attribute selection and SVM as a classifier. Using voice processing for obtaining numerous linguistic aspects. Multiple decision-making strategies were used for further analyzing the retrieved linguistic traits in same proportion from affected and unaffected persons with Alzheimer's. The ML model is then receiving the chosen parameters. When separating sufferers of Alzheimer's, the suggested ML model obtained the PRS of 79 percent.

To examine the efficacy of therapy at the beginning of Alzheimer's using common neurological assessments and easy cognitive tasks was suggested in [26]. The neurological assessments and the cognitive exercise were utilized to gather a variety of cognitive traits among 50 older people considered mentally intact and 28 moderate Alzheimer's patients. Utilizing the information from cognitive tasks and neurological test results for both separately and collectively. After using principal component analysis (PCA), these were categorized as Alzheimer's utilizing different trained ML algorithms. Wherein SVM beat other classifiers on the composite data set and RF fared superior for the dataset of neurological testing.

Rather than brain imaging, autogenic individual voice signals have been utilized in [27] to separate the people who had moderate Alzheimer's. It has been determined that integrating linguistic and auditory characteristics can increase the PRS of classification more than using any attribute alone. Additionally, it was anticipated that in the future, complete automation in voice processing of signals could serve as the foundation towards automated recognition of Alzheimer patients. In [28], an electroencephalogram (EEG) based technique was suggested to identify Alzheimer's disease by performing time as well as frequency component studies on EEG waves. An adaptive attribute selection method was used to prevent component repetition. These attributes were used for developing multiple ML techniques of classification for Alzheimer's disease.

The authors of [29] used a system consisting of three-layered ANN to demonstrate how well it works for diagnosing Alzheimer's. The diagnosis was made using cortical flow of blood data from more than 100 individuals, obtained using brain imaging from different regions. ANN proved to be more accurate and precise than PCA for differentiating Alzheimer's patients. An ML strategy for determining the existence of various phases of Alzheimer's disease was put forward in [30] by utilizing attribute selection as well as dimension reduction tool. Various performance indicators were used to demonstrate the suggested technique's advantage over traditional methodologies. In [31], a computerized diagnostic system for recognizing the symptoms of Alzheimer was developed. Its effectiveness was examined using 7 distinct kinds of attribute selection approaches. While similar attributes were taken into account, it was found that the Shearlet transform method worked better than the other methods for extracting attributes. Additionally, the Student's T-test method was applied while choosing attributes. The approach recommended in [32], which employs multiple phases classifiers made up of most recent classifiers like SVM and KNN. Additionally, PSO was employed for choosing appropriate features.

In [33], four modern ML classifiers like SVM, ANN, and NB were used in 3 distinct experimentations to anticipate Alzheimer's disease earlier. In the context of AURC, the classifiers ANN and NB perform better for conventional and automated biomarkers choices, respectively. Additionally, composite, or mixed modelling, which combines all four classification methods, significantly enhances categorization outcomes.

The identification of Dementia utilizing diffusion weight imaging data was established by employing an ML model in [34]. Three advanced ML classifiers like SVM, RF, and ANN were used to examine the recognition efficiency of Alzheimer's disease. The finding of this research raises the possibility that changes affecting the brain's intrinsic communication brought on by Dementia may serve as a valuable biomarker to identify neurological diseases.

A ML method called LR has been suggested in [35], in which spectrogram characteristics collected from audio recordings were used to recognize the people suffering from Dementia. The researchers constructed a repository by using the voice data. They acquired from Internet of Things equipment. Additionally, the suggested technique was validated using the already-existing Demcare dataset. According to the study's results, the suggested LR model performs better on the Demcare dataset.

Four key signs of Parkinson's disease were taken into consideration in a study that was published in [36]. The datasets from repository of University of California Irvine (UCI) were used to trained several ML techniques. The standard helical experiment utilizing the RF technique demonstrated the highest ACR of 99 percent among all experiments.

In [37], the second and third levels of Parkinson were identified using hand movement activities. The palm action indications, which were estimated through velocity, magnitude, and rate. Which were recorded using a 3D leap motion tracker. Multiple ML classifiers were developed utilizing vectors of attributes alone as well as multiple combinations. With the combined traits across all cognitive assignments, SVM had the highest average correctness 98 percent across the classifiers.

Both ML and DL related techniques have been examined in [38] to forecast various phases of Parkinson's disease. For Categorization, various techniques including SVM, DT, RF, and CNN were employed. Intensity summary statistics fared better than the other types of methods for extracting features. Additionally, CNN using Visual Geometry Group - 16 produced the most favorable results across all the classifiers with training ACR of 92 percent.

Speech was employed as an assessment paradigm in the suggested ML method for the initial recognition of Parkinson in [39]. Using distinct choosing attributes techniques were applied with DT, SVM, and ANN. The results of the study made it clear that SVM with optimal attributes had the better ACR.

A portable sensor system was employed in [40] to discriminate between Parkinson and developing supranuclear palsy. The characteristic picking strategy employed was the least actual shrinkage and function section. In order to discriminate from Parkinson to supranuclear palsy, a variety of data collected from sensors were input through the classifiers. On integrated operations, RF demonstrated the highest PRS in classification.

Utilizing Magnetic resonance imaging (MRI) scans from multiple sources, [41] demonstrated an automated system of categorization to successfully discriminate brain tumors at earlier stages of development. The approach has been defined as splitting, categorization, and preliminary processing with the Median filters. Depending upon the collected attributes, a dynamic KNN algorithm was used to distinguish between common and atypical photos. To identify the brain regions that have been impacted, the most effective stochastic FCM approach was used to segregate the anomalous ones.
By supplying a combination of attributes to the classifiers, the approach suggested in [42] distinguishes between distinct types of tumors in the brain. In order to segment pictures more accurately using PSO, the cerebral region extraction approach was used to eliminate non-brain components includes the skull and eyes from the pictures. Using an algorithm based on genetics, the best characteristics were chosen from the features that were extracted. The efficacy of the suggested approach was demonstrated to be stronger over existing methods by the results of the assessment obtained for various datasets.

Finding neurological markers of patients along with lateralization data were the primary objective of [43]. To do this, the characteristics obtained were divided into left and right categories using SVM and DT. There were several beneficial connections across memory and language levels when using two different datasets. Some cut off points that more accurately forecast the illness have been found.

Authors of [44] proposed to identify co-occurring psychiatric disorders in the majority of those with epilepsy, who are adolescents and young. Here, learning techniques determine the patient's suicide intent. The study's primary goal was to categorize individuals into the distinct categories, which were individuals with no psychiatric problems, those with psychiatric diseases but not suicidal tendencies, and those with any degree of suicidality.

Unsupervised based learning techniques were used in [45] to separate people with epilepsy into clusters, based on distinctive sociological traits. Employing KM, this strategy seeks to group sufferers into three distinct clusters like, high, moderate, and poor mental wellness. It has been found that bad clusters are associated with societal factors, while moderate clusters are primarily caused by seizure related disorders. Consequently, companionship can aid in enhancing patients’ wellness.

Soft computing techniques were used to classically separate EEG signals between focal and non-focal signals in [46]. Transformation, element computations, and their categorization are the three distinct segments that make up the entire process. Finally, the retrieved characteristics are categorized using the adaptable neuro-fuzzy assessment approach.

A comparison of epilepsy detection methods employing various ML algorithms was carried out in [47]. According to the findings, the precise Gaussian with SVM seemed most effective.

In [48], conceptual graphical analysis and algorithms based on ML were used to analyze lateral distribution in epilepsy cases. A comparison investigation on the identification of epilepsy through different classifiers was conducted in [49]. The findings using RF were the most effective compared to others. Overall summary for performance of various ML algorithms in terms of brain related diseases prediction are given in *Table 1*.

Table 1 Summary for performance of various ML methods in terms of brain related diseases prediction

Reference (Year of Publication)	**Name of Diseases**	**Database Used**	**Methodology Used**	**Performance Parameters**				
				ACR (%)	**PRS (%)**	**FSC (%)**	**RCL (%)**	**AURC (%)**
[23] (2018)	Alzheimer's	Uniport (gene Protien)	SVM	86	----	86	86	86
[24] (2018)	Alzheimer's	VITAS (MRI)	RF	77	----	50	----	----
[25] (2018)	Alzheimer's	Dementia bank (voice)	SVM	----	79	----	----	----
			DT		71			
			ANN		69			
[26] (2019)	Alzheimer's	Nuro phycological test data	RF	90	----	75	98	----
			SVM	75		40	96	
			Adaboost	86		79	90	
[27] (2019)	Alzheimer's	Hungairan (Speech)	SVM (Linear)	80	76	82	85	----
[28] (2018)	Alzheimer's	Autogenerated	Quadratic discriminant analysis (QDA)	75	----	65	79	----
			MLP	76		71	79	
			Linear Discriminant Analysis (LDA)	75		71	76	
[29] (2019)	Alzheimer's	Single photon emission computed tomography (SPECT)	ANN		100	93	97	
[30] (2019)	Alzheimer's	OASIS	SVM (Linear)	91	----	85	96	----
			SVM (Kernal)	93		88	95	
[31] (2019)	Alzheimer's	HMSD	KNN	98	98	100	100	
		University of Mississippi Medical Center (UMMC)		95	92	88	94	
[32] (2019)	Alzheimer's	Alzheimer's Disease Neuroimaging Initiative (ADNI)	NB with SVM and KNN	96	96	90	89	
[33] (2020)	Alzheimer's	OASIS	ANN, NB and SVM	98	----	98	----	99
[34] (2020)	Alzheimer's	ADNI	RF	74	----	77	71	82
			SVM	72		75	69	81
			ANN	75		76	80	83
[35] (2020)	Alzheimer's	VBSD (Speech)	LR	83	86	86	84	----
[36] (2020)	Parkinson’s	UCI repository	KNN	98	----	100	98	----
			RF	99		99	98	
[37] (2020)	Parkinson’s	Federal state budget institution	SVM	98		----	----	----
			DT	82				

Reference (Year of Publication)	**Name of Diseases**	**Database Used**	**Methodology Used**	**Performance Parameters**				
				ACR (%)	**PRS (%)**	**FSC (%)**	**RCL (%)**	**AURC (%)**
		(hand movement signal)	KNN	81	----			
			RF	84				
[38] (2020)	Parkinson's	E-Da Hospital	SVM	53	----	37	----	----
			RF	55		39		
[39] (2020)	Parkinson's	UCI repository	ANN	92	----	----	----	----
			SVM	94				
			CART	91				
[40] (2020)	Parkinson's	John Radclieef Hospital (sensor data)	RF	88	----	86	90	----
			LR	80		85	75	
[41] (2020)	Brain Tumors	Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) (MRI)	KNN (adaptive)	97	----	100	90	----
[42] (2020)	Brain Tumors	BRATS (MRI)	SVM	98	----	99	96	----
[43] (2020)	Epilepsy	Self-generated (EEG and MRI)	SVM	76	----	----	----	89
			XGBoost	77				80
[44] (2020)	Epilepsy	Self-generated (spoken)	SVM	72	----	----	----	----
[46] (2020)	Epilepsy	Bern-Barcelona	adaptive network-based fuzzy inference system (ANFIS)	99	99	99	99	----
[47] (2020)	Epilepsy	Born University (EEG)	SVM (Gaussian)	100	----	----	----	----
[48] (2020)	Epilepsy	Iranian brain mapping laboratory	SVM	92	----	----	----	91
[49] (2020)	Epilepsy	National center of neurology hospital, Tokyo	SVM (Linear)	87	----	86	88	84

2.2Heart related diseases

Heart disease become a global issue of public health due to lack of knowledge, improper eating, and poor lifestyle. India will soon become number one in death rate due to heart diseases and most of the deaths will be of young and middle age group. Hospitals and practitioners are currently faced with significant challenges in accurately predicting and diagnosing it. The advancement of computing technology has facilitated to healthcare agencies for data collection and archiving efforts to use in clinical decision-making [50]. In [51], a combination of ANN and GA was applied on Z-Alizadeh Sani heart diseases dataset, which consisted of fifty-four attributes of 303 patients. With GA, the overall percentage of ACR was increased by about 10 percent. For varying sample sizes of data, offered several feature selection (FS) methods. Several FS assessment criteria were examined in order to improve the performance of ML techniques as well as the issues that FS would face in the future. In [52], various FS issues were Emphasized, in the case of huge data, they talked about how important FS is in improving learning performance. The selection of features might be complicated by the presence of multiple dimensions containing data, 80% prediction ACR was achieved by using KNN method for UCI dataset. In [53], low support-based vector machine was applied on UCI data sets and performance was better as comparison to existing SVM. The ANN with GA was used for medical diagnosis, ACR was 91%. Classification, clustering, and their combinations may help to increase the prediction ACR. In [54] KNN was used with backward selection method (BSM) in which BSM was used in the selection of attributes for categorization KNN was used. Optimization-based framework can be developed, for improvising classifiers performance, PSO was used for attribute selection and NB, DT, KNN, and ANN was used for classification. These approaches may be tested on different diseases data sets.

In [55], over and under-fitting problems were resolved in DNN model, also focused on irrelevant attributes elimination and achieved ACR was 93%. In [56], ANFIS and LDA-based approach was developed, Korean National Health data set was used for experimentation and overall ACR obtained was 80%. In [57], Combined approach of PSO and tree based classification techniques were analyzed. The highest ACR was obtained in PSO with Bagged Tree. GA with Fuzzy system was used in [58]. Attribute selection can reduce the dimensions while also enhancing the efficiency and classification ACR. Influential FS in big data can also aid improve learning performance although it can be challenging when the data includes multiple dimensions. The ML classification and clustering techniques have been shown to have higher ACR percentages. In addition to certain unanticipated issues that can develop during FS. Various FS assessment measures can be helpful for increasing the convergence speed of ML algorithms [59]. In [60], various swarm-based optimization algorithms, such as Artificial Bee Colony (ABC), PSO, and ACO were applied with ANN and PSO was found to be the more efficient among them. In [61], A hybrid approach, GA along with the KM was applied for classifying heart disease, and claimed 94 percent ACR as result. In [62], ANN along with PCA and PSO algorithms were used in forecasting of cardiac disease, and claimed good results. Heart disease was diagnosed using a variety of classification approaches, and the PSO algorithm was presented for dimension reduction. Utilizing the dataset from the UCI library, various combined methodologies of ML methods with attributes selection were suggested for classification of cardio diseases and achieved good results in terms of ACR [63].

In [64], the overfitting and underfitting problem was analyzed, ANN was used for classification of heart diseases with achieved results that were better than others. In [65], random search algorithm (RSA) and PSO were used for selection of attributes, and classification techniques based on DT and NN were used for diseases prediction. Maximum PRS was achieved with PSO. Overall summary for performance of various ML algorithms in terms of heart related diseases prediction are given in *Table 2*.

Table 2 Summary for performance of various ML methods in terms of heart related diseases prediction

Reference with years of publication	**Diseases**	**Methods Used**	**Data**	**ACR / Results**
[66] (2019)	Coronary artery disease	PCA and SVM	Long term ST DB ECG signals	ACR = 99.2 %
[67] (2017)	Heart diseases	GA and ANN	Z-Alizadeh Sani Dataset	ACR = 94 %
[51] (2017)	Heart diseases	ANN, LR, KNN, SVM and DT	Cleveland	ACR = 93 - 94.5 %
[68] (2022)	Heart diseases types	SVM and ANN	UCI	ACR = 90 %
[69] (2018)	Heart diseases	Cox proportional hazards model	The PREDICT database (New Zealand)	ACR = 63 %
[70] (2017)	Heart diseases	Cloud based internet of things and ANN	UCI	ACR = 99 %
[71] (2019)	Heart diseases	SVM, RF and MLP	POF Hospital	ACR = 98 %
[72] (2017)	Heart failure	ANN	Electronic Health Record (EHR) data from real-world datasets	ACR = 73 %
[73] (2021)	Heart diseases	LR, DT and RF	UCI	ACR = 91-95 %
[74] (2017)	Heart diseases	Least-Squares SVM, ANN, and NB.	Tunstall	ACR = 95 %
[75] (2022)	Heart diseases	RF	UCI	ACR = 94.3 %
[76] (2018)	Heart failure	random survival forest.	Intelligent Monitoring in	ACR = 82 %

Reference with years of publication	Diseases	Methods Used	Data	ACR / Results
			Intensive Care	
[77] (2022)	Heart attack	KM	UCI	ACR = 96.45 %
[78] (2018)	Myocardial infarction	RF, C5.0, and fuzzy modeling.	UCI	ACR = 91 %
[79] (2017)	Coronary artery disease	RF	Clinical Cohorts in Coronary disease Collaboration, UK.	ACR = 72 %
[80] (2023)	Heart failure	LR, DT, SVM, RF and NB	UCI	ACR = 100 %
[81] (2023)	Ischemic heart disease and hypertension	SVM, support vector regression, KNN, extreme gradient boosting, long short-term memory (LSTM), and RF	Obtained from a local hospital according to ethical guidelines	Best ACR through RF = 99.4 %
[82] (2023)	Heart diseases	LR, DT, RF, KNN, NB, and SVM with Chi-Square and ANOVA and PCA	UCI	Best ACR = 99.92 %

3. DL Techniques

In this section, an overview has been provided of latest developments in DL techniques to detect and predict various heart and brain related diseases. For the prediction of diseases, researchers have been utilized the various DL methods in different ways as per their datasets and objectives.

3.1Brain related diseases

In [83], a computer-assisted detection approach was carried out, in which ANN was used to effectively identify the brain tumors characteristics from an MRI. Brain tumors MRIs were categorized, and the artificially generated characteristics were utilized during the convergence procedure for increasing recognition rate. The results assessment demonstrated that this approach can enhance the diagnostic outcomes.

In [84], a computerized brain identification technique utilizing deep LSTM was proposed. The framework was evaluated using data from the Ischemic Stroke Lesion Segmentation-2015 database and the six BRATS challenge dataset. The results of this study indicate that the suggested strategy can help radiologists for categorize brain tumors more effectively.

Using the radial, coronal, and sagittal dimensions of an MRI image, a neuroimaging investigation with deep CNN was carried out in [85] to identify several phases of Alzheimer's disease, including non-demented, extremely faint, mild, and moderate Alzheimer's disease. Although the ACR of diagnosing the non-demented and mildest stages of Alzheimer was good, it was unsatisfactory for recognizing the mild and moderate stages.

In [86] a deep C-LSTM system was proposed that achieves multiple classes of epileptic seizures, brain tumors, and eye activities by automatically extracting characteristics from EEG records that include three diseases and a pair of behaviors. In terms of both correctness and signal strength, the suggested deep C-LSTM fares better than LSTM and CNN. Additionally, a brief EEG signal component can be used by the deep C-LSTM to identify seizures. In [87], an innovative scanning tool was developed, and the pre-operative state among kids with selective epilepsy was examined using the DCNN segment categorization approach. Reference [88] primarily discriminated between epilepsy and non-epileptic paroxysmal recurrence.

In [89], authors have suggested a brand-new, eight-layered, three-dimensional CNN that was particularly adept at automatically identifying key properties essential to distinguish between Alzheimer's disease and normal condition. It was explained how several elements, including preliminary analysis, the data splitting technique, tuning of hyperparameters, and dataset, affected the outcomes.

Multi-level characteristics were taken using multiple levels of two pre-trained DL algorithms, namely Inception-v3 and DensNet201, followed by fused before the brain tumor is classified using the Softmax classifier, was proposed in [90]. A publicly available dataset including 708 gliomas, 1426 meningiomas, and 903 pituitary tumors was used to assess the suggested model. Comparing existing DL and ML models for brain tumor categorization, the suggested DL model performed better.

In [91], authors have verified the usage of DNN to identify various phases of dementia through mini-mental state examination (MMSE). According to the total PRS, this study came in third place in "The International challenge for automated prediction of mild cognitive impairment (MCI) from MRI Data." The effectiveness of this research demonstrates the suitability of DNN for upcoming advances in Alzheimer detection methods. In [92], a strategy for diagnosing primordial or preliminary Alzheimer utilizing RNN and LSTM is suggested. It was verified with respect to ACR that the recommended method was stronger to the traditional ML strategy.

In [93], the extracted MRI data were categorized using CNN-AlexNet into five groups: normal cognition (NC), notable memory issue, early MCI, late MCI, and Dementia. The unprocessed data underwent a significant amount of preliminary processing, such as the elimination of undesirable cells, segment time adjustments, spatial smoothing, high- passes altering, and spatial normalization, which led to very high identification ACR by AlexNet. To detect Alzheimer, and MCI, a stacked deep CNN with Softmax function was examined in [94], utilizing characteristics from 3D patches of MRI and positron emission tomography data. Findings have not merely demonstrated that multiple mediums is stronger to unimodality in addition to that deep CNN can distinguish Alzheimer from NC more accurately than autoencoder. To assess the effectiveness of distinct and combined multifunctional MRI images to accurately forecast diseases, a multiple interfaces DNN system was presented in [95]. In [96], a new approach to categorizing epilepsy phases was put out, combining both time and frequency domain parameters for multiple channels EEG. Considering epileptic Magnetoencephalography (MGG) spikes, computation of MGG data locates epileptic zones. It takes time to examine these peaks visually.

The characteristics of CNN and neural self-correcting allocation prediction were integrated into a DL-based combined approach that was proposed in [97] to categorize malignancies in the brain using T1-weighted contrast-enhanced MRI images of 708 meningioma, 1426 glioma, and 930 pituitary brain tumors from 233 subjects. When compared to other well-known models, this hybrid model maintained a comparable degree of ACR while using less computational resources.

In [98], authors have integrated additional neural structure by FreeSurfer with hippocampus structure characteristics from 2.5D sections through CNN to identify MCI and Alzheimer. When both types of feature mining were used, ACR was higher than when only one form of pattern retrieval was considered. The most significant segments from 256 2D processed MRI segments were chosen in [99], based on picture entropy. The automatic detection of patients with Alzheimer was achieved with excellent levels of ACR utilizing a method for categorization using CNN that was put forward in [100].

In order to aid in the prevention of epilepsy, a DL technique to identify people's interictal and preictal stages was examined in [101]. In [102], a newly created method for categorization based on the unconstrained FCM clustering method was put out to improve system performance and robustness over current techniques.

Utilizing one of the most modern DL object identification methods, Alzheimer's disease was identified in [103]. Three different DL methods were applied without using the image preprocessing. In [104], a DL method was studied in which discriminative localized areas and cerebral areas were derived from MRI digitally. In order to recognize Alzheimer growth, a multidimensional ensemble DL technique was suggested in [105], wherein local as well as longitudinal characteristics were retrieved from each modality. Furthermore, local characteristics were extracted using prior knowledge. After that, all the collected characteristics were combined for the regression and classification tasks.

Automated hippocampus segmentation was conducted to facilitate the classification of Alzheimer in [106], which advocated a multidimensional process. A simple RNN model was suggested in [107] utilizing more than 1600 patients for predicting the course of longitudinal dementia. It was determined that the suggested model outperformed the baseline methods in terms of effectiveness in classification.

Untrained CNN was employed for picking out features and then classifier model was implemented to make the final selection to identify individuals suffering from Alzheimer in [108], which described an automated forecasting strategy employing untrained DL. In a study published in [109], deep nearby connection and neighboring location characteristics were obtained using convolutional and recurrent learning, respectively, to solve a network of brain cells categorization issue for diagnosing Alzheimer using two DL approaches. Finally, the boosted structure was put in place to enhance learning capacity.

An internet of things-based treatment paradigm was proposed in [110] towards the benefit of Alzheimer sufferers. Using data analyzed through multiple devices integrated into the online network healthcare environment, an RNN approach was used to pinpoint individuals suffering from Alzheimer. Additionally, CNN-based recognition of emotions and language analysis with time stamps window techniques were examined to monitor the anomalous behaviors of people with Alzheimer. A DL strategy for detecting the presence of Alzheimer was explored in [111] using sagittal MRI, and an acceptable outcome was observed when compared to the most recent technique. In [112], authors have offered a DL approach to enhance the recognition of Alzheimer via multidimensional inputs. The system was tested against several databases after being trained using Alzheimer and NC participants from ADNI.

In [113], a Whale Harris Hawks optimization methodology mutually evolved from Whale optimization Algorithm and Harris Hawks optimization method was proposed as part of an investigation into a deep CNN-based cerebral tumor categorization technique. Molecular automata and basic theory of sets were used for segmenting MRI images. When contrasted with other approaches, the suggested optimized method of classification performed better with respect to of ACR, sensitivity, and specificity.

A powerful attribute acquisition procedure was created by the authors of [114] using the adaptable grey wolf optimization algorithm and a sparse self-encoding neural network. The speech sample was used to obtain potential characteristics using the proposed pattern extraction. Six distinct ML techniques were used to classify attributes in order to find Alzheimer. LDA was performed best in the classifiers.

The SVM and CNN model's dominance over the other published classification algorithms demonstrated the DL model's immense promise for use in healthcare diagnosis [115]. In [116], a multidimensional DL technique utilizing combination of CNN and DBN was proposed. It was clear through the results of the experiment that the combined approach fared better than traditional methods like SVM, CNN, and DNN. In [117], a CNN-based DL method was investigated. Only the data from OASIS was employed for learning, and the Minimal Interval Resonance Imaging dataset was utilized merely for model assessment. The findings of this article revealed that MCI patients were harder to recognize than those suffering from Alzheimer.

By combining DBN and unsupervised methodology, a novel DL approach to monitoring Parkinson development was created in [118]. The Siamese CNN framework was investigated in [119] for the multiclass categorization of Alzheimer's, with inspiration from Oxford Net. A superb classification ACR of 99 % was obtained. Diffusion maps and GM volumes were explored in [120] to identify individuals with Alzheimer's. The influence of more than one scan per person was reportedly studied for the first time in this study, according to the researchers. Overall summary for performance of various DL algorithms in terms of brain related diseases prediction are given in *Table 3.*

Table 3 Summary for performance of various DL algorithms in terms of brain related diseases prediction

Reference (Year of Publication)	**Name of Diseases**	**Database Used**	**Methodology Used**	**Performance Parameters**				
				ACR (%)	**PRS (%)**	**FSC (%)**	**RCL (%)**	**AURC (%)**
[83] (2023)	Brain Tumors	Glioblastoma (GBM) (MRI)	ANN with autoencoders	----	71.7	71.3	71.2	----
[84] (2020)	Brain Tumors	BRATS	LSTM (SoftMax)	92	----	92	93	----
[85] (2018)	Alzheimer's	OASIS	CNN	----	75	50	60	----
[86] (2020)	Epilepsy	UCI repository	Deep LSTM	99	----	100	100	----

Reference (Year of Publication)	Name of Diseases	Database Used	Methodology Used	Performance Parameters				
				ACR (%)	PRS (%)	FSC (%)	RCL (%)	AURC (%)
[87] (2020)	Epilepsy	Children's Hospital Boston, Massachusetts Institute of Technology	DCNN	92			99	----
[88] (2020)	Epilepsy	Autogenerated (EEG)	DCNN (SoftMax)	80	----	90	77	81
[89] (2018)	Alzheimer's	ADNI	CNN (3D)	99				
[90] (2020)	Brain Tumors	Figshare (MRI)	Inception-V3	99	----	----	----	99
			Densnet	100				100
[91] (2018)	Alzheimer's	ADNI (MRI)	DNN	56	75	88	----	
[92] (2018)	Alzheimer's	NACC (non-image data)	RNN	94				
[93] (2018)	Alzheimer's	ADNI (MRI)	CNN (alexnet)	98	----		----	94
[94] (2018)	Alzheimer's	ADNI (MRI)	CNN (SoftMax)	85	----	83	87	90
			ANN	75		76	80	83
[96] (2020)	Epilepsy	Children's hospital Boston, Massachusetts institute of technology	DNN	99				
		iNeuro (EEG)		92				
[97] (2020)	Brain Tumors	Figshare (MRI)	CNN	95	94	97	94	95
[114] (2020)	Parkinson's	UCI repository (voice)	Sparse autoencoder with LDA	95	----	96	98	----
[121] (2023)	Cognitive task	BIOPAC-MP-160	CNN and Bi-LSTM	97.9	---	----	----	----

3.2Heart related diseases

Articles on DL for healthcare imaging have greatly risen during the last couple of decades. In [122], the impact of various unbalanced data management approaches on cardiac disorders was examined using DL methodologies. In balanced data rather than unbalanced information, the majority of techniques have demonstrated greater ACR. Using SMOTETomek composite balancing strategies, SVM, Ensemble of LR, and MLP were able to attain ACR rates of 96% on functioned data. Each approach's effectiveness was evaluated using ACR, PRS, RCL, FSC, Specificity, Cohen Kappa, and AURC.

With the help of optic pictures and a DL methodology, authors of [123] developed a satisfactory framework for heart related diseases. However, gathering optic pictures is frequently time- and money-consuming. We can infer considering the works mentioned earlier that the information set is unbalanced and that there is a lack of strokes records. Authors of [124] suggested a DNN-based approach to forecast stroke on an unbalanced dataset consisting of 43 400 information of patients with 783 occurrences of stroke in order to address the discrepancy challenge. The disparities and tiny data problems of the stroke statistics, nevertheless, cannot be resolved by the techniques mentioned above.

The problems of stroke risk prediction involving tiny and unbalanced stroke data have been solved in [125]. Hybrid deep transfer learning-based stroke risk prediction framework was used in their work. They also used the concept of active instance transfer for managing stroke-related facts with the most insightful produced circumstances, Network Weight Transfer for using information gathered from strongly associated disorders such as high blood pressure or diabetes), and generative instance transfer for using exterior stroke data distribution across various medical centers while maintaining privacy. In both simulated and real-world circumstances, their suggested framework surpasses the most recent models.

Utilizing the concept of in-depth CNN classifier, [31] developed an internet of things (IoT) architecture for CHD prediction. For initialization, the individual's electronic wristwatch and heart rate monitor had been connected to track their arterial pressure and electrocardiogram (ECG). The acquired data from sensors was then divided into healthy and unhealthy categories using proposed approach. It fared better than the compared methods, including LR and DNN classifiers. On the Cleveland, Framingham, and Sensor datasets, the ACR rate was 93.3%, 98.2%, and 96.3%, respectively.

Forecasting models cannot be trained effectively from real-world datasets because they typically contain an erratic fraction with more variation than the majority of the data. An effective strategy for predicting the chance of coronary cardiovascular disease through the use of two DNN developed on harmonious learning data sets has been suggested in [126]. To create precise forecasting models, the strategy they recommend creates training datasets by dividing regular and extremely biased subsets. The preliminary dataset was prepared in two steps: the initial training dataset was split into two groups for PCA, and the heavily biased group was then enriched using variationally AE. The dataset from the Korean National Health and Nutritional Examination Survey was utilized to test the DNN classifier. The Neural network ensemble technique was suggested in [127] for the accurate identification of cardiac disorders. The Chi-square-based strategies combine the backward probability of various models to produce novel ones. This may generate models that are more useful in experimental assessments. The combined model was created utilizing three different neural network models, and it enables the individual to interact with a variety of performance evaluation techniques. It provides the person using it to evaluate the functioning of the device across a variety of angles.

Authors of [128] were implemented the DNN to diagnose cardiovascular conditions, and outcomes were observed through 5-phase DNN structure. They were designed an architecture which was influenced from optimization and autonomously manages missing information along with anomalies with excellent ACR. The MCCS and k cross-validation have both been used to assess the optimized structures. This study is conducted using a publicly accessible dataset of healthcare information from Cleveland and open-source efforts to employ DNNs in the medical field.

RNN was proposed by [129] to facilitate the early recognition of cardiac failure. Additionally, the newly developed neural network models have been modified to recognize occurrences within a period of time of 20 to eighteen months and regulate timely occurrences (such as the identification of a disease, pharmaceutical guidelines, operational instructions, etc.). Models effectiveness indicators were compared to regularized LR, in which the KNN was analyzed using neural networks and vector based support systems. For the time line short time observation, DL models that take advantage of time associations performed better in occurrence cardiac arrest prediction. According to [130], applications related to bioinformatics were used for obtaining trends in datasets using different ML approaches using the ANN for the forecasting of cardiac disease. In predictive mining, qualities are successfully extracted with great success. Overall summary for performance of various DL algorithms in terms of heart related diseases prediction are given in *Table 4*

Table 4 summary for performance of various DL algorithms in terms of heart related diseases prediction

Reference with year of publication	**Diseases**	**Methods Used**	**Data**	ACR **/ Results**
[131] (2017)	Acute coronary syndrome	Regularized stacked denoising auto-encoder	From Chinese People’s Liberation Army General Hospital, China	ACR = 73 % AURC = 87 %
[132] (2018)	Heart diseases	CNN	UoC-murmur and PhysioNet database	ACR = 85 %
[133] (2023)	Heart failure	LSTM with extreme gradient boosting	Kaggle database	ACR = 98.96 %

Reference with year of publication	Diseases	Methods Used	Data	ACR / Results
[134] (2017)	Heart diseases	CNN	PhysioNet database	ACR = 97 %
[126] (2021)	Coronary heart disease	PCA, Variational autoencoder and DNN	Korean National Health and Nutritional Examination Survey	ACR = 0.892 Specificity = 0.840 PRS = 0.911 RCL = 0.920 F-measure = 0.915 AURC = 0.882
[135] (2019)	Coronary heart disease	Reconstruction error based DNN with deep autoencoder	Korean National Health and Nutritional Examination Survey	ACR = 86.3371% PRS = 91.3716% RCL = 82.9024% F-measure = 86.9148% AURC = 86.6568%
[136] (2020)	Heart coronary artery segmentation	Improved three-dimensional U-net CNN	Centerline data set	Average dice coefficient = 0.8752
[137] (2023)	Heart diseases	Residual neural networks and VGG16	UCI repository datasets	FSC = 80 %
[138] (2022)	Arrhythmia	1 D CNN	Massachusetts institute of technology-Beth Israel hospital (MITBIH) arrhythmia database	Sensitivity = 94.35% PRS = 94.02% Specificity = 99.5% ACR = 99.65%
[139] (2023)	Heart diseases	Nearest Neighbors, Gaussian Process, Linear SVM, DT, NB, AdaBoost, Bagging, Boosting and dense neural network	Cleveland, Hungarian, Long Beach and Switzerland	For Clevland: Sensitivity= 87.35% FSC=84.02% Specificity=77.5% ACR=82.65%
[140] (2023)	Coronary heart disease	HY_OptGBM using the optimized Light GBM classifier	Data from the Framingham Heart Institute	AURC = 97.8%, MCCS = 0.861 PRS = 0.963 RCL = 0.897 FSC = 0.929
[141] (2023)	Cardiovascular diseases	LSTM-based DNN	2621 medical records from UAE hospitals	ACR= 91% (with optimal set of features)
[142] (2023)	Cardiomegaly diseases	DNN and CNN with different optimizers	NIH X chest ray dataset	Best ACR with ADAM and Nadam optimizer was 94%

4.Discussion

In developed countries, hospitals gather and keep patient data in a digitally accessible format. These diseases have been recognized as a serious public health issue worldwide not only in specific regions [8]. Physicians can forecast with the help of algorithms that consider the assessment of multiple reputable standard risk factors in addition to a number of clinical biomarkers. Learning is the process of constructing a model based on the knowledge which has been extracted from data. While ML is the intricate computer process for automatically recognizing patterns and generating intelligent decisions on the basis of training data. It comes under the concept of artificial intelligence, which has the power to learn the machine from a huge set of data. ML algorithms of classification and clustering have the capability to predict diseases based on past data. Many of the researchers used various ML algorithms for predicting different diseases with good ACR [23–29], [71–75]. They have employed classification algorithms such as DT, SVM, KNN, NB, and others, according to the review. However, any method based on DT is complicated and time-consuming especially when working with a large data set with many branches. Similarly, because the SVM classifier is a discriminator, it did not perform better when the support vectors were huge. Although the KNN method can be used for classification and regression, it is not ideal for large data sets. NB is a basic probabilistic classifier based on Bayes theorem. However, using a single classification approach is insufficient for successful prediction with high AR; hence, a hybrid of several optimization methods and classifiers is required to improve predictive AR. For this, based on combined approaches like ML with DL [139–142], ML with feature optimization and DL with optimization approach are considered by various researchers [83-114].

For varying sample sizes of data, offered several FS methods were discussed various authors [20, 27, 31, 42, 83, 109, 114]. Several FS assessment criteria were examined in order to improve the performance of ML techniques as well as the issues that FS would face in the future. Various FS issues were Emphasized, in the case of huge data, they talked about how important FS is in improving learning performance. The selection of features might be complicated by the presence of multiple dimensions containing data. Adequate proportion of data is required for training and testing in ML model. We can improve the performance of ML algorithms by balancing training and testing datasets optimally. Attribute selection can reduce the dimensions while also enhancing the efficiency and classification ACR. Influential FS in big data can also aid improve learning performance although it can be challenging when the data includes multiple dimensions. The ML classification and clustering techniques have been shown to have higher ACR percentages. In addition to certain unanticipated issues that can develop during FS. Various FS assessment measures can be helpful for increasing the convergence speed of ML algorithms. Various swarm-based optimization algorithms, such as ABC, PSO, and ACO were applied with ANN and PSO was found to be the more efficient in feature optimization. Some of the authors suggested a combined methods for detecting heart illness consisting of binary particle swarm optimization (BPSO) with SVM, as well as KNN and "leave-one-out cross-validation". They used these approaches to analyze various heart sound signals from healthy people and people with heart valve illnesses such as aortic stenosis, aortic regurgitation, and mitral stenosis and regurgitation. They were used BPSO for FS and SVM for classification of heart signals and achieved ACR of more than 95%. Some of them were used KNN and GA for classifying heart disease. Several efforts that address the challenges with tiny and unbalanced data. It could be roughly characterized as resizing along with information replenishment [20, 42, 62]. Data gets under-sampled as well as over-sampled over the initially collected data in the re-sampling process. SMOTE is a well-known excessive sampling technique. It creates specimens based on the minority's proximity to their closest neighbour. The geometric manipulation, turning movement, trimming, and other data enhancement methods are commonly employed. Nevertheless, the majority of the strategies described previously are restricted to being used to photographic input. Generating adversarial networks are alternative augmentation of data technique. That may produce fictional samples with parameters that are identical to the actual sample. Furthermore, Generating adversarial networks may mitigate disclosure of data in contrast with other strategies.

It has been observed that DL strategies are used in different way like, expense responsive learning, multifunctional learning, and transfer learning (TL). While a lot of the research examined adopted a dataset with imbalances to conduct their testing, some of them included expenditure of data for a learning method involving extra expense-sensitive losses. Each of these experiments altered the missing rate of the DL system to penalize identification of the minority class. Unbalanced collections of data are more prevalent in the medical care industry, because patients with diseases are less numerous compared to healthy individuals. Furthermore, the majority of the minority class forecasting assignments affect serious medical decisions, like recognizing those with illnesses that will probably to pass away in the next few hours or people who will become icteric in a relatively short time frame.

However, they cannot use more data while additional data assets are available. TL may resolve the tiny data constraint through constructing a system on an associated huge database after which applying the resulting model's experience to the intended assignment, notably when several associated resources are readily accessible [42]. However, TL can't deal with the discrepancy situation. In the beginning phases of deeper time period forecasting in medical services, CNN model was regularly utilised. It was ultimately proved to be repeatedly surpassed in recurring models. But with the latest technological developments, layers with convolution are being used as a supplement to Gated Recurrent Unit and LSTM. A meta-analysis recommends employing CNN to improve RNN predictive ACR rather than utilising singly. Other emerging pattern that has recently been reported involves the division of complete chronologies into subsequent sequences for distinct time intervals, followed by the use of convolutions of varying sizes for filters to identify seasonal trends throughout each time cycle.

It is possible to estimate disease rates manually, using the vast amount of diseases data collected from hospitals around the world. However, it has not yet been effectively correlated with disease risk and symptoms. Various effective methods have been worked out by researchers to identify heart problems. Age is directly related to the number of deaths from heart disease, indicating an increase in risk with increasing years. We can increase the performance of ML algorithms by proper balancing of training and testing datasets. FS can reduce dimensionality and increases efficiency as well as AR of classification. It has been analyzed from different methodological approaches that a combination of ML and optimization methods may be effective in classifying disease dataset. DNN, CNN and RNN algorithms of DL can be effective for classifying large datasets.

A complete list of abbreviations is shown in *Appendix I.*

5.Conclusion

In the present study, a comprehensive review was conducted of articles that explored the impact of various ML and DL approaches on disease categorization and prediction, with a specific focus on heart and brain-related diseases. Regarding ML techniques, it was observed that most researchers favoured SVM and tree-based methods due to their ability to achieve high prediction accuracy. In the realm of DL models, CNN and RNN design principles, particularly their single-layer LSTM and GRU variants, were identified as prominent structures in existing research. Notably, recent studies showcased a growing trend of integrating RNN and CNN in a hybrid manner. Further research is necessary to determine the optimal network architecture for diverse healthcare environments and learning challenges. During the evaluation process, the selection of impactful features played a crucial role in both ML and DL models, exerting a significant influence on overall performance parameters such as accuracy, time efficiency, and cost. Various nature-inspired optimization techniques like ABC, PSO, ACO, and TLBO proved to be valuable in the context of ML and DL models. Addressing the knowledge gap of developing cost-sensitive learning methods within DL is a crucial area for future exploration. Researchers have already demonstrated the advantages of multitasking in learning, leading to improved performance across various medical prediction tasks. However, further investigation is needed to identify the specific network layers, elements, or types of retrieved temporal trends within the architectural layout that benefit from multitasking. Several studies have illustrated the potential for applying well-established time series forecasting models to extensive medical datasets with high-dimensional inputs. Nonetheless, the analysis of complex network designs described in recent publications warrants consideration as a potential avenue for future research. It is also beneficial to identify scenarios where DL models, despite their greater complexity and execution times, may be unnecessary. During the evaluation of these models, the deployment of real-time data systems could offer more effective guidance to clinical decision-makers.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
Animesh Kumar Dubey: Conceptualization, Investigation, Data curation, Writing – original draft, Writing – review and editing. **Amit Kumar Sinhal**: Data collection, Conceptualization, Writing – original draft, Analysis and Interpretation of results, and Supervision. **Richa Sharma**: Study Conception, Data collection, Supervision, Investigation on challenges and Draft manuscript preparation.

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Animesh Kumar Dubey is a PhD Research Scholar in Computer Science and Engineering at JK Lakshmipat University, Jaipur, India. He completed his Master's degree and B.Tech in Computer Science and Engineering from RGPV University, Bhopal. He has published more than 15 papers in reputed journals and conferences. His research areas encompass Automaton, Machine Learning, Deep Learning, and Optimization.
Email: animeshdubey@jklu.edu.in

Prof. Amit Kumar Sinhal is currently serving as a Professor in the Department of Computer Science & Engineering at the Institute of Engineering & Technology, JK Lakshmipat University, Jaipur. He holds a Bachelor of Engineering (B.E.) degree in Computer Engineering from Sardar Vallabhbhai National Institute of Technology (SVNIT), Surat. His educational journey continued with a Master's and Doctorate in Computer Science & Engineering from Rajeev Gandhi Technical University, Bhopal (M.P.). Dr. Sinhal possesses more than two and a half decades of rich experience, encompassing research, teaching, and the IT industry. He has a notable international stint, having worked in Atlanta, USA, on an on-site project for CoreCard Inc. His research interests span diverse areas, including Software Engineering, Soft Computing, AI, ML, and NLP. He holds credit for filing three patents and serves as the Editor-in-chief of the Scopus Indexed International Journal IJETAE. Additionally, he has authored four book chapters and two books with international publishers. He is a Life Member of prestigious professional associations, including ISTE, CSI, IAENG, AMLE, and CSTA.
Email: amit.sinhal@jklu.edu.in

Dr. Richa Sharma is an Associate Professor of Mathematics in JK Lakshmipat University, Jaipur. She received her M. Sc. and Ph. D. degrees in Mathematics from Dr B. R. Ambedkar University, Agra. She was appointed as reviewer of many reputed international journals. She has twelve years of research and teaching experience. Her research area includes Queueing Theory, Probability Theory, Reliability Theory, Stochastic Modelling and Optimization. She has published fifty-one research papers in refereed International/National journals. She has also published one patent by Government of India. She has participated and presented her research papers in fifty-nine International/National conferences, workshops and training programs and coordinated two training programs. She has presented her research work in various international conferences held at Politecnico di Milano, Italy; Zhejiang Sci-Tech University, Hangzhou, China; Hong Kong, Turkey, and Kathmandu, Nepal.
Email:richasharma@jklu.edu.in

Appendix I

S. No.	Abbreviation	Description
1	ACO	Ant Colony Optimization
2	AE	Autoencoders
3	ANN	Artificial Neural Networks
4	CART	Classification and Regression Tree
5	CHAID	Chi-Square Automatic Interaction Detection
6	CNN	Convolutional Neural Network
7	CSO	Cat Swarm Optimization
8	DBN	Deep Belief Network
9	DL	Deep Learning

10	DNN	Deep Neural Network
11	DT	Decision Tree
12	FCM	Fuzzy C-Means
13	FS	Feature Selection
14	GA	Genetic Algorithm
15	HR	Hierarchical
16	HM	Hidden Markov
17	ID3	Iterative Dichotomiser 3
18	KM	K-Means
19	KNN	k-Nearest Neighbors
20	KSVM	Kernel-SVM
21	LR	Logistic Regression
22	LSVM	Linear-SVM
23	ML	Machine Learning
24	MLP	Multilayer Perceptron
25	NB	Naive Bayes
26	NCBI	National Center for Biotechnology Information
27	PSO	Particle Swarm Optimization
28	RF	Random Forest
29	RNN	Recurrent Neural Network
30	SVM	Support Vector Machine
31	SVMG	Support Vector Machine with Grid Search
32	TLBO	Teaching Learning based Optimization
33	WHO	World Health Organization