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A SURVEY ON IDENTIFICATION AND DIAGNOSIS OF DISEASES USING MACHINE LEARNING

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ABSTRACT
The field of artificial intelligence to which machine learning belongs. We use machine learning methods like K-nearest neighbor(KNN), and Linear regression algorithm to detect and diagnose illnesses in this work. The dataset is trained using supervised learning, Reinforcement learning methods in order to construct a logical mathematical model. In the context of learning models, the datasets are employed for purposes such as data analysis and illness diagnosis. The purpose of the Disease Prediction using Machine Learning (ML) system is to make predictions about diseases based on the symptoms reported by patients or other users. The user inputs their symptoms, and the machine returns the likelihood that they have a certain ailment. In machine learning, disease prognosis relies on disease prediction.
KEYWORDS: Machine learning, Disease, Reinforcement learning, Supervised learning

1.INTRODUCTION
ML is a subfield of AI that enables computers to "self-learn" from data sets and gradually improve in performance without being explicitly programmed. Patterns in data can be spotted and used by machine learning algorithms to inform their own forecasting. A machine learning system may learn from past data, create predictive models, and then apply those models to fresh data to anticipate an outcome. The larger the dataset, the better the model that can be constructed, and therefore the more accurate the predictions of the output.

1.1 CLASSIFICATION OF MACHINE LEARNING
Semisupervised learning
Regression, and prediction are just some of the techniques that benefit from this form of learning. When the expense of labels prevents a completely labelled training procedure, semisupervised learning might be a helpful alternative.

Reinforcement learning
The algorithm learns via trial and error what kinds of behaviour are most likely to result in positive outcomes by employing reinforcement learning. There are three main parts to this sort of learning: the agent, the environment, and the actions taken by the agent. The goal is to have the agent make decisions that maximise expected benefit over some time horizon. If the agent follows a sound policy, he or she will complete the task considerably more quickly. When using reinforcement learning, the objective is to figure out what course of action works best.

1.2 DIAGNOSIS OF DISEASES
Machine learning's potential in areas like illness diagnosis and management ensures it will play an increasingly important role in the healthcare industry. When used to illness diagnosis, machine learning techniques allow for faster decision making with fewer false positives. Several popular machine learning techniques are covered. The likes of cancer, diabetes, epilepsy, heart attacks, and other significant ailments are diagnosed with the use of these algorithms. The condition is diagnosed using the theoretical and mathematical framework of machine learning algorithm's accuracy, precision, recall, and F1 score statistics.

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2. LITERATURE SURVEY

Following the work of Nicolas Vivaldi, and Meijun Ye [1], we assessed the efficacy of popular supervised machine learning algorithms for differentiating between patients with and without a previous history of traumatic brain injury (TBI) and those with a stroke history and/or normal electroencephalogram (EEG) (Electroencephalogram). Models using a rich feature set extracted from the Temple EEG Corpus were developed for two-class classification of TBI patients vs normal subjects and for three-class classification of TBI, stroke, and normal individuals. Both two-class and three-class classification performed exceptionally well with (LDA) feature selection and support vector machine models in both Cross validation and Independent validation. When comparing TBI and stroke patients to healthy controls, we found that coherence and relative Power spectral density in the delta frequency range were decreased, whereas power in the alpha, mu, beta, and gamma ranges were increased.

In a study conducted by Simona Turco, Aya Kamaya, Thodsawit Tiyarattanachai, Kambez Ebrahimkheil, John Eisenbrey, and Ahmed El Kaffas [2], we developed an interpretable radiomics technique to distinguish between malignant on contrast-enhanced ultrasonography (CEUS). Despite the fact that CEUS has showed promise for differential FLLs diagnosis, qualitative examination of contrast enhancement patterns is still the only method used in clinical assessment. Although quantitative analysis is essential, it is sometimes complicated by motion artefacts and the intricate spatiotemporal architecture of liver contrast enhancement, which consists of many, overlapping vascular phases learning classifiers and optimising their performance. The location of a suspected lesion must be entered manually.

B. Deepa, M. Murugappan, M. G., and Mabrook S. Al-Rakhami [3], suggest a unique approach to classifying brain abnormalities of the complex amplitude data for the sample is encoded as fringe patterns in the raw digital hologram. Create a training approach that uses deep and feature-based machine learning models to automatically extract this data without resorting to the time-consuming and error-prone traditional reconstruction method.

Thanh Minh Vo, Tan Nhat Pham, and Son Vu Truong Dao [4] employed Gray Wolf Optimization and Adaptive Particle Swam Optimization to develop multilayer Perceptrons in order to detect diabetes.

Gazara, Muaffaq M. Nofal, Sohom Chakrabarty, and M. Mursaleen [5] suggest a sophisticated pseudo-reinforcement learning method that overcomes the major class asymmetrical problem in a constricted dataset by incorporating simulated data into the major parameter space.

A comprehensive framework for phenotyping biologic samples was devised by Mattia Delli Priscoli, Lisa Miccio, Francesco Bardozzo, and others [6]. Involves fusing of computational holography and label-free individual unit detection in a transmit optical system.

Using data from nationally representative surveys of people's health and demographics, Drs. Kamrul Hasan, Tasnim Jawad, Akhtarul Islam, Mehedi Masud, and Jehad F. Al-Amri [7] classify measles vaccine use and identify the factors that contribute to it using an ensemble machine learning approach. Several methods of missing value imputation and feature selection have been utilised to determine the most important characteristics for making vaccination predictions for measles. Grid search hyperparameter optimization was used to fine-tune the hyperparameters of many machine learning models, including Naive Bayes, random forest, decision tree, XGboost, and lightgbm. Using our suggested (BDHS) dataset, we report on the classification performance of each individual optimal Machine learning model and all of its ensembles. When the suggested weighted ensemble of XGboost and lightgbm method was modified with the same preprocessing, the results were promising enough to advocate their use for the measles vaccine.

Blood pressure may be estimated from photoelectric plethysmography data, and Sumbal Maqsood, Shuxiang Xu, Matthew Springer, and Rami Mohawesh [8] have done a detailed examination of feature extraction approaches for doing so. In order to further examine the relevance of each approach for feature extraction, we further subdivided them into three categories. Features from the time domain are presented in Group A, features extracted statistically are shown in Group B, and features

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from the frequency domain are presented in Group C. Multiple machine learning techniques were used in the investigation, and their results were examined from a variety of angles. Two publicly accessible datasets were used to show that the collection of characteristics belonging to group A was more trustworthy than other strategies for blood pressure measurement.

To ensure precise readings of blood pressure, Xiaohui Chen, Shuyang Yu, Yongfang Zhang, Fangfang Chu, and Bin Sun [9] established a support vector machine regression model and a random forest regression model. By collecting photoelectric plethysmography and electrocardiogram readings from persons of varying ages, we can get a good approximation of their blood pressure using the high-quality physiological signals and the vascular elastic cavity perfect. The blood pressure prediction model takes into account personal features as input parameters. Prediction performance may be enhanced by experimenting with various parameter settings in the model. To produce reliable readings of blood pressure, the best model for making such predictions is chosen. Experimental results show that the random forest optimization model has superior performance to the support vector machine regression model under the same conditions, with an average absolute error of diastolic and systolic blood pressure of less than 5mmHg, in line with the method of the mercury sphygmomanometer.

In this research, we present the MaLCaDD (Machine Learning based Cardiovascular Disease Diagnosis) developed by Aqsa Rahim, Yawar Rasheed, Farooque Abdul Wahab Muzaffar, and Muhammad Waseem Anwar [10]. The framework initially corrects for any discrepancies or missing data (using a mean replacement method). When choosing features, the feature importance method is applied. For more precise forecasting, we propose using a combination of logistic regression and k-nearest neighbor classifiers.

In a study conducted by Md. Rashed-Al-Mahfuz, Salem A. Alyami, Julian M. W. Quinn, Mohammad Ali Moni, Abedul Haque, and Akm Azad [11], we used machine learning to determine the features of clinical tests that would help in the early, accurate identification of chronic kidney disease (CKD). By taking this measure, both time and money may be saved throughout the diagnostic screening process. We used k-fold cross-validation to compare the efficacy of different classifiers on datasets enhanced by the inclusion of these carefully chosen characteristics of clinical tests. Our proposed machine learning methods for CKD diagnosis work particularly well with optimised datasets including relevant features. We looked at the features of inexpensive clinical tests including urine and blood analysis, as well as other clinical indicators. With the optimised and pathologically characterised characteristics set, the best performing predictive model for CKD diagnosis was a random forest (RF) classifier.

Molecular biomarkers are discussed in this study by Kai Shi, Wei Lin, and Xing-Ming Zhao [12]. Molecular biomarkers are individual molecules or groups of molecules that can aid in the diagnosis or prognosis of a disease or ailment. As high-throughput technologies have developed, an enormous quantity of data on molecular 'omics' has been collected. These omics data allow for the screening of potential biomarkers for illnesses and disorders. Several computational methods have been designed to then classify the machine learning methods into supervised, un-supervised, and recommendation techniques.

Inflammatory bowel diseases (IBDs), as defined by Davide Chicco and Giuseppe Jurman [13], are a category of illnesses characterised by persistent inflammation of the small intestine and colon. The two most frequent forms of IBD are Chron's disease and ulcerative colitis. Patients with inflammatory bowel disease are at increased risk of having an arterial event, such as a stroke or an acute coronary syndrome. Information on patient's risk of developing vascular disorders may be gleaned quickly and cheaply from their electronic medical records after they have been diagnosed with inflammatory bowel disease using computational data mining methods. We looked at data from 90 people with IBD, 30 of whom also had some form of vascular illness. We reran the analysis on a sample of 30 patients with IBD and arterial disease after identifying the capacity to predict the arterial event and the most critical variables throughout the whole dataset. An arterial event and its subtype (stroke) may be accurately predicted from medical records using machine learning, and the method can also rank the most significant clinical characteristics in the dataset.

With Jung-Gu Choi, Inhwan Ko, and Sanghoon Han [14], we presented a machine learning based classification system for assessing the severity of depressive episodes from actigraphy data. We used a logistic regression model that included fourteen features of the circadian rhythm (activity minimum, amplitude, alpha, beta, acrotime, upmesor, downmesor, mesor,

f_pseudo, interdaily stability (IS), intradaily classifier etc.,), intradaily classifier performed best in classifying depression levels out of the four potential classifiers. For purposes of feature extraction and classification, the actigraphy data of two days was ideal.

Written by N. García-D'urso, P. Climent-Pérez et al. [15], we introduced a machine learning method for predicting cholesterol levels from readily available and non-invasive data. Clinical and anthropometric information collected by dietitians during weight reduction interventions are used. The goal of analysing the predictive capacity of various patient factors is to boost the accuracy of non-invasive diagnostics and the efficiency of screening for related disorders. Different groups of patients that share specific traits that have been relatively hidden but may contain crucial diagnosis or prognosis information have been identified using a clustering study.

Sarria to further enhance the prediction accuracy of the ensembled model, we included hybrid classifiers utilising the majority voting approach [16] by E. A. Ashri, M. M. El-Gayar, and Eman M. El-Daydamony. In order to improve prediction performance and overall time consumption, a genetic algorithm-based preprocessing approach and features selection is presented.

We used the accurate classification of Cushing's syndrome developed by Senol Isci, Derya Sema Yaman Kalender, Firat Yaman [17], which plays an important role in providing the early and correct analysis of Cushing's syndrome, which may facilitate treatment and improve patient outcomes. In order to arrive at an accurate diagnosis of cushing's syndrome, doctors need to look at a number of factors all at once, including the patient's history, the results of several biochemical tests, and the results of medical imaging. With the goal of improving cushing's syndrome diagnosis, prognosis, and therapy, we apply machine learning algorithms to evaluate and categorise patient data in order to showcase their potential as a clinical decision support system.

Md. Abdul Awal, Md. Shahadat Hossain, Abdullah Al-Mamun Bulbul, Mehedi Masud, S. M. Hasan Mahmud, and Anupam Kumar Bairagi [18] designed and optimised a machine learning-based approach to address this disease using inpatient facility data. The dataset's COVID and non-COVID classes are balanced using the proposed framework's Adaptive Synthetic (ADASYN) technique, and their hyperparameters are optimised using Bayesian optimization. Despite the efficiency of the proposed strategy.

We propose an effective strategy for employing an artificial recurrent neural network in the continuous early prediction of intracranial pressure(ICP) evaluation in patients with traumatic brain injury in this paper by Guochang Ye, Vignesh Balasubramanian, John K-J. Li2, and Mehmet Kaya [19]. Following preprocessing of the ICP data, the learning model is developed for thirteen patients to constantly anticipate the occurrence of the ICP signal and categorise events for the following 10 minutes.

The Four Khan Brothers: Usama Ahmed, Muhammad Adnan Khan, Shabib Aftab, and Muhammad Farhan Khan, this study by Ghassan F. Issa, Raed A. T. Said, Taher M. Ghazal, and Munir Ahmad [20] depicts a model for diabetes prediction that makes use of a hybrid machine learning strategy. Conceptual framework employs two models; the support vector machine model and the artificial neural network model. It is the job of these models to examine the data and conclude whether or not a patient has diabetes.

P. Thirumoorthy, K. S. Bhuvaneshwari, C. Kamalanathan, P. Sunita, E. Prabhu et al. [21], In this paper, a key agreement-based Kerberos protocol for secure M-health data transmission across wireless networks was presented. The processed patient data is accessible to doctors and caregivers via a cloud server. To preserve the secrecy and integrity of authentication, the suggested protocol is

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utilised to access data transfer between patients, servers, and physicians. The effectiveness of the suggested algorithm is contrasted with that of the existing protocols.

K.Shanmugapriya, C.N.Marimuthu, N.Sridhar, S.Sameema Begam [22], the goal of this work's proposed anomaly detection system is to identify IoT vulnerabilities and notify an organization's executive or service administrations. The proposed system uses the supervised machine learning algorithm Random Forest (RF) and the unsupervised machine learning method K-Nearest Neighbor (KNN) to adjust parameters in a distributed network. As a result, this system leverages cross validation to create a fit and a metric score while maximising model performance without overfitting(CV).

D.Vanathi, S.Prabhadevi, P.Sabarishamalathi, Mohanraj.K.P [23], to achieve private collaboration, it is imperative to use a distributed collaborative-based privacy-preserving approach. Critical components known as IDSs (Intrusion detection structures) are able to reduce threats by spotting malicious behaviour. The privatised situation nodes exchange facts among themselves, which is a significant barrier to joint study.

Avadhesh Kumar Dixit, S Karuppusamy, Sonu Kumar, Jyothi N M [24], Dermal sensors networking used in all-encompassing medical technologies provide a very high volume of information knowledge that must be constantly managed, preserved for current analysis, and used both now and in the future. Digital technology is a relatively recent invention that involves the management of personal information of electronic devices, as well as interpretations, particularly in conjunction with the underlying concept of networked information (IoT).

Dr.D. Vanathi, P. Uma, M. Parvathi and K. Shanmugapriya [25], Recommender systems have proliferated in recent years. To meet the incredibly diverse needs of its clients, businesses like Amazon and eBay have produced a huge array of goods. There are more and more options available to customers. As a result, in order to locate what they genuinely need during this new level of personalization, clients should create a model or approach from the vast amout of data offered by businesses.

3. COMPARATIVE ANALYSIS

In comparative analysis, the various machine learning algorithms, parameter analysis, tools used, future improvement are compared.

Table 3.1: Comparative Analysis

S.No	Paper title	Techniques and Algorithms	Parameter Analysis	Tools used	Future Work
1	Evaluating Performance of EEG Data-Driven Machine Learning for Traumatic Brain Injury Classification[1]	Support vector machine, K-nearest neighbor(KNN) and Principle Component Analysis technique	Cross validation and Independent validation	EEG data-driven machine learning	Some methods, such as LASSO(Least Absolute Shrinkage and Selection Operator) and CNN, may be used to enhance the dimensionality reduction and, may be, the classification outcomes.

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2	Interpretable Machine Learning for Characterization of Focal Liver Lesions by Contrast-Enhanced Ultrasound[2]	Random forest, K-nearest neighbor(KNN) and Synthetic Minority Over-sampling technique(SMOTE)	Estimated perfusion parameters, reproducible quantitative parameters	MATLAB toolbox implemented by Vallieres	Motion correction before feature extraction may enhance the similarity feature's ability to discriminate.
3	Pattern Descriptors Orientation and MAP Firefly Algorithm Based Brain Pathology Classification Using Hybridized Machine Learning Algorithm[3]	Support vector machine, Random forest methods and Hybridized classification technique	Hyper parameter such as tumor and stroke	Magnetic Resonance Imaging (MRI)	May employ deep learning without any data augmentation.
4	A Novel WrapperBased Feature Selection for Early Diabetes Prediction Enhanced With a Metaheuristic[4]	Support Vector Machine(SVM), Decision Tree (DT) and K-Nearest Neighbor (KNN)	Agents, beta, alpha	WEKA tool	Apply auto-tuning to the MLP Architecture to increase the number of hidden nodes and hidden layers, as well as the activation functions and feature selection algorithm's parameters, to improve performance.
5	Reinforcing Synthetic Data for Meticulous Survival Prediction of Patients Suffering From Left Ventricular Systolic Dysfunction[5]	Reinforcement learning algorithm, Support vector machine algorithm and Aalen's Additive Regression Model	Anaemia, High BP, Platelets	MATLAB toolbox	Based on its critical threshold levels, the subset of traits can be employed as a stand-alone determinant for effectively anticipating a potential death event.
6	Neuroblastoma Cells Classification Through Learning Approaches by	Adamoptimization algorithm, Principal Component Analysis (PCA) and Non-invasive	Shape parameter	Image Processing Toolbox	Utilising the multiple object tracking (MOT) developments for holographic video broadcasts. The

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	Direct Analysis of Digital Holograms[6]	optical techniques			ability of CNNs to properly detect hundreds of objects in a single frame is well recognised.
7	Associating Measles Vaccine Uptake Classification and Its Underlying Factors Using an Ensemble of Machine Learning Models[7]	Gaussian Naive Bayes(GNB), Bernoulli Naive Bayes (BNB), Decision Tree (DT), Unsupervised attribute selection technique and Filling Missing Value (FMV) technique	Hyper parameter	MATLAB	A weighted ensemble Machine Learning(ML) model is proposed after the hyperparameters of individual ML-based models are optimised.
8	A Benchmark Study of Machine Learning for Analysis of Signal Feature Extraction Techniques for Blood Pressure Estimation Using Photoplethysmogr a-phy (PPG)[8]	Adaptive Boosting Algorithm (Adaboost), Random forest, Linear regression algorithm and Plethysmograph technique	Body temperature, physical activity, heart rate, including estimated systolic blood pressure (SBP) and diastolic blood pressure(DB P)	MATLAB	Developing models that reduce error for more reliable findings. Determine which signal's waveform sequence significantly affects the goal by probing the attention process and weights.
9	Machine Learning Method for Continuous Noninvasive Blood Pressure Detection Based on Random Forest[9]	Random Forest, Supervised learning technique	Human body characteristic s parameter	Mercury Sphygmoman ometer	Better model than the support vector machine regression under the same conditions model.
10	An Integrated Machine Learning Framework for Effective Prediction of Cardiovascular Diseases[10]	Machine Learning based Cardiovascular Disease Diagnosis (MaLCaDD) and Synthetic Minority Over-sampling	Kernel and c	ARM tool	To share the real time evaluation results of MaLCaDD on different patients in future.

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		technique(SMOTE)			
11	Clinically Applicable Machine Learning Approaches to Identify Attributes of Chronic Kidney Disease (CKD) for Use in Low Cost Diagnostic Screening[11]	Gradient boosting algorithm, Random forest and Shapley Additive explanations (SHAP) technique	Clinical parameter	Cost-effective computer-aided CKD detection tools	Low packed cell volume is related with the onset of CKD, a conclusion that is in line with what is already known.
12	Identifying Molecular Biomarkers for Diseases With Machine Learning Based on Integrative Omics[12]	Genetic algorithm, Random forest algorithm and Clustering algorithm	Biomarkers include single gene	MATLAB	Biomedical data that might offer problems for machine learning and point the way to future biomarker identification.
13	Arterial Disease Computationl Prediction and Health Record Feature Ranking Among Patients Diagnosed With Inflammatory Bowel Disease[13]	Support Vector Machine, Random Forest, XGBoost, Machine learning and biostatistics techniques	Hyperparameter configurations	MATLAB simulation tool	We intend to use our computational intelligence and statistical methodologies to genomes and transcriptomics datasets from patients with inflammatory bowel disease in order to learn more about this condition.
14	Depression Level Classification Using Machine Learning Classifiers Based on Actigraphy Data[14]	Classification algorithms (XGBoost, Support Vector Machine, ML classifiers)	A random search to determine the optimal hyperparameters	All codes for ML classifies and data preprocessing were written using Python (version 3.7.1, scikit-learn, version 2.4.1) and R (version 4.0.3)	To generalise our system, we need to include external validation using datasets acquired from other nations.
15	A Non-Invasive Approach for Total Cholesterol Level Prediction	Principle component analysis,	Clusters	MATLAB	Incorporating a) digital anthropometry data, b) a bigger

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	Using Machine Learning[15]	Clustering technique			sample size, and c) new variables, particularly those used in automated body composition analysis, can all help reduce the error rate.
16	Heart Disease Prediction Framework Based on Hybrid Classifiers and Genetic Algorithm[16]	Genetic algorithm, Support vector machine and Hybrid classification technique	Hyper parameter	WEKA and KEEL tools	Can forecast health status in real time using health related streaming data such as twitter heart disease streaming data.
17	Machine Learning Models for Classification of Cushing's Syndrome Using Retrospective Data[17]	Support vector machine, Random forest and Generalization of AdaBoost for multiclass classification technique	Max depth of decision trees, split criterion, and class weight criterion	Python scikit-learn ML library v0.21.3	To differentiate between distinct types of cushing's syndrome, clinical evaluations of individuals with the ailment might benefit from employing a multiclass ALL model.
18	A Novel Bayesian Optimization-Based Machine Learning Framework for COVID-19 Detection From Inpatient Facility Data[18]	K-Nearest Neighbor(KNN), Random Forest and Bayesian optimization techniques	Hyperparameter of decision tree are criterion, max_depth and max_features	Clinically operable simple tree based tool, Graphical user interface tool	Clinically operable decision trees will benefit clinical personnel and the development of an efficient recommender system.
19	Machine Learning-Based Continuous Intracranial Pressure Prediction for Traumatic Injury Patients[19]	Adaptive boosting algorithm, Data processing and Invasive technique	Physiological parameter	MATLAB	Predicting and monitoring intracranial pressure continuously may save the lives of people who have suffered severe brain injuries.
20	Prediction of Diabetes Empowered With Fused	Decision Tree, Artificial Neural Network(ANN), Ensemble learning, Pre-	The outcome parameters for ANN and SVM are either	Weka tool	The combined models are stored in the cloud for further use.

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	Machine Learning[20]	processing techniques	positive or negative		
21	Improved key agreement based kerberos protocol for m-health security[21]	CP-ABE technique	Health parameters	Kinit	The future of this work will be extended with other security protocols that use biometrics.
22	Anomaly Detection of IoT Using Machine Learning[22]	K-Nearest Neighbor (KNN), Random forest (RF)	Hyperparameterand Fine tuned parameter	Scikit-Learn's Randomized Search CV method tool	Intended to detect IoT vulnerabilities and alert an organization's senior management or service managers.
23	Machine Learning Based Collaborative Privacy-Preserving Intrusion Detection System for VANETs[23]	K-means algorithm, allies technique	Privatives parameter	Computing tool	Future work is to create a trained classifier for detecting VANET intrusions.
24	Applications of IoT Principles in Healthcare[24]	Digital Technology, Broadband technology	Sensor	Sensor tool	Future work includes demonstrating how new IoT methodologies can be used for ubiquitous healthcare.
25	Review of Recommendation System Methodologies, International Journal of Psychosocial Rehabilitation[25]	Clinical technology	Accuracy	Clinical tool	In the future, the analysis will cover a wide range of progressive deep recommendation systems.

4. CONCLUSION

The capacity of machine learning to help in the early diagnosis of disease has led to its widespread use in the healthcare industry. It is only after illnesses have been detected that a diagnosis may be

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made. In this work, we examine the diagnostic process for a number of disorders, including IBD, IHD, and chronic kidney disease. Better judgments, the ability to spot trends and breakthroughs, and increased research and clinical trial efficiency are all made possible by the efficient application of machine learning in the healthcare industry. Machine learning has several potential applications in healthcare, such as improved diagnostic accuracy, better pharmaceutical suggestions, readmission prediction, and patient risk stratification. These forecasts are grounded in the patient's anonymized medical records and their displayed symptoms.

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