IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Critical Review On Online Consultation, E-Pharmacy And Use Of ML In Area Of Healthcare Sector

Sahil Lokhande[1], Prathmesh Mathankar[2], Rhutwik Gaidhani[3], Sanket Bhute[4], Sanket Gulhane[5]

[1]Research Scholars, Department of Computer Technology, Priyadarshini College of Engineering, Nagpur, Maharashtra

[2]Research Scholars, Department of Computer Technology, Priyadarshini College of Engineering, Nagpur, Maharashtra

[3]Research Scholars, Department of Computer Technology, Priyadarshini College of Engineering, Nagpur, Maharashtra

[4]Research Scholars, Department of Computer Technology, Priyadarshini College of Engineering, Nagpur, Maharashtra

[5]Research Scholars, Department of Computer Technology, Priyadarshini College of Engineering, Nagpur, Maharashtra

Abstract: *The Smart Healthcare and Online Consultation initiative is revolutionizing the healthcare industry by utilizing AI and ML to provide patients with convenient, individualized services. This includes real-time video consultations, appointment scheduling, prescription administration, and health record management. Future health behaviors will prioritize safety and convenience through specialized online doctors and pharmacies. ML-driven health platforms play a vital role in healthcare by employing big data analytics and learning methodologies. This study examines machine learning methods for sickness diagnosis and health outcome prediction, focusing on multiple illness prediction. It also discusses the development of chatbots and the global popularity of online medicine purchasing. The study highlights the convenience, cost-effectiveness, confidentiality, and second opinions of online consultations, as well as the impact of online medicine purchasing on the Indian healthcare market.*

Keywords - *Healthcare, Machine Learning, E-pharmacy, Doctor Consultation, Health Prediction, Medical Field, Electronic Health Records, Health Bot.*

I. Introduction

Machine learning (ML) is a subfield of artificial intelligence that trains machines to recognize patterns in data and draw conclusions from them. ML allows computers to evaluate medical data, recognize health trends, and generate predictions without the requirement for explicit programming in the context of medical therapy. Models, training, and assessment are some of the components that make up the core idea of machine learning.[1][2]

A model is a mathematical representation of data relationships, enabling computers to identify hidden patterns. It accurately represents these relationships. In machine learning (ML), a model is trained using data to identify patterns and provide accurate predictions. After training, the model's performance on untested data is evaluated to determine how well it can apply the patterns it has learned.

Utilizing assessment metrics like F1-score [1], ROC, confusion-matrix [1], MAE, accuracy [3-4], recall, and precision enables thorough evaluation of a model's predictive accuracy, crucial for mitigating medical care risks.

Patient diagnosis data is crucial in specialty hospitals, and accurate encoding is essential for the learning algorithm to function. Machine learning should automatically analyze and compare data to similar problems, enabling quick, easy, and accurate diagnosis of new instances, benefiting both students and nonspecialists.[6]

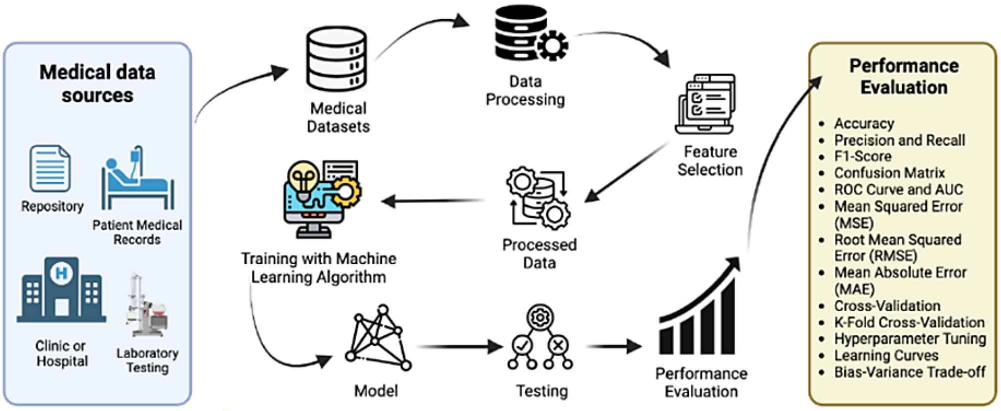

Figure 1 – Illustration of applying ML in the medical field.

There are methods available with machine learning that can handle massive volumes of data that are incomprehensible to humans. For instance, demographic information, photos, test results, genetic information, medical records, and sensor data can all be considered health data. Different sources for data creation in the healthcare industry appear in Figure 3. [7] [8]

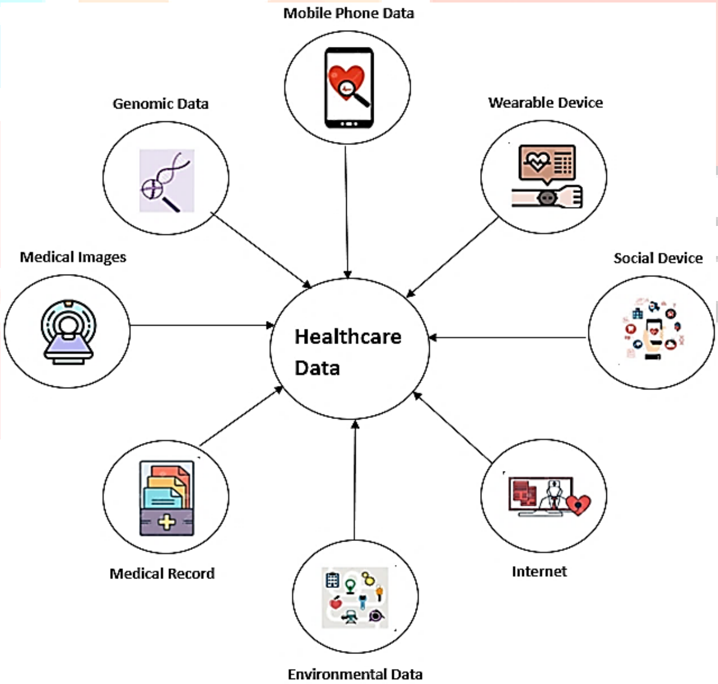

Figure 2 – Different sources for data creation in the healthcare industry

II. FUNDAMENTAL CONCEPT OF ML IN MEDICAL TREATEMENT

2.1 Healthcare using ML

The term machine learning (ML) describes the instruments, protocols, and strategies used in many domains (e.g., medical). If machine learning is seamlessly incorporated into the complex healthcare sector, it holds the capability to revolutionize the processes of diagnosis, prediction, and care delivery. [9]

Through advancements in picture registration, annotation, medical assistance, and diagnostic processes, machine learning (ML) is transforming the healthcare industry. By combining and segmenting multimodal pictures, it overcomes the constraints in intricate operations and improves accuracy and efficiency. This technology improves medical assistance quality, leading to more precise and effective outcomes. [10]

Both patient-clinician communication and healthcare expenses may be improved by machine learning. It can assist medical experts in finding customized drugs and treatments and patients in remembering follow-up visits. However, its social impacts in the healthcare sector may be limited.[10]

In healthcare, a vast amount of information, including EMRs, is available, including structured and unstructured data. Structured health information includes statistics, classes, patient weights, and generic symptoms. Notes, pictures, reports, audio and video recordings, and discharge summaries are examples of unstructured information. The inherently personal character of these encounters makes it difficult to analyze tailored communications between providers and patients.[10]

2.2 The Primary Mechanism for Building a ML Model:

To guarantee a medical learning model's efficacy and dependability, a methodical framework must be designed. Designing a learning model for the healthcare sector involves a systematic approach with five crucial stages. [11] Figure 4 illustrates these phases or stages.

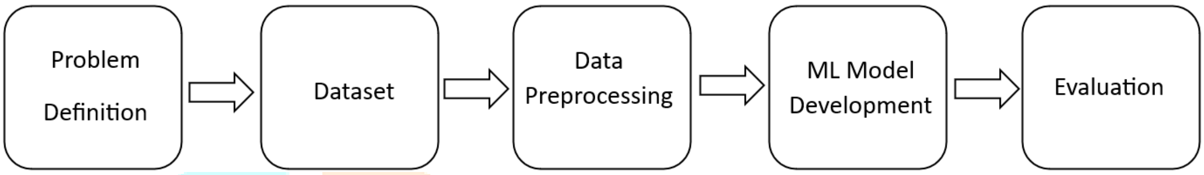

Figure 3 – Stages involved in creating a learning model.

Problem Definition: Give a clear explanation of the medical issue or task that the learning model is meant to solve. This could involve tasks such as disease prediction, medical image analysis, or treatment optimization.

Database: To train and evaluate the model, gather pertinent data. This may involve obtaining medical records, diagnostic images, patient histories, or any other pertinent information. Make sure the dataset accurately reflects the issue area.[12]

Data Processing: To prepare the data for model training, clean it up and perform some preprocessing. This covers dealing with outliers, normalizing data, addressing missing values, and formatting data such that algorithms for machine learning can understand it.

ML Model Development: Machine learning algorithms like ensemble approaches, decision trees, support vector machines, and neural networks are suitable for medical applications, but require a specific training dataset to create models. [13] A carefully chosen dataset is used to train the machine learning model, and its settings and parameters are adjusted to maximize efficiency and performanceUse techniques such as cross-validation to ensure the model's robustness. [7]

Evaluation: Evaluate the model's functionality with a different test dataset. Medical assessment methods are evaluated using criteria like accuracy, precision, recall, F1 score, and area under the ROC curve. Analyze how well the model applies to fresh, untested data. Validate the model's results with domain experts or through clinical validation. If necessary, iterate on the model design, adjusting parameters or incorporating additional features based on feedback to enhance its accuracy and utility.[7]

Measuring a completed model's performance: The final model's performance has to be assessed once it has been built and trained using the following criteria:

- *Correctness:* This part evaluates the degree of agreement between the current and expected outputs of the learning system. A list of the scales used for assessments in this discipline is provided below:

True positive is when the classifier correctly identifies positive cases, true negative is when it correctly identifies negative cases, false positive is when it incorrectly predicts positive when it's negative, and false negative is when it incorrectly predicts negative when it's positive.

We list the essential metrics for evaluating a learning model in the sections that follow. These scores are based on the model's propensity to generate false positives and false negatives, as well as its accuracy in identifying real positives and true negatives.

Sensitivity*:* Sensitivity, or true positive rate (TPR), assesses how well a model identifies true positives among actual positives, crucial for evaluating its accuracy. The following formula is used to compute it:

$$Sensitivity = \frac{TP}{TP + FN}. \quad (1)$$

Specificity: Specificity evaluates a model's accuracy in identifying true negatives and avoiding false positives, with a formula used for computation. It gauges the model's precision in recognizing actual negatives. The formula is used to compute it:

$$Specificity = \frac{TN}{TN + FP}. \quad (2)$$

Positive predicted value (PPV): PPV is a key metric in a model's accuracy, showing the proportion of predicted positive instances that are actually true positives. It helps evaluate the precision of the model's positive predictions.. The following formula is used to compute it:

$$PPV = \frac{TP}{TP + FP}. \quad (3)$$

Negative predicted value (NPV): NPV is a crucial learning model evaluation metric, assessing its ability to accurately identify true negatives and avoid false negatives, providing valuable insights. The following formula is used to compute it:

$$NPV = \frac{TN}{TN + FN}. \quad (4)$$

Accuracy: Accuracy is a crucial metric for assessing a learning model's effectiveness in making correct classifications across all classes, considering both true positives and negatives. The following formula is used to compute it:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \quad (5)$$

Matthews correlation coefficient (MCC): Matthews Correlation Coefficient (MCC) is a metric used to assess the performance of a learning model, particularly useful in binary classification tasks, considering true positives, false negatives, and true negatives. The following formula is used to compute it:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}}. \quad (6)$$

False discovery rate (FDR): False Discovery Rate (FDR) is a metric used to assess a learning model's performance by comparing the proportion of false positives among its positive predictions. The following formula is used to compute it:

$$FDR = \frac{FP}{FP + TP}. \quad (7)$$

AU-ROC: The AU-ROC is a metric used to assess the performance of a learning model, particularly in binary classification
tasks, indicating better discrimination and predictive ability at different classification thresholds. The formula used to compute it:

$$AU - ROC = \frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right). \quad (8)$$

F1-Score: The F1-Score measures a learning model's precision and recall, ranging from 0 to 1, with higher scores indicating better performance in identifying positive instances. . The following formula is used to compute it:

$$F1 - Score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right). \quad (9)$$

- Model Relevance: By evaluating model-to-data disparities, the parameter leads to both overfitting and underfitting. Insufficient data can lead to model mismatch, which calls for cross-validation. Techniques can be employed even while overfitting tolerance is unknown. [7]

- Efficiency: Machine learning systems' efficiency is influenced by the learning model runtime, which is a representation of the pace of learning and prediction. For best results, ML designers should take learning algorithm runtime into account. [7]

- Interpretability: A learning model represents the pace of learning and prediction, crucial for medical care decisions. Interpretability, the user's understanding of machine learning choices, is challenging to describe mathematically. Various methods assess interpretability, but sluggish learning or prediction processes can lead to efficiency issues. For this reason, ML designers should take the learning algorithm runtime into account to guarantee that the model will be accepted by society.

2.3 Different Learning Approaches in ML

Machine learning is a cross-disciplinary field that draws from statistics, mathematics, data processing, and knowledge analytics.. It is a specialized sort of artificial intelligence that gathers data from training sets without intervention. It is difficult to characterize machine learning in a new way because of its fundamental structure, which is similar to a tree with many branches and sub-branches. [10] The following groups are shown visually in Figure 5, which shows how machine learning is categorized.

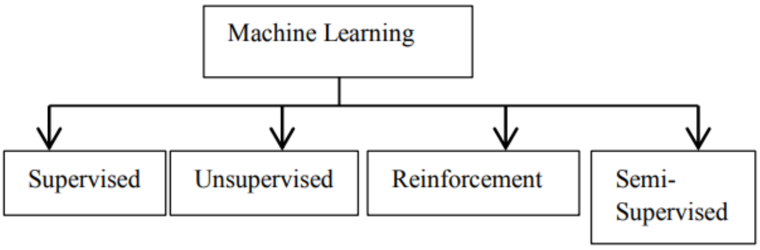

Figure 4 - Categories for Machine Learning

2.3.1 Supervised Machine Learning

Supervised learning teaches algorithms to predict or classify based on past examples, forming a key approach in machine learning. It involves training models using labeled data to enhance their predictive abilities.. It utilizes a labeled dataset to learn patterns and relationships, and then applies this knowledge to new, unlabeled data for predictions. Popular supervised learning techniques include Artificial Neural Networks, Random Forests, Decision Trees, and Support Vector Machines. Potential repercussions are determined using decision tree algorithms, which produce a decision support tool. SVM are methods for classification that find the biggest margin hyperplane and offer the best fit for data organization via the use of supervised learning. In order to ensure correct data structure and categorization, these approaches are commonly employed in the healthcare industry for image detection, hospital outcome identification, and sickness prediction. [14]

The algorithm uses this learning during training to create an activity that associates inputs with corresponding outcomes. A typical example of a supervised learning job is the categorization problem. [10]

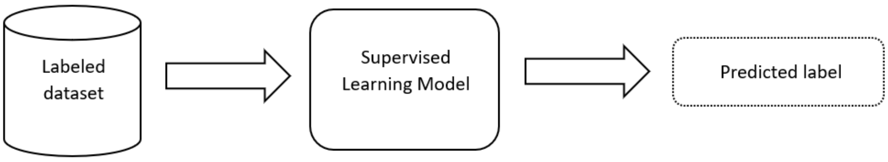

Figure 5 – Learning Scheme - Supervised Learning.

Different Techniques in Supervised Learning:

1. Naïve Bayes Classifications: Statistical classifiers, such as Bayesian classifiers, employ the Naive Bayes method to estimate the likelihood of belonging to a certain class based on provided labels. This simplifies the classification process by requiring just one pass through the data. [7][10] NB has demonstrated excellent performance in resolving numerous real-world issues.

2. Decision tree: Decision Tree (DT) is a classification technique with internal and leaf nodes, each associated with a specific class label, providing a clear, comprehensible framework for classification models. [8] A decision tree, consisting of root, internal, and leaf nodes, is a structured pathway for making decisions based on features or class labels. [7]

3. Artificial neural network (ANN): ANN are organized into three layers: input, hidden, and output. The input layer receives raw data, the hidden layer processes and learns from this information, and the output layer presents the results of these learned tasks. The optimal configuration of hidden layers and neurons is typically determined through a process of trial and error. [7]

4. Ensemble learning system: Multiple categorization systems, or ensemble learning, is a flexible method that may be used in a variety of problem-solving situations. [15] Ensemble systems combine various learning methods to enhance prediction accuracy and create robust classification models. These systems have three main components: diversity, training, and the combination of ensemble members, working in synergy to achieve improved overall performance.

5. Random forest (RF): The Random Forest (RF) is a swift, precise, and resilient classifier that employs decision trees for data classification. It generates numerous independent trees from an initial training set, predicts labels for each tree, and ultimately determines the final label through a majority voting process.

6. Deep learning (DL): Deep learning is a specific category within artificial neural networks (ANN), operating under the framework of supervised learning. It involves the use of hidden layers positioned between input and output layers to extract intricate features from datasets, whether labeled or unlabeled. Through training, these networks can accomplish a wide range of objectives by learning and representing complex patterns and relationships within the data. [16]

7. Support Vector Machine (SVM): It is a straightforward yet influential technique in machine learning. Primarily utilized for tasks involving categorization and predicting numerical values. SVM divides training samples into distinct categories to effectively solve various problems. [10]

8. K-nearest neighbour (KNN): The K-nearest neighbour method is a commonly employed approach for classifying samples. This technique involves calculating the distance from a given data point to the N nearest training samples, allowing for effective categorization based on proximity in feature space. [10]

2.3.2 Semi-supervised Machine Learning

The technique achieves robust classification performance by selecting the best classifier from data with and without labels. However, its success is contingent upon a small number of fundamental assumptions.. [7][10]

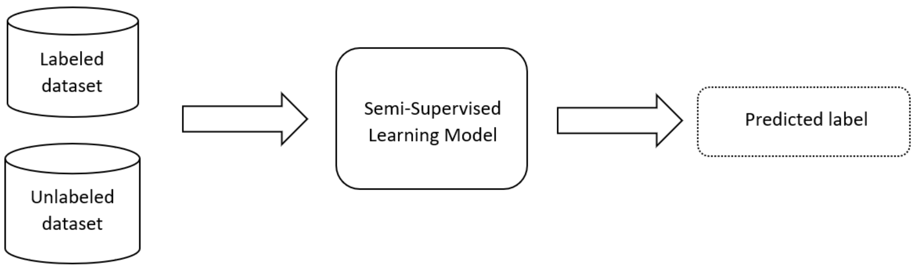

Figure 6 – Learning Scheme - Semi-supervised Learning.

2.3.3 Unsupervised Machine Learning

Unsupervised learning is a machine learning approach that concentrates on data reduction, stratification, and analysis rather than prediction. It is utilized for data assessment and clustering. It organizes unclassified data using techniques such as k-Means, deep belief networks, and convolutional neural networks. Despite its usefulness and speed, unsupervised approaches are only marginally popular in the healthcare industry due to data homogeneity and predefined outcomes. [14]

Unsupervised learning uses algorithms like clustering and association rule mining to organize data by identifying patterns or similarities without labeled examples. It helps develop frameworks using data samples, uncovering hidden structures and relationships. These algorithms contribute to pattern recognition, anomaly detection, and insightful analysis without explicit labels, making them valuable tools for extracting meaningful insights from unstructured datasets. [10]

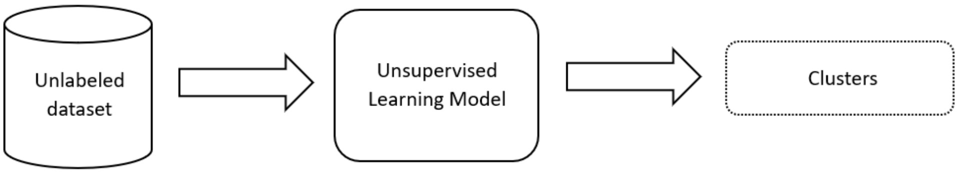

Figure 7 – Learning Scheme - Unsupervised Learning.

Different Techniques in Unsupervised Learning:

1. Fuzzy logic: Engineering applications frequently employ fuzzy logic, a well-liked approach developed from fuzzy set theory, for values between 0 and 1. [10]

2. K-means clustering: K-means is an iterative clustering technique that groups n data samples into k clusters based on randomly assigned centers. It continuously refines cluster centers by recalculating them within each cluster until convergence is achieved. [7]

3. Hierarchical clustering: The clustering scheme divides data points into clusters using both top-to-down (Divisive clustering) and bottom-to-up (Agglomerative clustering) approaches. Similar groups merge to form larger clusters, without requiring pre-defined information about cluster numbers.

2.3.4 Reinforcement Learning

Reinforcement learning is another learning technique that is in the middle between supervised and unsupervised learning. In this learning paradigm, an objective is accomplished through the interaction of a computer program and a dynamic environment. The program receives feedback, expressed through rewards and punishments, as it navigates challenges. This iterative process allows the program to adapt and optimize its performance within the given environment. [10]

Reinforcement learning in healthcare faces limitations due to structure, diverse data, incentive formulation, and computational resources, but has the potential to significantly advance the field.[14]

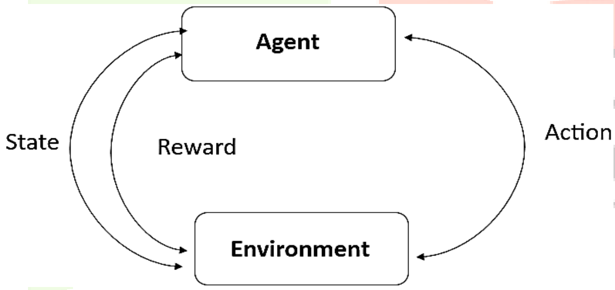

Figure 8 – Learning Scheme - Reinforcement Learning.

Different Techniques in Reinforcement Learning:

1. Dynamic programming (DP): The collection of procedures includes Markov decision process (MDP) and other strategies for figuring out the best course of action for the entire environment model.

2. Monte Carlo (MC) methods: Free-model Monte Carlo (MC) learns through experiences, utilizing return averaging to address reinforcement learning challenges, especially in episodic tasks. MC is a progressive plan that is implemented episode after episode. [10, 17].

3. Q-Learning: To maximize the Q-value, action-state pairings and their accompanying values are stored in a Q-Table, which is the foundation of the well-known reinforcement learning method known as Q-Learning. [17].

4. State Action Reward State Action (SARSA): Both SARSA and Q-Learning are reinforcement learning techniques for learning MDP policies, however they vary primarily in that Q-Learning is an off-policy scheme, whereas SARSA is an on-policy technique that selects actions based on preexisting policies. [17].

5. Deep reinforcement learning (DRL): Reinforcement learning and deep learning work together to solve complicated problems and increase the intelligence of agents. Because reinforcement learning doesn't require a database to function, agents may create datasets by interacting with their surroundings. [17].

Table 1 - A comparative analysis of different teaching approaches.

Approach	Goal	Dataset Used
Supervised learning	Predicting the labels for the testing set and comprehending the connection between inputs and outputs are the primary objectives.	There is usage of labeled datasets.
Semi-supervised learning	The objective is to predict or anticipate the labels of the testing set.	This method makes use of both labeled and unlabeled datasets.
Unsupervised Learning	The current goal involve identifying patterns within data and structuring data samples.	It uses unlabeled dataset
Reinforcement learning	Assessing a situation and deciding on the most appropriate course of action through active engagement and consideration.	--

III. ML IN DISEASE PREDICTION AND TREATEMENT:

3.1 Disease Progression Prediction

ML plays a crucial role in predicting disease progression by analyzing patient data like medical history, symptoms, and images.

For instance, ML can predict diabetes risk by analyzing blood glucose levels, body mass index, and family history. This method

can identify significant risk factors and provide more accurate predictions than traditional methods, guiding early interventions and

preventing severe complications. [1] Thus, ML is a valuable tool in disease prediction.

3.2 Personalization of Treatment and Therapy

Personalized treatment and therapy are essential in modern medical care, as each patient's unique characteristics influence their response to treatment.[5] Machine learning (ML) aids in personalized cancer treatment by analyzing genetic information and past responses, avoiding generic approaches and ensuring tailored care for each patient. [1]

IV. CONSULTATION WITH A DOCTOR ONLINE:

The Online Doctor Consultation System enhances patient-doctor connections, enhances efficiency, and promotes global connectivity. It addresses issues faced by doctors and patients during pandemic situations, ensuring efficient communication and problem-solving.[19] Online health consultations have gained popularity due to resource scarcity and inefficiency. Broadband and video conferencing platforms offer cost savings, convenience, accessibility, and improved privacy. COVID-19 has made online consultations relevant, but further research is needed to validate this technique in plastic surgery. Doctors and surgeons are developing new technology to improve results, lower costs, and convenience. [18]

V. CHATBOTS IN HEALTH COMMUNICATION:

A chatbot is a chatting robot that can converse. It's a computer application that simulates communication. It all comes down to the dialogue you have with the user. Speaking with a chatbot is a relatively easy process. It answers the questions that the user poses. When a chatbot is being created, how does it interact with the user? It is crucial to consider the manner in which the user and the chatbot will converse.[20] Figure 10 illustrates a chatbot's design:

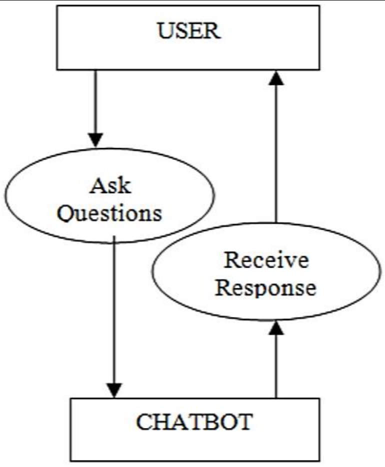

Figure 9 - Use Case Diagram for designing a chatbot.

VI. ONLINE PHARMACY

The internet has significantly impacted various fields, including pharmacies, leading to an increase in online purchasing of pharmaceutical preparations. In India, the internet has significantly transformed the doctor-patient relationship, allowing patients to buy medicine online after meeting safety standards. Online pharmacies have become a common practice among Indian patients, transforming the aspect of diagnosis, prescription generation, and filling. This has led to India becoming a center for health concerns such as fast-growing infections, cardiovascular disease, diabetes, arthritis, and various malignancies. [21]

E-pharmacy is a pharmacy that sells drugs and medicines online, making it easier and more convenient for patients to order and receive their medications. This trend is growing globally, with the increasing use of e-prescriptions in hospitals. The e-pharmacy industry is expected to decrease pharmacy income in India by 5-15%, particularly for under-served populations and those with chronic diseases in a binuclear family. The global e-pharmacy market is expected to grow at a CAGR of 14.26 between 2019 and 2025. Key players in this industry include PharmEasy, Medlife, 1MG, Netmeds Myra, and Pharma Secure.

Table 2 - Comparison Between Online Pharmacy and Offline Pharmacy

Sr. No.	Online Pharmacy	Offline Pharmacy
1.	More convenient as one can order drug online from anywhere	Less convenient as patient need to go to a store to buy medicine
2.	Save time	Time consuming
3.	Pass savings to bulk buyers through discounted pricing for affordability.	Margin are lower so they are not in position to offer discount like online pharmacy
4.	Large inventory	Limited inventory
5.	Maintain confidentially and privacy of patient about drug and disease	Since patient ask for drug while standing at store they find it hard to describe their need.

6.1 HOW DOES AN E-PHARMACY MODEL WORK?

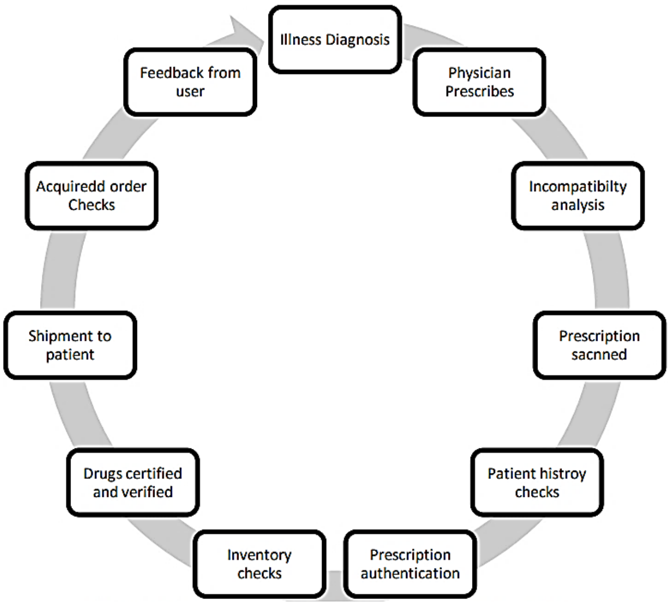

Figure 10 - E-pharmacy Model [24]

1. Customers need to upload the scanned photocopy of the prescription and placing a request for drugs. [22]
2. All orders are required to be validated and verified by registered pharmacists. [22]
3. The verified prescriptions are forwards to the pharmacy shop from which place the drugs are dispensed by the registered pharmacists. [22]
4. The online-based pharmacy is regulated below the Information Technology Act (2000) and this act promotes the connection among customers and pharmacy shops. Electronic records and online interchanges are also covered in this act (Brushwood D, 2001) [23]

VII. APPLICATIONS OF ML IN HEALTHCARE

Table 6 – Applications of ML in healthcare

S. No.	Application	Description	Reference
1	Utilizing ML algorithms for healthcare management	To identify illnesses early and analyze complex patterns in large amounts of data, machine learning is essential, assisting in diagnosis and treatment decisions, and predicting emergency department wait times using patient data and facility layout.	[7], [8]
3	Chatbots for patient care	Healthcare chatbots improve medical communication, fulfill high demand for services, carry out health surveys, evaluate medical information, and offer prompt assistance and illness forecasting. KBot is an Android chatbot designed to aid asthma self-management, utilizing online knowledge and clinical partner inputs. Its rise in interest has led to its referred to as the "future of therapy."	[25], [26], [27]
4	Gather the patient's medical history with accuracy	Machine learning can assist healthcare professionals in accurately collecting patient history, sending intelligent reminders, helping with scheduling, and recognizing typical roadblocks for patients with restricted mobility.	[28], [29], [30]
5	Enhance the quality of Healthcare services.	ML-assisted platforms enhance healthcare experiences, combine profit-generating purposes, and solve medication discovery problems. Start-up companies use reinforcement learning and natural language processing to evaluate data and build high-dimensional representations.	[31], [32], [33]
6	Enhance the treatment process.	ML improves healthcare by improving treatment processes, but fragmented data and handwritten document scans can lead to insufficient insights. Proper formatting and cleaning are needed.	[34], [35]
7	Make a prompt choice.	By analyzing large amounts of data, offering insights, and facilitating patient exams, machine learning (ML) in the healthcare industry may	[36], [37]

		support well-informed decision-making. It can predict disease likelihood, automate tasks, and revolutionize medical practice.	
8	Find a health issue	Through real-time data analysis and precision medicine, machine learning (ML) in healthcare helps early health issue identification, administrative work automation, and early pharmaceutical development.	[38]
9	Enhance healthcare system	In addition to improving illness prediction, data administration, and patient care, machine learning (ML) is showing promise in the healthcare industry. It can help diagnose tumors, cancer, and uncommon diseases.	[39], [40]

VIII. LITERATURE REVIEW

An application for chatbot that provides conversational mental health care services through the use of chat assistant technology and emotion recognition methods. Through continuous user monitoring, the program does not consider the user's mental state. [41]

Lin Ni(B), Chenhao Lu, Niu Liu, and Jiamou Liu develop a chatbot namely "MANDY0. "This offers a text-to-text dialogue feature that inquires about the user's health concerns. It is possible to communicate with other users, much like in-person chat. Next, to diagnose and provide guidance on the various symptoms to help identify the ailment, the bot poses a series of queries to the user regarding their symptoms. lacks comprehensive information No characteristics, such as the length or severity of the symptoms, etc. [42]

This chatbot aims to provide users with a basic diagnosis of their symptoms, despite its complex interface, time-consuming nature, and high installation cost. [43]

According to Kavitha, B. and C. R. Murthy (2019), this research use a variety of machine learning classification methods to identify the kind of disease based on a patient's clinical parameters. The Naive Bayes method achieves the maximum accuracy of 98.4%. The Graphical User Interface (GUI) was created to make it simple for dermatologists and physicians to use this prediction module. [44]

As documented by Rimi, T. A., Sultana, N., & Ahmed Foysal, M. F. (2020), they have attempted to create a prototype that uses CNN to identify skin conditions. Deep neural networks, or DNNs, have been used in detection work in the past. We now provide seminars on the identification of common skin conditions such as ulcers, lichen simplex, dermatitis hand, eczema subcute, and statis dermatitis. This study is a hybrid of machine learning and photo processing techniques. [45]

Table7 presents a number of literature reviews on the use of ML in the medical industry. Table 7 presents a comprehensive overview of research on Machine Learning (ML) applications in various medical fields, from disease diagnosis to cancer detection. It details the diseases, data sources, algorithms, assessment methods, conclusions, and study years. This comprehensive overview highlights the depth and breadth of ML research in this field.

Table 7 - Literature Study of ML Application in Medical / Diagnosis of Various Disease.

Ref.	Disease	DS	Data source	Algo.	ToA	Result	Year
[46]	Colorectal Cancer	Patients with stage IV colorectal adenocarcinoma	Database BioStudies	LR, DT, GB, lightGBM	CL	LR Accuracy: 91%, DT Accuracy: 89%, GB Accuracy: 84.5%, lightGBM Accuracy: 83.64%	2020
[47]	Rare (CTCs)	Optical and raw-cell microscopy images	Microscopy	CNN	CL	Accuracy: 97%	2020
[48]	Lungs and colon Cancers	Lungs and colon cancer histopathological image	LC25000 dataset from Kaggle	CNN	CL	Accuracy: 96.33%	2021

[49]	Patient's diagnosis	MRI and CT	Private medical center "HT Medica"	SVM, RF, CNN, BiLSTM, NLP	CL	Accuracy: 92.2% (CS=CT), Accuracy: 86.9% (DS=MRI)	2021
[50]	Breast Cancer tumor	Breast cancer tumor gene expression data	The cancer Genome Atlas	KNN, NB, DT, SVM	CL	KNN Accuracy: 92.99%, SVM Accuracy: 96.17%, XGBoost Accuracy: 94.96%, LightGBM Accuracy: 99.86%	2022
[51]	Brain Tumor	CCKS Dataset	CHIP2018, CCKS2019, and CCKS2020	CNN	CL	Accuracy: >85% F1 value: 74.68	2022
[52]	Breast Tumor	Breast ultrasound image	Local hospital	KNN, SVM, RF, XGBoost, LightGBM	CL	KNN Accuracy: 92.99% , SVM Accuracy: 96.17% , RF Accuracy: 95.08% , XGBoost Accuracy: 94.96% , LightGBM Accuracy: 99.86%	2022
[53]	Brain Tumor	MRI Dataset	Kaggle Website	CNN	CL	Accuracy: 92%	2023
[54]	Heart Disease	UCI	UCI	J48 SVM	CL	J48 Accuracy: 84.35%, SVM Accuracy: 85.03%	2018
[55]	Detecting heart disease	Cleveland		SVM	CL	Accuracy: 92.37%	2020
[56]	Diabetic Prediction using Classification Method	UCI	UCI	SVM, Naives Bayes, Voting classidiers	CL	Accuracy: 83.98%	2020
[57]	Heart Disease Prediction	Kaggle	Kaggle	logistic regression, Naïve bayes, SVM, KNN, DT, random forest and artificial neural network	CL	Accuracy: 90%	2022
[58]	skin lesion classification and Melanoma detection	HAM10000 public dataset	HAM10000 public dataset	DCNN, DenseNet201 neural network model		Accuracy: 78%	2020

DS: Dataset, Algo: Algorithm, ToA: Types of Algorithms, CL: Classification, SVM: Support Vector Machine, BiLSTM: Bidirectional Long Short-Term Memory, NPL: Natural Language Processing, DT: Decision Tree, LR: Logistic Regression, GA: Genetic Algorithm, MLP: Multilayer Perception, GB: Gradient Boosting, lightGBM: Light Gradient-Boosting machine, CNN: Convolutional Neural Network, CT: Computed Tomography, MRI: Magnetic Resonance Imageing, KNN: K-nearest neighbour, NB: Naïve Bayes, CTSs: circulating tumor cells, RF: Random Forest, DCNN: Deep Convolutional Neutral Network, CRF: Conditional Random Field

The table presenting research findings enables a notable conclusion about the influence and role of machine learning in the medical field. The studies enhance our understanding of Machine Learning's role in diagnosing and classifying medical conditions, enhancing clinical decision-making. Comparing findings provides insights into opportunities and challenges, and highlights potential benefits and improvement areas within the intersection of ML and medical diagnostics.

8.1 RECENT ADVANCEMENT IN MACHINE LEARNING

The Generative Pre-Trained Transformer 3 (GPT-3), a language model created by OpenAI, represents a notable breakthrough in the field of ML. This is a huge development—the machine can now generate text that closely mimics human language. This specific model is one of the largest language models created to date, with 175 billion parameters. The utilization of GPT-3 has been observed across a diverse spectrum of applications, encompassing, but not limited to, language translation, chatbots and text completion, as documented by Ali, Kumar, Alghamdi, Kateb, and Alarfaj (2023). [59]

Another interesting development in machine learning recently is generative adversarial networks, or GANs. GANs are a class of artificial neural networks capable of producing novel data that exhibit similarities to the original training data. They have made it possible to create material more creatively and efficiently by generating images, videos, and music. (Sharma et al., 2022). [60]

Federated Learning has emerged as a potentially viable explanation for machine learning that maintains privacy across decentralized data sources, such as Internet of Things or mobile devices. Data security and privacy problems may be addressed by using Federated Learning, which allows models to be trained on decentralized data sources while protecting user privacy (Zhang et al., 2023) [61]

Machine learning holds the promise of substantial impact across various domains, including natural language processing, healthcare, robotics, and content production. Recent advancements in this field suggest a shift towards more transparent, interpretable, and privacy-preserving models. These developments aim to enhance the effectiveness and efficiency of machine learning techniques.

Table 8 – Summary of ML techniques applied in medical field

ML technique	Medical field applied	Reference
Federated learning	Privacy-preserving machine learning on decentralized data sources	[61]
Generative pre-trained transformer 3 (GPT-3) AlphaFold	Protein structure prediction, targeted treatment development ML in postoperative process planning Language translation, chatbots, text completion	[62] [63]
Unsupervised learning	Text mining and literature retrieval	[64]
Supervised learning	Estimating mortality risk in critical care units Identification of ischemic heart disease and Unidentified diabetes identification	[65] [66], [67]

IX. CHALLENGES AND ISSUES:

- Large databases are needed for training ML-based models, necessitating innovative techniques for electronically capturing medical data in order to boost efficiency and lower error rates. [7]
- Error rates rise as a result of purposeful or inadvertent mistakes made when capturing data, underscoring the need of data quality. While improper labeling may cause complications, data pretreatment techniques may greatly lessen these concerns and enhance the quality of the dataset.[7]

- High dimensionality, growing model complexity, learning time, and overfitting are characteristics of real-time healthcare datasets. This problem should be solved using ML-based approaches that make use of feature selection and extraction strategies. To create more effective techniques, further study is necessary.[7]
- In healthcare, machine learning (ML)-based models are helpful in resolving complex issues, albeit they might not always be required. Because traditional approaches are useless or confusing owing to complicated data or ambiguous causes, researchers must use accurate and fast machine learning techniques to solve difficult issues. [7]
- Machine learning techniques are essential in complex, uncertain situations where traditional methods fail, enabling researchers to tackle complex problems involving unclear factors and intricate data. [7]
- The majority of the Indian population, including 21.9% below the poverty line, lacks access to mobile phones and the internet due to affordability and health literacy issues. Despite the increased accessibility of mHealth apps, health literacy remains low, making it difficult for those with financial means to fully utilize these resources.
- Online pharmacy faces challenges such as legal guidelines, drug promotion to minors, internet ignorance, prescription issues, identity issues, consumer rights, virtual signature accessibility, child shipping, privacy, and unclear international drug transfer guidelines.

X. CONCLUSION

The paper examines machine learning's (ML) use in healthcare and medicine, highlighting both the field's promising future and major obstacles. Machine learning (ML) is revolutionizing healthcare by improving treatment quality, speed, and precision. E-pharmacy, or online pharmacies, operate over the internet, selling prescription and non-prescription medications. They have advantages like traditional pharmacies but lack personal touch. The Online Doctor Consultation System is a positive move in the medical system, bridging the gap between doctors and patients efficiently through the internet. It enhances appointments and consultations by creating a superior, innovative, and hassle-free environment for online consultations. Medical picture interpretation and illness detection using ML algorithms are significantly more accurate, with some surpassing 90%. Techniques like CNNs and SVM play a crucial role in achieving these results. But there are still issues with handling complicated datasets, correcting algorithm variances, and maintaining data quality. Overcoming these requires standardized data formats, robust encryption, interpretability, comprehensive clinician training, and enhanced collaboration among stakeholders. Developing algorithms to handle unstructured data or optimizing data collecting, archiving, and distribution are two ways to overcome obstacles in machine learning algorithms.

This study presents a model design framework and investigates machine learning (ML) techniques in the healthcare industry. It divides ML-based techniques into four categories: learning, applications, evaluation, and data pre-processing. The purpose of the study is to introduce researchers to new ideas and applications of machine learning in healthcare. Socioeconomic status and health-related habits are important indicators of general health, and machine learning models can detect individuals who are more likely to acquire chronic illnesses that can be avoided.

XI. ACKNOWLEDGMENT

We could like to acknowledge the support and guidance of Dr. Mahesh G. Panjwani. We would like to extend our gratitude to our colleagues and mentors who provided us with valuable insights and advice. Their insights and expertise have greatly enriched our critical review on online consultation, e-pharmacy, and the utilization of machine learning in the healthcare sector.

XII. REFERENCE

[1] Furizal, Furizal & Ma'arif, Alfian & Rifaldi, Dianda. (2023). Application of Machine Learning in Healthcare and Medicine: A Review. Journal of Robotics and Control (JRC). 4. 2023.

[2] A. Saboor, M. Usman, S. Ali, A. Samad, M.F. Abrar, and N. Ullah, “A Method for Improving Prediction of Human Heart Disease Using Machine Learning Algorithm,” Mobile Information Systems, vol 2022, pp. 1-9, Mar. 2022.

[3] A. Helisa, T. H. Saragih, I. Budiman, F. Indriani, D. Kartini, " Prediction of Post-Operative Survival Expectancy in Thoracic Lung Cancer Surgery Using Extreme Learning Machine and SMOTE" Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), vol. 9, no. 2, pp. 239-249, 2023

[4] Y. Achour and H. R. Pourghasemi, "How do machine learning techniques help in increasing accuracy of landslide susceptibility maps?", Geoscience Frontiers, vol. 11, no.3, pp. 871-883, May 2020.

[5] I. S. Hofer, M. Kupina, L. Laddaran, and E. Halperin, "Intergration of feature vectors from raw laboratory, medication and procedure names improves the precision and recall of models to predict postoperative mortality and acute kidney injury," Sci. Rep., vol. 12, no. 1, p. 10254, Jun. 2022.

[6] Mohammad Shehab, Laith Abualigah, Qusai Shambour, Muhannad A. Abu-Hashem, Mohd Khaled Yousef Shambour, Ahmed Izzat Alsalibi, Amir H. Gandomi, Machine learning in medical applications: A review of state-of-the-art methods, Computers in Biology and Medicine, Volume 145, 2022

[7] Rahmani, A. M., Yousefpoor, E., Yousefpoor, M. S., Mehmood, Z., Haider, A., Hosseinzadeh, M., & Ali Naqvi, R. (2020). Machine Learning (ML) in Medicine: Review, Applications, and Challenges. Mathematics, 9(22), 2970.

[8] Yu, K., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2(10), 719-731.

[9] Bundi, D.N. (2023), "Adoption of machine learning systems within the health sector: a systematic review, synthesis and research agenda", Digital Transformation and Society, Vol. ahead-of-print No. ahead-of-print.

[10] Shailaja, K., Seetharamulu, B., & Jabbar, M. A. (2018). Machine Learning in Healthcare: A Review. 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA).

[11] Chen, P., Liu, Y., & Peng, L. (2019). How to develop machine learning models for healthcare. Nature Materials, 18(5), 410-414.

[12] Alizadehsani, R., Roshanzamir, M., Abdar, M. et al. A database for using machine learning and data mining techniques for coronary artery disease diagnosis. Sci Data 6, 227 (2019).

[13] Indrajit Mandal (2017) Machine learning algorithms for the creation of clinical healthcare enterprise systems, Enterprise Information Systems, 11:9, 1374-1400.

[14] Habehh, H., & Gohel, S. (2021). Machine Learning in Healthcare. Current Genomics, 22(4), 291-300.

[15] Gottwald, G.A.; Reich, S. Supervised learning from noisy observations: Combining machine-learning techniques with data assimilation. Phys. D Nonlinear Phenom. 2021, 423, 132911.

[16] Piccialli, F.; Di Somma, V.; Giampaolo, F.; Cuomo, S.; Fortino, G. A survey on deep learning in medicine: Why, how and when? Inf. Fusion 2021, 66, 111–137.

[17] Coronato, A.; Naeem, M.; Pietro, G.D.; Paragliola, G. Reinforcement learning for intelligent healthcare applications: A survey. Artif. Intell. Med. 2020, 109, 101964.

[18] M. Munasinghe, D. Gunasekera, N. Wedasinghe. A review: Impact of Internet on online medical consultancy platform. 39th National Information Technology Conference At: Colombo, Oct. 2021

[19] ONLINE DOCTOR CONSULTATION SYSTEM Moksha Jain, Naman Tenguria, Rochak Sharma, Samarth Gupta, International Research Journal of Modernization in Engineering Technology and Science, Volume:04/Issue:11/November-2022 Impact Factor- 6.752.

[20] M. Dahiya , A Tool of Conversation: Chatbot , International Journal of Computer Sciences and Engineering, Volume-5, Issue-5 E-ISSN: 2347-2693

[21] Vikesh Rathwa , Avnish Paswan , Anand Thakor , Keshav Mahla , Dhrutika Patel (2022). Review Article on E-Pharmacy, International Journal of Innovative Science and Research Technology, Volume 7, Issue 4, April – 2022.

[22] Selvam, Roshini & N., Venugopal. (2021). e-Pharmacy -A boon or bane. International Journal of Pharmaceutical Research. 13. 10.31838/ijpr/2021.13.02.246.

[23] Chordiya, S., Garge, B. (2019). E-pharmacy vs conventional pharmacy. IP International Journal of Comprehensive and Advanced Pharmacology, 3(4):121-123

[24] Samant, P. (2018). Vigilance for Sale of Drugs through Online Pharmacies. Advancements in Case Studies, 1(3).

[25] Siddique, S., & Chow, J. C. (2021). Machine Learning in Healthcare Communication. Encyclopedia, 1(1), 220-239.

[26] Kadariya, D.; Venkataramanan, R.; Yip, H.Y.; Kalra, M.; Thirunarayanan, K.; Sheth, A. kBot: Knowledge-enabled Personalized Chatbot for Asthma Self-Management. In Proceedings of the 2019 IEEE International Conference on Smart Computing (SMARTCOMP), Washington, DC, USA, 12–15 June 2019; pp. 138–143

[27] Vaidyam, A.N.; Wisniewski, H.; Halamka, J.D.; Kashavan, M.S.; Torous, J.B. Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape. Can. J. Psychiatry 2019, 64, 456–464

[28] C. E. Ait Zaouiat and A. Latif. 2017. Internet of Things and Machine Learning Convergence: The E-healthcare Revolution. In Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems (ICCWCS'17). Association for Computing Machinery, New York, NY, USA, Article 62, 1–5.

[29] Feldman, K., Faust, L., Wu, X., Huang, C., Chawla, N.V. (2017). Beyond Volume: The Impact of Complex Healthcare Data on the Machine Learning Pipeline. In: Holzinger, A., Goebel, R., Ferri, M., Palade, V. (eds) Towards Integrative Machine Learning and Knowledge Extraction. Lecture Notes in Computer Science(), vol 10344. Springer, Cham.

[30] Swagato Chatterjee, Divesh Goyal, Atul Prakash, Jiwan Sharma, Exploring healthcare/health-product ecommerce satisfaction: A text mining and machine learning application, Journal of Business Research, Volume 131, 2021, Pages 815-825, ISSN 0148-2963.

[31] Hu, Liangyuan, et al. "Identifying and understanding determinants of high healthcare costs for breast cancer: a quantile regression machine learning approach." BMC health services research 20.1 (2020): 1-10.

[32] Veerawali Behal & Ramandeep Singh (2021) Personalised healthcare model for monitoring and prediction of airpollution: machine learning approach, Journal of Experimental & Theoretical Artificial Intelligence, 33:3, 425-449

[33] Maes, F., Robben, D., Vandermeulen, D., Suetens, P. (2019). The Role of Medical Image Computing and Machine Learning in Healthcare. In: Ranschaert, E., Morozov, S., Algra, P. (eds) Artificial Intelligence in Medical Imaging. Springer, Cham.

[34] H. K. Bharadwaj et al., "A Review on the Role of Machine Learning in Enabling IoT Based Healthcare Applications," in IEEE Access, vol. 9, pp. 38859-38890, 2021,

[35] Ambigavathi, M., Sridharan, D. (2020). Analysis of Clustering Algorithms in Machine Learning for Healthcare Data. In: Singh, M., Gupta, P., Tyagi, V., Flusser, J., Ören, T., Valentino, G. (eds) Advances in Computing and Data Sciences. ICACDS 2020. Communications in Computer and Information Science, vol 1244. Springer, Singapore.

[36] Chen, Richard J., et al. "Synthetic data in machine learning for medicine and healthcare." Nature Biomedical Engineering 5.6 (2021): 493-497.

[37] Vimont, Alexandre, Henri Leleu, and Isabelle Durand-Zaleski. "Machine learning versus regression modelling in predicting individual healthcare costs from a representative sample of the nationwide claims database in France." The European Journal of Health Economics 23.2 (2022): 211-223.

[38] López Seguí, F.; Ander Egg Aguilar, R.; de Maeztu, G.; García-Altés, A.; García Cuyàs, F.; Walsh, S.; Sagarra Castro, M.; Vidal-Alaball, J. Teleconsultations between Patients and Healthcare Professionals in Primary Care in Catalonia: The Evaluation of Text Classification Algorithms Using Supervised Machine Learning. Int. J. Environ. Res. Public Health 2020, 17, 1093.

[39] Haleem, A., & Javaid, M. (2020). Medical 4.0 and its role in healthcare during COVID-19 pandemic: A review. Journal of Industrial Integration and Management.

[40] AlZubi, A.A., Al-Maitah, M. & Alarifi, A. Cyber-attack detection in healthcare using cyber-physical system and machine learning techniques. Soft Comput 25, 12319–12332 (2021).

[41] Hiba Hussain, Komal Aswani, Mahima Gupta, Dr. G. T. Thampi, "Implementation of Disease Prediction Chatbot and Report Analyzer using the Concepts of NLP, Machine Learning and OCR," IRJET, Apr 2020.

[42] Lin Ni(B), Chenhao Lu, Niu Liu, and Jiamou Liu," MANDY: Towards a Smart Primary Care Chatbot Application", SPRINGER,2017.

[43] Kavitha, B. and C. R. Murthy (2019). Chatbot for healthcare system using artificial intelligence.

[44] Suganiya Murugan, S.R. Srividhya, S. Pradeep Kumar, & B. Rubini, (2023), "A Machine Learning Approach to Predict Skin Diseases and Treatment Recommendation System". 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT).

[45] Rimi, T. A., Sultana, N., & Ahmed Foysal, M. F. (2020). "Derm-NN: Skin Diseases Detection Using Convolutional Neural Network". 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)

[46] Y. Xu, L. Ju, J. Tong, C-M. Zhou, and J,-J, Yang, "Machine Learning Algorithms for Predicting the Recurrence of Stage IV Colorectal Cancer After Tumor Resection," Sci. Rep., vol. 10, no. 1, p. 2519, Feb. 2020.

[47] S. Wang, Y. Zhou, X. Qin, S. Nair, X. Huang, and Y. Liu, "Label-freedetection of rare circulating tumor cells by image analysis and machine learning," Sci. Rep., vol. 10, no. 1, p. 12226, Jul. 2020.

[48] M. Masud, N. Sikder, A.-A. Nahid, A. K. Bairagi, and M. A. AlZain, "A Machine Learning Approach to Diagnosing Lung and Colon Cancer using a Deep Learning-Based Classification Framework," Sensors, vol. 21, no. 3, p. 748, Jan. 2021.

[49] P. Lopez-Ubeda, M. C. Diaz-Galiano, T. Martin-Noguerol, A. Luna, L. A. Urena-Lopz, and M. T. Martin-Valdivia, "Automatic medical protocol classification using machine learning approaches," Computer Methods and Programs in Biomedicine, vol. 200, p. 105939, Mar. 2021.

[50] J. Wu and C. Hicks, "Breast Cancer Type Classification Using Machine Learning," J. Pers. Med., vol. 11, no. 2, p. 61, Jan. 2021.

[51] G. Dhiman et al., "A Novel Machine-Learning-Based Hybrid CNN Model for Tumor Identification in Medical Image Processing," Sustainability, vol. 14, no. 3, p. 1447, Jan 2022

[52] E. Michael, H. Ma, H. Li, and S. Qi, "An Optimized Framework for Breast Cancer Classification Using Machine Learning," Biomed. Res. Int., vol. 2022, pp. 1-18, Feb. 2022

[53] A. Muis, S. Sunardi, and A. Yudhana, "Comparison Analysis of Brain Image Classification Based on Thresholding Segmentation With Convolutional Neural Network," Journal of Applied Engineering and Technological Science (JAETS), vol. 4, no. 2, pp. 664-673, Jun. 2023.

[54] Chaurasia, V. and S. Pal, "Data Mining Approach to Detect Heart Disease", International Journal of Advanced Computer Science and Information Technology, vol.2,pp.56-66,2018.

[55] Li, J.P.; Haq, A.U.; Din, S.U.; Khan, J.; Khan, A.; Saboor, A. Heart disease identification method using machine learning classification in e-healthcare. IEEE Access 2020, 8, 107562–107582.

[56] Sen, Vimal & Gupta, Krishna. (2020). Diabetic Prediction using Classification Method. International Journal of Recent Technology and Engineering (IJRTE). 9. 264-268. 10.35940/ijrte.F9718.079220.

[57] Manak, Manaswi, Pankaj Kumar, Garima Gupta. **Heart Disease Prediction.** International Journal of Innovative Science and Research Technology, Volume 7 – 2022.

[58] Waweru, A. K., Ahmed, K., Miao, Y., & Kawan, P. (2020), "Deep Learning in Skin Lesion Analysis Towards Cancer Detection". 2020 24th International Conference Information Visualisation (IV).

[59] Ali, F., Kumar, H., Alghamdi, W., Kateb, F. A., & Alarfaj, F. K. (2023). Recent advances in machine learning-based models for prediction of antiviral peptides. Archives of Computational Methods in Engineering, 1(12), 231. doi:10.1007/s11831-023-09933-w.

[60] Sharma, P., Said, Z., Kumar, A., Nizetic, S., Pandey, A., Hoang, A. T., ... Tran, V. C. (2022). Recent advances in machine learning research for nanofluid-based heat transfer in renewable energy system. Energy & Fuels, 36(13), 6626–6658

[61] Zhang, Y., Tang, Y., Zhang, Z., Li, M., Li, Z., Khan, S., ... Cheng, G. (2023). Blockchain-based practical and privacy-preserving federated learning with verifiable fairness. Mathematics, 11(5), 1091. doi: 10.3390/math11051091.

[62] Nussinov, R., Zhang, M., Liu, Y., & Jang, H. (2022). AlphaFold, artificial intelligence (AI), and allostery. Journal of Physical Chemistry B, 126(34), 6372–6383. doi: 10.1021/acs.jpcb.2c04346.

[63] Crowson, M. G., Ranisau, J., Eskander, A., Babier, A., Xu, B., Kahmke, R. R., & Chan, T. C. (2020). A contemporary review of machine learning in otolaryngology–head and neck surgery. The Laryngoscope, 130(1), 45–51.

[64] Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database, 2020. Available from: https://doi.org/10.1093/database/baaa010 (accessed 10 January 2023).

[65] Bouvarel, B., Carrat, F., & Lapidus, N. (2022). Updating mortality risk estimation in intensive care units from high-dimensional electronic health records with incomplete data. MedRxiv. doi: 10. 1101/2022.04.28.22274405

[66] Hani, S. H. B., & Ahmad, M. M. (2022). Machine-learning algorithms for ischemic heart disease prediction: A systematic review. Current Cardiology Reviews, 19(1). doi: 10.2174/ 1573403x18666220609123053.

[67] Johanson, C., Huang, H., Idryo, D., Broome, R. G., Rioth, M. J., & Matsuno, R. K. (2022). Machine learning application to find patients with lower-risk myelodysplastic syndrome from real-world data. Journal of Clinical Oncology, 40(16), 1555. doi: 10.1200/jco.2022.40.16_suppl.1555.

[68] N. N and N. G, Cholli, "Early Identification of Alzheimer's Disease using Medical imaging: A Review From a Machine Learning Approach Perspective," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), vol. 9, no. 3, 2023.

[69] S. Dixit, A. Kumar, and K. Srinivasan, "A Current Review of Machine Learning and Deep Learning in Oral Cancer Diagnosis: Recent Technologies, Open Challenges, and Future Research Directions," Diagnostics, vol. 13, no. 7, p. 1353, Apr. 2023.

[70] S. Aminizadeh et al., “The applications of machine learning techniques in medical data processing based on distributed computing and the Internet of Things,” Computer Methods and programs in Biomedicine, vol. 241, p. 107745, Nov. 2023.

[71] Agarwal N, Biswas B. Doctor Consultation through Mobile Applications in India: An Overview, Challenges and the Way Forward. Healthc Inform Res. 2020 Apr;26(2):153-158.