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A Review of Machine Learning Tools in Healthcare: Addressing Challenges and Opportunities

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Abstract- Traditional healthcare services may be modernised with the help of artificial intelligence (AI), which will benefit society in a more efficient way. With the use of machine learning algorithms, doctors may automate the diagnostic process and quickly provide patients with medical advice by processing massive amounts of clinical data. Machine learning technologies' contributions to the medical field will be examined in this research. The healthcare industry's use of machine learning for prediction systems, drug development and human trials, surgical procedures aided by machine learning, and more will be covered.

Keywords-*Machine Learning, Health Care, Automated Diagnosis,*

I. INTRODUCTION

This review examines the integration of machine learning (ML) tools in healthcare, focusing on challenges and opportunities. It explores the technical complexities of developing robust models, regulatory and privacy concerns, and ethical implications of ML for medical decision-making. It highlights successful case studies and emerging trends, offering actionable recommendations for researchers, clinicians, policymakers, and industry stakeholders to overcome challenges and harness the full potential of ML tools in improving patient outcomes and shaping the future of healthcare. Medical professionals practicing traditional medicine diagnose patients based on their symptoms and provide appropriate remedies. Because of the complexity and length of time required for human processing of the massive amounts of clinical data generated by all of these processes, diagnostic delays and patients' inability to recover quickly from illness are also possible outcomes. The medical industry's use of advanced technology has led to better diagnosis, lower treatment costs, and faster patient recoveries. However, these methods generate massive amounts of medical data, which is challenging to manage and understand manually. Because of this, creating a healthcare system capable of handling massive amounts of data is becoming more important. Researchers have developed a framework called the Health Care System (HCS) that can digitally store any form of data (text, images, etc.) and provide methods for analysing that data in order to keep medical records safe. Scientists instituted image processing technologies to aid in the understanding of visual data. Establishing associations between text data and visual data allows for the tracking of a patient's medical history, as seen in Figure.

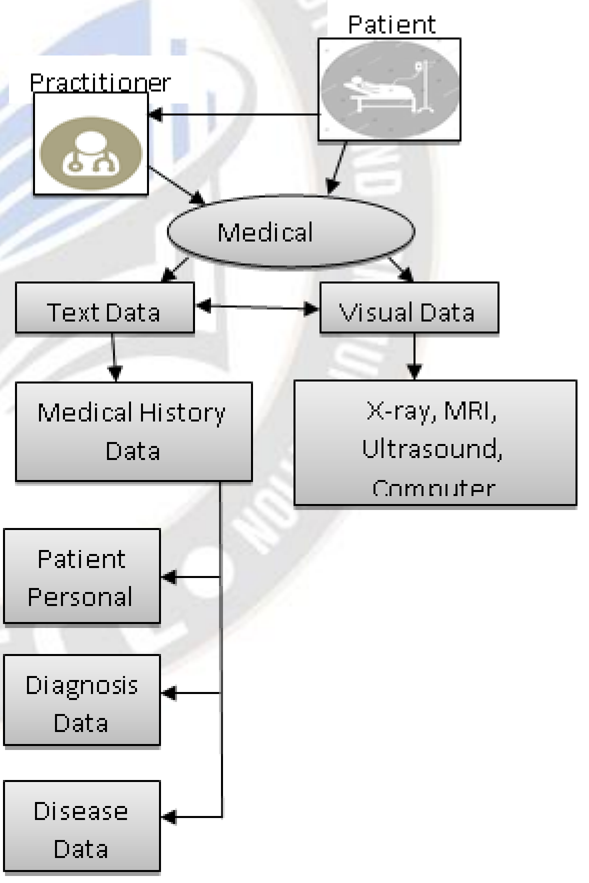

Figure Healthcare system

Necessities of huge volume Medical Data handling

Managing the bulk processing of medical data presents several challenges due to the unpredictable frequency of data creation and the incompatible processing cycles for receiving data. These constraints can lead to delays and inefficiencies in delivering timely diagnoses and treatments to patients.

Moreover, the susceptibility of diagnostic recommendations to errors further complicates the process, requiring robust error detection and correction mechanisms. Despite these challenges, the imperative for quick decision-making remains paramount in ensuring prompt and effective patient care, underscoring the need for agile and adaptive data processing frameworks in medical settings.

Barriersfor Text data processing: Text data processing in healthcare faces significant barriers that can impede the performance of Healthcare Systems (HCS). One major challenge lies in the diverse types of content and their organization within medical records. The variability in formats, terminology, and structure across different healthcare providers and systems complicates the efficient extraction and interpretation of relevant information. Additionally, the process of identifying and extracting pertinent data from these records requires sophisticated techniques to handle the complexity and ensure accuracy. These barriers not only strain the performance of HCS but also highlight the critical need for advanced tools and methodologies that can effectively manage and process textual data in healthcare contexts. Addressing these challenges is essential for enhancing the efficiency and reliability of medical data processing, ultimately improving patient care outcomes.

Constraint of Medical Image data processing: Processing medical image data presents several constraints that significantly impact the extraction and analysis process. Visual data from medical photographs requires skilled analysts to interpret accurately, as errors in analysis can profoundly influence clinical decision-making. The task of recognizing, classifying, and categorizing individual photographs is inherently complex and demands specialized knowledge and training. Moreover, the time-consuming nature of analyzing medical imaging data can potentially delay disease detection and diagnosis, impacting patient outcomes. Additionally, while older image processing techniques may offer certain advantages, they often lack scalability and efficiency when dealing with large datasets of medical images. Balancing the benefits and drawbacks of different processing approaches is crucial in optimizing the use of technology for accurate and timely medical image analysis in healthcare settings. Addressing these challenges requires ongoing advancements in technology and methodologies to improve the speed, accuracy, and reliability of medical image data processing.

Obstacles for decision making

Effective decision-making in any context, particularly in complex domains like healthcare, faces numerous obstacles that can significantly impact outcomes. One critical challenge lies in the reliability of input data sources and the ability to uncover hidden information within this data. Ensuring the accuracy, completeness, and relevance of input data is essential for making informed decisions, yet the validation and verification processes can be resource-intensive and time-consuming. Another obstacle is the absence of standardized guidelines to ensure the quality of input data. The lack of clear criteria or frameworks for assessing data integrity and reliability can lead to uncertainty and inconsistency in decision-making processes. This issue is exacerbated in fields where data variability and ambiguity are prevalent, such as in healthcare diagnostics and treatment planning. Furthermore, the challenge of justifying decisions adds another layer of complexity. Without transparent and well-documented rationale for decisions made, stakeholders may question the validity or fairness of outcomes, impacting trust and confidence in the decision-making process. Addressing these obstacles requires robust systems and methodologies that prioritize data reliability, establish clear quality standards, and provide mechanisms for transparent decision justification. By enhancing these aspects, organizations can improve the efficacy and trustworthiness of decision-making processes, ultimately leading to better outcomes and patient care in healthcare and beyond. The Image form of clinical data consists of:

(a) Medical Images: These images canbe produced using different technologies as given below [37-42]:

Figure 2 CT scan of Lungs [51]

Figure 2 shows the CT scan of Lungs that is produced by using multiple x-ray images having different angles/cross-sections.

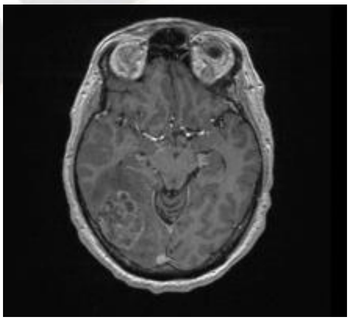

Figure 3 MRI scan of Brain[52]

Figure 3 shows the Magnetic Resonance Imaging (MRI) scan of brain that is produced using radio waves and magnetic fields.

Figure 4 Ultrasound image of Lever[53]

Figure 5 X-ray ofChest[54]

The ultrasonic picture of Lever created by use of high-frequency sound waves is shown in Figure 4. The X-ray picture of the chest produced by ionising radiation is shown in Figure 5.

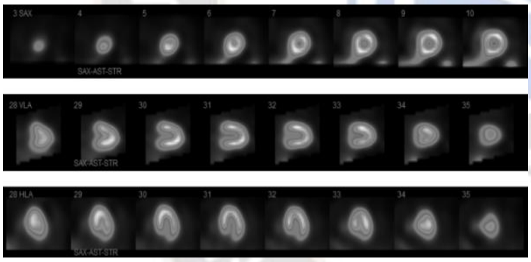

Figure 6 Nuclear medicine of Heart[55]

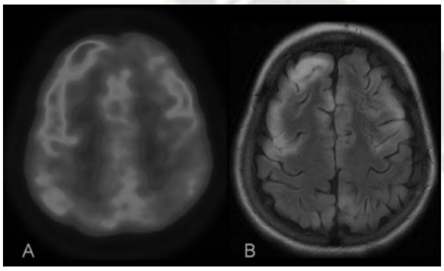

Figure 7 Positron-emission Tomography of Brain[56]

Nuclear medicine creates images of the heart using radioactive tracers and The picture of the brain created by PET utilizing radionuclide's is shown in Figure 7. Each patient is given a specific sort of scan based on the practitioner's needs. Following Figure7 shows the Text form of clinical data that is consists of:

- Meta Data: Data pertaining to the patient's medical history, lab results, personal information, feedback, illness, diagnosis, and therapy, and so on.

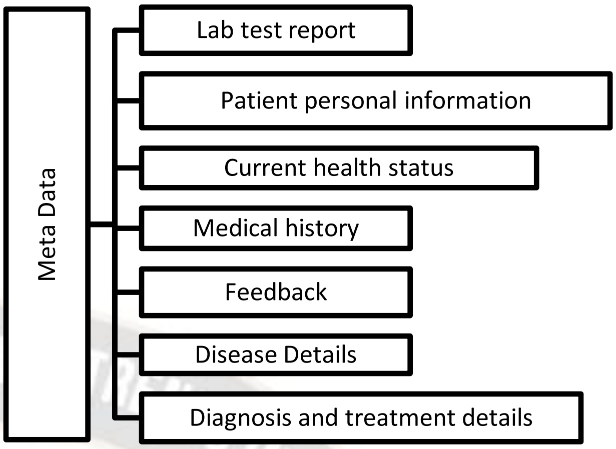

Figure 8 Meta Data

With the assistance of different machine learning algorithms, AI can extract the customised information from the aforementioned data, which is utilised to construct a comprehensive medical record of patients. Some possible uses for these facts are:

- Prediction of diseaseand diagnosis through
  - Medical image processing
  - Clinical Text data mining
- Development of automated decision support system
- Drug discovery and human trials
- Surgical operations using robotics

Following figure 8 shows the various approaches that can be adapted for machine learning to achieve the above discussed points:

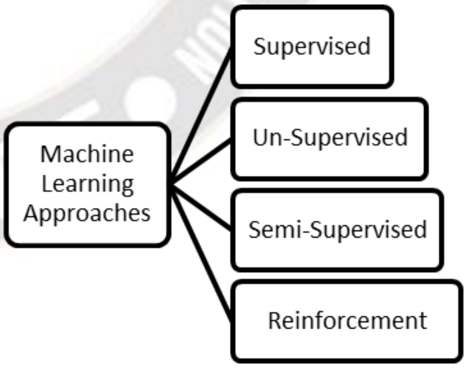

Figure 8. Machine learning Approaches

While supervised learning makes use of input datasets for training, unsupervised learning does not while semi-supervised learning makes use of labelled datasets. The output is fine-tuned via reinforcement learning using feedback values [1–5]. Following are the algorithms, applications and merits of these learning approaches:

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1) Supervised Learning methods: Supervised learning methods such as logistic and linear regression, support vector machines, decision trees, k-nearest neighbors, and naive Bayes are integral to various applications across diverse fields. In bioinformatics, these techniques are employed for tasks like gene expression analysis and protein structure prediction. Object recognition systems utilize these methods to classify objects in images, while character and speech recognition applications rely on them for accurate transcription and understanding of spoken language.

Applications

However, these methods also come with limitations. One significant challenge is the trade-off between bias and variance, where overly complex models may fit training data too closely (high variance) but fail to generalize well to new data (high bias). Another limitation involves the diversity of input data types, dimensions, and volumes, which can affect the performance and scalability of supervised learning algorithms.

Merits

The merits of supervised learning include the ability to leverage known facts and existing knowledge bases, allowing for continuous updates and improvements as new data becomes available. Training methods in supervised learning can be generalized to minimize errors and enhance predictive accuracy across different scenarios and datasets.

Limitations

Despite these challenges, supervised learning methods continue to be essential tools in data-driven decision-making processes, offering powerful capabilities in classification, prediction, and pattern recognition tasks across numerous domains, including healthcare, finance, and technology.

2) Un-Supervised Learning methods: Unsupervised learning methods like principal component analysis (PCA), cluster analysis, anomaly detection, and neural networks play crucial roles in various applications where data lacks predefined labels or categories. PCA is used for selective feature selection, reducing the dimensionality of data while retaining its essential characteristics. Cluster analysis groups similar data points together, enabling segmentation of complex datasets into meaningful subsets. Anomaly detection identifies unusual patterns or outliers that deviate from expected behavior, crucial in fraud detection and system monitoring.

Applications

However, unsupervised learning methods also have limitations. They generally produce less accurate results compared to supervised learning because there is no ground truth for validation. Evaluating the effectiveness of clustering or anomaly detection algorithms can be subjective and context-dependent, requiring domain expertise for interpretation.

Merits

The merits of unsupervised learning lie in its ability to discover underlying patterns and structures in data where facts and relationships are initially unknown. These methods allow models to autonomously learn from the data environment, revealing insights that may not be apparent through manual analysis.

Limitations

Despite these challenges, ongoing research aims to improve the accuracy and efficiency of unsupervised learning techniques through advancements in algorithmic design, computational resources, and applications of hybrid approaches that combine supervised and unsupervised learning principles.

3) Semi- Supervised Learning methods: Semi-supervised learning methods, such as generative models, low-density separation, Laplacian regularization, and heuristic methodologies, bridge the gap between supervised and unsupervised learning by leveraging both labeled and unlabeled data. Generative models create synthetic data to augment training sets, enhancing model robustness and performance.

Applications

These methods find applications in diverse fields such as sound wave analysis for speech recognition, content classification in natural language processing, and pattern sequencing in genomic research.

Merits

However, semi-supervised learning also presents limitations. The accuracy of models can be sensitive to the iterations and adjustments made during training, requiring careful optimization to achieve optimal results.

Limitations

Continued advancements in semi-supervised learning aim to address these challenges, enhancing the adaptability and effectiveness of these techniques across various applications.

Reinforcement Learning methods: Reinforcement learning methods, such as the criterion of optimality, brute force, value function, and direct policy search, represent a powerful approach to training machine learning models through interaction with an environment to maximize cumulative rewards. These methods are categorized into associative reinforcement, deep reinforcement, inverse reinforcement, and safe reinforcement, each tailored to different types of learning tasks and environments.

Applications

These techniques find applications across diverse fields such as healthcare services, where they optimize treatment plans and patient monitoring systems, and in finance and trading for algorithmic trading strategies.

Merits

The merits of reinforcement learning include its ability to refine outcomes through extensive simulations, enabling models to learn from trial and error to find optimal solutions. This makes it particularly suitable for solving complex problems where traditional methods may struggle to find effective strategies.

Limitations

Despite these limitations, ongoing research and advancements in reinforcement learning algorithms and techniques continue to expand its applicability and effectiveness across various domains, promising continued innovation in automated decision-making and adaptive systems development.

Combination of machine learning approaches with HCS can boost the overall diagnosis process as well it can also enhance the decision making process.

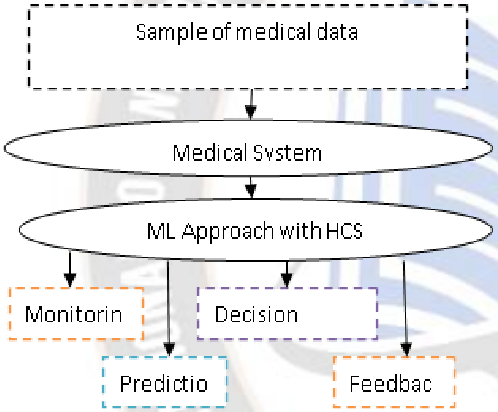

Figure 9 Machine learning with healthcare system

Machine learning methods cannot process the medical data directly, first of all, its preprocessing is required as shown in flow chart:

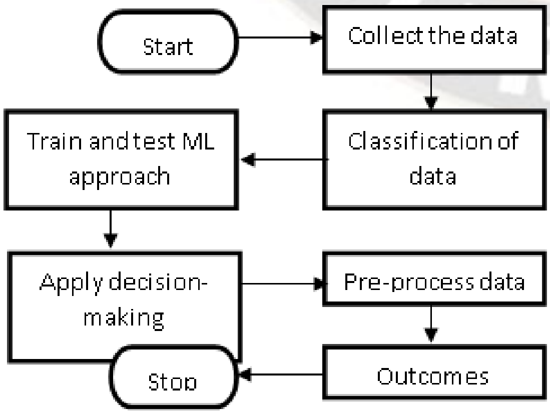

Fig Flow Chart Machine learning based medical data processing

The process begins with the collection and categorization of medical data according to specific needs. The next step is to create training models and choose a machine learning approach. Finally, the data is processed to provide results that can be used for diagnosis and decision-making. The following sections discuss the work of different researchers and how it has benefited various stakeholders, including patients and practitioners.

II. Machine Learning Based Prediction Schemes for Healthcare Industry

Machine learning algorithms may improve the accuracy of illness detection and diagnosis by creating training datasets from clinical data and estimating the current disease stage and health state.The prediction for healthcare services based on machine learning is described in the following section:

Machine learning-based approaches that may accurately predict survival from echocardiogram results utilising a small number of input factors were investigated by M. D. Samadet al. [6].Compared to machine learning algorithms, conventional approaches' reliance on ejection fraction and comorbidity-based prediction models yields worse accuracy, according to the study.

Analytical findings show that the Functional Independence Measure technique outperforms the standard methods when compared to a patient readmission prediction model established by Y. Xue et al. [7]. The model was compared to methods based on Support Vector Machine and Random Tree. By determining the best receiver operating characteristic curve cutoff point, we were able to refine the model's sensitivity and accuracy throughout training and validation using preexisting clinical data. The findings show that it has the potential to both enhance healthcare service quality and decrease total treatment costs.

After looking at the correlation between hypertension and chest noises, A. Clim et al. [8] concluded that a prediction technique based on Kullback-Leibler Divergence might improve clinical decision support over more conventional approaches.

Researchers C. R. Olsen et al. [9] looked at how ML algorithms might help with cardiac illness detection. Findings from the study suggest that these techniques may be useful for both diagnosis and the development of prediction models based on patient categorization. Combining these techniques with the BigData framework also allows for the analysis of large-scale illness datasets.

A prediction framework for the study of older patients' health was created by F. Y. Qin et al. [10]. It perfumes the feature classification to generate the predicates. The last step is to utilise a dataset for both training and validation. In comparison to more conventional methods (ANNs and SVMs), experimental data demonstrate that it achieves superior prediction accuracy.

In order to identify patients with early-stage cancer symptoms, X. Du et al. [11] created a perdition model.

Analysis reveals that the suggested scheme beats conventional techniques in terms of a number of characteristics, including sensitivity, specificity, F1-Score, precision, recall, ROC curoff, and more. It processes input parameters using both linear and non-linear models.

A method for predicting the likelihood of mental issues after brain surgery was devised by Y. Wang [12] and colleagues. By identifying potential dangers and then tailoring therapies, medications, and treatments accordingly, medical professionals may lessen the likelihood of patients developing certain diseases. A number of measures, including sensitivity, specificity, F1-score, precision, recall, ROC curve, and others, were used to analyse the proposed scheme using several algorithms, including decision tree, regression, random forest, and gradient boosting. The use of machine learning algorithms has the potential to lower the prevalence of mental diseases, according to experimental findings.

In order to gather patient data that may be used for cardiac disease predictions, K. N. Qureshi et al. [13] used a mobile platform. In terms of ideal accuracy, sensitivity, and specificity, it surpasses current approaches such as neural networks, support vector machines, and native bayes. It has the potential to be expanded in order to study the effects of different types of brain injury on humans.

Using several binary classification models, A. Akbulut et al. [14] created a prediction technique that makes use of clinical information to forecast the state of anomalies. Among the models tested, decision tree based models outperformed the others, including logistic regression, decision forest, boosted decision tree, averaged perceptron, bayes point machine, decision jungle, locally-deep support vector machine, neural network, and averaged perceptron. It can be easily transferred to a mobile platform for analysis of massive datasets.

In order to forecast whether or not a patient will be dissatisfied after knee surgery, K. N. Kunze et al. [15] used a random forest method. As input for the prediction chart, it takes into account numerous factors, such as age and medication allergies. Based on the findings of the experiments, it is possible to optimally forecast health risks and dissatisfaction levels utilising feedback, and patients' health condition may be improved. The problem of inadequate data validation, however, remains unsolved and may be addressed in due course.

To forecast the severity of childhood malnutrition, A. Talukder et al. [16] used a variety of machine learning methods, including logistic regression, linear discriminant analysis, support vector machines, k-nearest neighbours, and random forest. Data was gathered from all throughout the country and used for the aim of perdition. According to the results, random forest is the best technique since it has better specificity, accuracy, and sensitivity. Additional applications of this research include healthcare service improvement, identification of related health risks, and management of malnutrition.

Table 1 Prediction schemes for healthcare industry

Ref. ID	**contribution**	**Algorithms/tools used**
6	Prediction Model for the survival and risk assessment of heart patients after diagnosis	Random Forest Tree
7	Prediction Model for patient readmission	Regression, SVM, Random Tree
8	Prediction of hypertension through sound analysis	Kullback-Leibler Divergence
9	Prediction of heart failure	Regression
10	Prediction of health status of eldery patients	Artificial Neural Network
11	Perdition model for the detection of cancer symptoms in patients at early stages	Linear / non-linear models
12	Predict the probability of mental disorders	Decision Tree / Regression /Random Forest / Gradient Boosting
13	Forecasting of heart disease	Neural Network / SVM / Native Bayes
14	Prediction of anomaly status	different binary classification models
15	Prediction of dissatisfaction after knee surgery	random forest
16	Prediction of malnutrition level in children	logistic regression / linear discriminate analysis / SVM / KNN / random forest

III. Automated Decision support system

In the case of the primary healthcare system, clinicians must manually review potentially error-prone and very complicated and time-consuming clinical data. All of these things have an impact on the diagnostic process and reduce the effectiveness of decision making. Using machine learning algorithms may change the traditional approach of analyzing medical data for decision making. Researchers' contributions to these fields are detailed in the section that follows.

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H. Yin et al. [17] created a system that can gather information from computationally aided medical systems and a variety of wearable sensors. To process and categorise patients according to illness types, a technique based on machine learning is used. Decision making and diagnostic purposes also make use of the output data. Both the treatment accuracy and the ability of practitioners to use different datasets to enhance healthcare services may be shown by experimental findings.

For the purpose of diagnosing chronic pulmonary disorders, S. Anakal et al. [18] presented a decision support system. Various machine learning approaches, such as Decision Trees, Support Vector Machines, Neural Networks, Classifier Ensembles, etc., are used. Based on the outcomes of the experiments, medical professionals may adjust their treatment plans and use the system feedback to control their patients' dosages. Support for telemedicine in outlying locations is possible via integration with cloud platforms.

The need to handle large-scale medical data, which may be provided in text or picture form, and the complexity of storing and correlating the facts in this data were examined by A. P. Eremeev et al. [19] in order to make decisions. Research indicates that, in comparison to conventional databases, NoSql databases are better suited to hold such datasets since they allow for excellent query execution response times and are readily integrated with machine learning technologies.

Medical conditions such as heart disease, diabetes, and cancer may be better diagnosed and treated with the use of machine learning techniques, according to research by K. Shailaja et al. [20]. According to the research, various schemes have varying degrees of accuracy for different diseases. For example, when it comes to heart diseases, native bayes has the highest level of accuracy, while diabetes patients get better results from methods based on classification and regression, and when it comes to cancer, support vector machine gives the best predictions. The study's analytical data may be used to enhance the precision of other machine learning technologies.

An alternate treatment type may be used by practitioners to prevent these adverse effects, as H. R. Mansilla et al. [21] shown a decision support system that can analyse the risk of infection following surgery. The accuracy level of the outputs is balanced by combining support vector machine and decision tree. The results of the experiments demonstrate that the diagnostic techniques may be optimised by the calculation of infection risk.

A decision support system for diabetic patients was created by A. Yahyaoui et al. [22]. It uses a deep learning technique for illness prediction and diagnostic assistance. When compared to more conventional methods (Random Forest/Support vector machine), the experimental findings demonstrate its superior performance in terms of prediction accuracy. Incorporating deep feature extraction may significantly improve its accuracy.

Based on existing datasets constructed from various medical data resources (lab test/patient health records), C. Comito et al. [23] created an automated decision support system that may aid practitioners. Experimental findings demonstrate that early symptom detection and diagnostic plan suggestion for specified illnesses may be achieved using deep learning.

In order to forecast and control paediatric obesity, A. Triantafyllidis et al. [24] investigated the possibility of combining machine learning algorithms with electronic health records and decision support systems. Based on the results, decision tree/neural networks may make accurate predictions, and early detection of obesity can lead to more successful treatment methods. The results of this study's analyses might be useful for developing a mobile diagnostic platform.

W. O. N.d. Hollosy et al. [25] built a decision-support system to identify low back pain patients using supervised learning approaches (Decision Tree/Boosted Tree/Random Forest).According to the results, only few metrics (specificity, accuracy, sensitivity, and precision) change during the testing and validation processes. Nevertheless, this system may interact with global large-scale databases and shorten the whole diagnostic procedure.

The use of machine learning techniques to decision support systems was studied by N. P. Smadja et al. [26]. Research shows that these schemes' effectiveness is dependent on input datasets that lack comprehensive symptom information, and that the accuracy of decisions may vary across different types of diseases.

A number of technologies, including machine learning, classification, and picture fusion, were investigated by M. Diwakara [43] in relation to the identification of cardiac illness.

Automatic Decision Support System (Table 2)

The results demonstrate that these techniques can improve decision making, and the data collected from this research may be used to create new techniques.

Ref. ID	**Contribution**	**Algorithms/tools used**
17	Decsion support system for detection and diagnosis of diseases	K-base learner / Meta learner
18	Decision support system for chronical lung disease	SVM / Decision Tree / NN Classifier
19	Decision support system for infection over surgical sites	SVM/Decision Tree

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20	Decision support system for the diabetic patients	SVM / Random forest / Neural networks
21	Automated framework for decision support to detect the diseases at earlier stages	Deep learning / NLP/ Neural networks
22	Decision support framework for diabetic patients	Random Forest/Support vector machine
23	Automated decision support system to assist the practitioners	deep learning
24	Integration of machine learning schemes with electronics health records and decision support system	decision tree/neural networks
25	Diagnose of low back pain	Decision Tree / Random Forest
26	Survey	Decision support
43	Survey for methods to detect heart disease	ML / classification / image fusion

IV. Drug discovery and human trials using machine learning

Drug Depending on factors such as the kind of illness, symptoms, dosage, frequency of ingestion, etc., the creation process might be lengthy and intricate.

Since new drugs might have negative impacts on human bodies, it's crucial to identify the potential dangers of the medication's development process and its consequences on patients' health and illnesses before conducting human drug trials. The medication development and testing processes may be automated with the use of machine learning. The next section delves into the answers that other researchers in the relevant field have come up with:

The difficulties of pharmaceutical research and medication development were studied by L. Zhao et al. [27]. Research indicated that there are few factors (datasource, quality, format, validity, authenticity, data rate, volume, values) that directly affect the cost of drug development.By integrating machine learning and deep learning algorithms across big data platforms, we can analyse large-scale drug-related data. This might potentially reduce the total cost of drug research and development.

The influence of disease-drug associations on medication development was investigated in a survey by C. Réda et al. [28]. According to the research, machine learning algorithms can help build a comprehensive database of diseases. This could cut down on research costs, allow for earlier human trials, and use the data from those trials to improve drug modelling, dosage, accuracy, and more.

In order to determine the correlation between medication responses and patients, R. Ietswaart et al. [29] created a model based on the random forest technique. Machine learning offers a platform for random experiments without the need for humans or animals, and a large-scale analysis of drug reaction associations can optimise the failure rate of drug trials. Various parameters, such as accuracy, correlation coefficient, recall curve, and precision, were used to verify the model's performance.

N. T. Issa et al. [30] investigated cancer-related drug development challenges and discovered that drug repurposing strategies can be defined for disease diagnosis and drug development cost optimisation can be achieved by processing existing large-scale cell datasets through machine learning algorithms. According to the results, training datasets may be revised with the use of comments in order to keep experiment accuracy high.

To find the best machine learning methods for cancer detection and diagnosis, M. Ali et al. [31] looked at several different methods for extracting cell-related data from cancer patients and creating training datasets. Results show that cell feature extraction and medication response to patient health may both optimise drug development costs and forecast how cancer treatments will work.

In order to determine the effects of machine learning-assisted drug development, P. Bannigan [44] performed a survey. A new study suggests that the pharmaceutical sector may benefit from automated drug discovery processes, which might lead to the development of more effective treatments in less time.Machine learning approaches may optimise the time, cost, and effort spent on medication development, according to the analysis.

L. Adlung [45] undertook an extensive study to determine the benefits of automated approaches compared to conventional decision-making processes. Research shows that with the use of machine learning, human processors of clinical data may achieve higher accuracy.

A study by R.S. Joshi [46] sought to understand the role of ML in surgical procedures; results showed that ML may help surgeons assess patients' present condition and make diagnostic recommendations.

Ref. ID	**contribution**	**Algorithms/tools used**
27	Computer assisted drug development	Bigdata, machine learning

28	Automated drug development for pharmaceutical industry	Feature extraction using Machine / Deep learning
29	Drug reactions and development of safer healthcare solutions	Random Forest
30	drug repurposing using machine learning	Random Forest, NLP, SVM
31	Prediction model for drug response and sensitivity against disease	Multiple kernel learning
44	Survey	Impact analysis of ML assisted drug discovery
45	Survey	Automation of decision making
46	Survey	Impact analysis of ML in surgical operations

V. Surgical operations with machine learning assistance

Patients' prognoses for recovery after a complex surgical procedure are uncertain. The risk of adverse effects on the patient's health persists even after the procedure has healed. The potential dangers and adverse consequences of surgery on patients' health must be thoroughly investigated. To get around these problems, you may use machine learning methods, which are detailed below:

In their study, L. Štěpánek et al. [32] examined how machine learning is used to plastic surgery. They utilised a dataset of numerous facial expressions and conducted multivariate linear regression in R. Neural networks and Bayesian naïve classifiers/decision trees may both map face images to emotions more accurately, according to the experimental data.

The dangers of surgical wards were investigated by T. J. Loftus et al. [33]. In these settings, rapid evaluation of high-risk patients is crucial, and healthcare services run the risk of failing due to incorrect diagnoses and treatment suggestions. Wearable sensors may provide electronic health records in real time, and medical data can be further analysed using machine learning techniques to detect symptoms early and achieve improved diagnostic accuracy, all of which mitigate these kinds of dangers.

The use of VR in surgical procedures and how it interacts with machine learning systems were the subjects of research by A. W. Schwartz et al. [34]. According to the research, stakeholders may benefit from a large-scale knowledgebase that is built using a mix of the two technologies.

In order to improve the results of face cosmetic surgery, L. Štěpánek et al. [35] examined the extraction and categorization of facial characteristics using a machine learning algorithm. It is possible to enforce geometrical characteristics and have enough datasets as proof that both contribute to face beauty quality, according to analytical data.

In order to find a way to use decision tree models to anticipate problems, K. Merath et al. [36] examined the datasets linked to several surgical procedures (liver, pancreatic, and colon). The results of the experiments demonstrate its effectiveness in terms of more precise prediction and more efficient diagnosis-related risk analysis. Using an EHR system may expand its applications.

Ref. ID	**contribution**
32	Machine learning based assistance for plastic surgery
33	Machine learning based risk assessment of patients
34	AI applications for medical experts
35	features extraction
36	Prediction model for surgical operations

Highlights the above discussed contribution of various researchers in this domain:

Table 4 Surgical operations with machine learning assistance.

	Contribution
Section-I	This section introduced the concept and role of artificial intelligence based solutions for healthcare industry. It described the various sources of clinical data, its forms and the available machine learning based approaches etc.
Section-II	This section described about the various existing solutions that can be used for prediction of disease and its diagnosis purpose, patient's health status etc.
Section-III	This section discussed about the automated decision support system and clinical data collection/processing based on machine learning approaches.

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Section-IV	This section explored the complex stages of drug discovery and its trial over patients and how machine learning algorithms can optimize this time consuming process.
Section-V	This section investigated the side effects of surgery over patient's health, risks and machine learning assisted surgical operations etc.

Table 5 Summary

VI. CONCLUSION

The issues of AI and machine learning were discussed. These principles inspired many academics to build the modern healthcare system. Readmission, hypertension, heart disease/cancer symptoms, geriatric patient mental issues, abnormal status, patient dissatisfaction after surgery, children's health care and malnutrition, etc. may be predicted using perdition models.For training, validation, and diagnosis, machine learning with traditional decision support systems lets practitioners utilise existing datasets. Research suggests electronic health records, wearable sensors, and real-time patient data may enhance diagnosis and treatment. Machine learning algorithms can detect patient illness behaviour and therapy effects. Automated drug trials may cut drug development expenses. This chapter covered AI and ML. The contemporary healthcare system would not exist without researchers who saw the promise in these technologies. Readmission, hypertension, heart disease or cancer symptoms, elderly mental health issues, abnormality status, patient discontent after surgery, child malnutrition, and poor health treatment are perdition models.

Machine learning enhances training, validation, and diagnosis in classical decision support systems utilising previous datasets. Electronic health records and wearable sensors can monitor patients' data in real time to improve diagnosis and treatment, according to studies. Machine learning algorithms may assist explain how diseases and therapies impact patients' behaviours and health. Automatic drug trials may reduce medication development expenses by eliminating human or animal testing. Cost, quality, data rate, how medicines influence illnesses, trial success rate, and other drug research and development aspects were examined.

Machine learning may assist surgeons analyse patient health risks and predict surgical results to reduce risk. Patient input may improve diagnosis. Virtual reality in surgery, facial expression classification, and health hazards were studied. Machine learning may improve medical data analysis and treatment. This will lower large-scale healthcare data processing and testing expenses. The study's methodology and conclusions included concerns with pharmaceutical modelling, medical data integration with automated systems, input data validation, processing enormous medical data prediction models for sickness diagnosis, and treatment cost. Using machine learning to enhance healthcare is planned.

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