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A Comprehensive Survey of Machine Learning and Deep Learning Methods for Clinical Decision Support Systems

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Abstract

A Clinical Decision Support System (CDSS) is a type of health information technology that helps doctors and nurses make clinical decisions. Health information technology (HIT), especially clinical decision support systems (CDSSs) that work with electronic health records (EHRs), can help people make more consistent judgments based on evidence. There have been many published examples of CDSS success stories in the last ten years or more. CDSS has evolved as an essential component in contemporary healthcare, thereby altering the method in which medical professionals make decisions, with the goals of enhancing clinical decision-making, improving patient outcomes, and optimizing healthcare delivery. CDSSs can help in diagnosis, treatment, patient management, and prevention, which can lead to better patient outcomes, fewer medical errors, and better quality. Clinicians generally use modern CDSS solutions at the point of care, where the system gives them data-driven insights and suggestions that help them improve their skills. Priorities include investing in strong IT infrastructure, extensive training programs, and public awareness campaigns, as well as making CDSSs work better with EHR platforms. India can use CDSSs to improve patient care and outcomes if government agencies, healthcare institutions, and technology suppliers work together to remove these impediments. Overall, CDSS is a big step forward for smart healthcare systems. It makes clinical workflow more efficient and helps patients get better results. Finally, it is evaluated with two datasets from the UCI repository, and its performance is high in deep learning when compared with the other techniques in terms of accuracy, sensitivity, and specificity.

Keywords: Clinical Decision Support Systems, Electronic Health Records, Public Health, Patient Safety, and Health Information Technology

1. Introduction

CDSS (Clinical Decision Support System) aims to enhance clinical decision-making by integrating knowledge from various sources, such as clinical guidelines, medical literature, patient data, and expert opinions, to generate actionable insights and recommendations. These systems can be standalone software applications or integrated into electronic health record (EHR) systems, allowing seamless access to decision support functionalities within the clinical workflow. Good decision-making is a difficult undertaking, especially when it comes to health. For many years, clinical decision-making has profited from the application of several strategies to assist, expedite, or improve decisions [1]. Utilization of decision making in Health Information Technology (HIT), and more specifically in Clinical Decision Support Systems (CDSSs), provides a solution to solve these difficulties. India is well-known for its wide socioeconomic and ethnic variety, which presents both opportunities and challenges for the provision of healthcare that is equal. The cultural, religious, linguistic, and social diversity exist in India presents a unique set of obstacles when it comes to providing an equal healthcare system. Since its inception, the healthcare system in India has been plagued by a number of challenges, including inconsistent service quality, fragmented data, and limited access to inexpensive medical treatment. The introduction of Health Information Technologies (HITs) provides clinicians with newfound hope in regard to these urgent concerns. In areas with limited resources, Health Information Technology (HIT) presents a one-of-a-kind opportunity to close gaps in clinical capacity and decision making. According to a number of studies, Health Information Technology (HIT) frequently results in greater relative advantages in low-resource or undeveloped settings, which are characterized by a lack of traditional healthcare infrastructure [2]. Clinical Decision Support System (CDSS) is a system that is built on a foundation of medical knowledge, algorithms, and patient data. Its primary objective is to bridge the gap between huge amounts of medical information and fast, educated clinical judgments. At its foundation, the Clinical Decision Support System (CDSS) functions as a cognitive aid, providing doctors with assistance in navigating the intricacies of modern medicine. To provide healthcare providers with individualized recommendations, reminders, and alerts during the process of providing care, it performs an analysis of patient data, medical literature, and best practices. In light of the extensive implementation of electronic health record (EHR) systems, clinical decision support (CDS) has emerged as an essential element of the contemporary healthcare infrastructure. Computerized alerts and reminders, clinical recommendations, diagnostic support tools, order sets, and risk assessment models are all examples of potentially useful interventions that can be implemented by CDS. The goal of clinical decision support (CDS) is to increase adherence to best practices, reduce variability in care, and minimize preventable medical errors by integrating these technologies into clinical processes [3]. The use of Artificial Intelligence-driven Clinical Decision Support Systems (AI-CDSS) in healthcare has changed the way doctors work, promising better diagnosis, better treatment results, and more efficient operations. As these systems get better and more people use them, they are having a bigger impact on how healthcare resources are used and how priorities are set. AI-CDSS have been employed in triage systems to enhance patient prioritization in emergency departments. An AI-integrated clinical decision support systems (CDSS) have the potential to provide assistance in a variety of clinical activities, including but not limited to diagnosing, devising treatments, and evaluating risks. This helps to alleviate the burden of duty that physicians have while simultaneously improving patient outcomes. Because of the complex structure of health systems and the enormous amount of information that they contain, there is an extremely high demand for tools that are both intelligent and adaptable [4]. Fig 1 illustrates how the clinical decision support works.

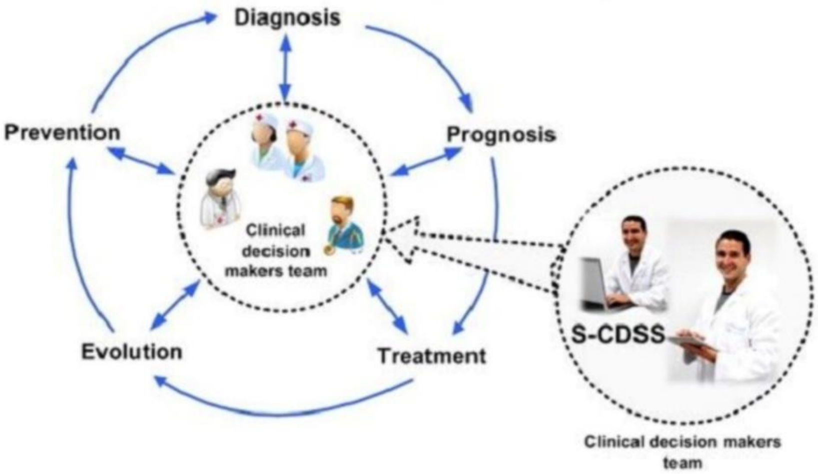

Figure 1: An overview of Clinical Decision Support

1.1. Clinical Decision Support Systems with and without AI

For decades, Clinical Decision Support Systems (CDSS) have been used in healthcare to help medical staff make fewer mistakes. CDSS are meant to make healthcare better by giving clinicians relevant, timely, and valuable clinical knowledge that helps them decide on diagnosis, prognosis, and therapy. The simplest CDSS works by comparing a patient's traits to a computerized clinical knowledge source[31].

Early rules-based clinical decision support systems (CDSS) only gave basic diagnostic help, but they were still useful in clinical decision support because they found high-risk patient groups and cut down on misdiagnosis. CDSS can help with many parts of the healthcare process, such as illness prevention, screening, diagnosis, treatment, and follow-up. They can also save medical expenditures by lowering the negative effects of pharmacological treatments. In today's world of electronic health records (EHR), CDSS are commonly part of the EHR. Nonetheless, some physicians have articulated apprehensions regarding their confidence in CDSS upon its integration into their workflows.

Researchers have looked into AI interventions in healthcare through randomized controlled studies. AI-CDSS have developed to deliver predictive clinical insights by utilizing medical data from many domains, resulting in the publication of over 500 clinical prediction models based on EHR data and 44 reports on implementation studies. A small majority of EHR-based AI-CDSS used in published research have shown some improvement in clinical outcomes after they were put into use. For instance, CDSS have demonstrated the ability to forecast the likelihood of diabetic complications in persons with diabetes and assist doctors in determining the most suitable timing for diagnostic tests. AI models can give explanations that are either global or local. Global explanations explain the whole model, whereas local explanations explain just one prediction. Ante-hoc or inherently explainable procedures are clear on their own, while post-hoc understandability approaches give information about an output after the model has made it. Recent progress in explainable AI-CDSS to boost clinician trust has included text, graphical, and visual explanations, among other things. For instance, a convolutional neural network that helped diagnose glaucoma used class activation mapping to make heat maps for visual processing. An AI-CDSS for detecting women at risk for gestational diabetes mellitus utilized Shapley additive explanations to visually depict model properties. Stakeholder analysis indicates that clinicians favor AI-CDSS characterized by feature importance and transparency concerning the model's confidence or uncertainty in its predictions. Our research offers both qualitative and quantitative assessments of usability for an AI-CDSS employing post-hoc techniques, so enhancing the comprehension of clinicians' faith in the utilization of AI-CDSS. Fig illustrates the key interactions in knowledge-based and non-knowledge-based CDSS, and AI-powered interfaces.

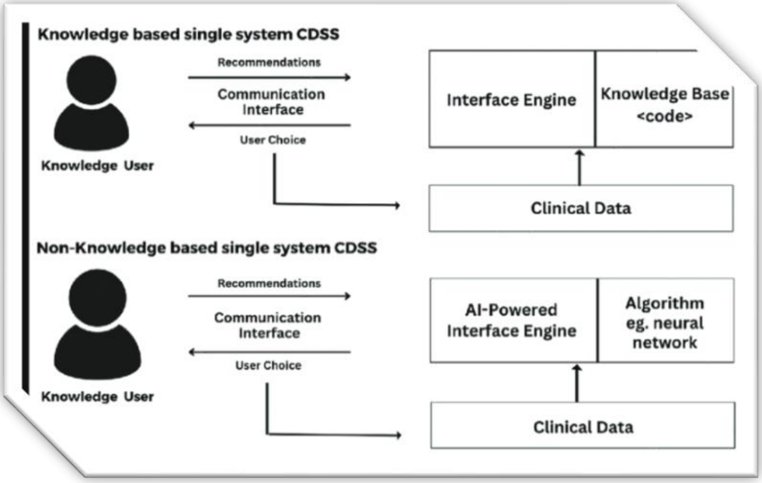

Figure 2: Diagram of key interactions in knowledge-based and non-knowledge-based CDSS

1.2. Classification of CDSS

Clinical Decision Support Systems (CDSS) can be categorized according to their application domain, technology, functionality, and knowledge source. The following are the main categories.

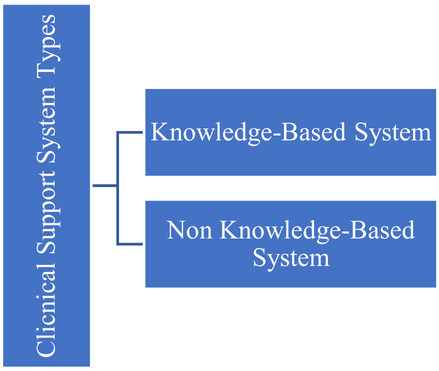

Figure 3: Types of Clinical Decision Support Systems

1.2.1. Knowledge-based systems

Techniques used in Knowledge-based systems.

- Rule-Based Systems - Rule-based systems, also known as expert systems, are a method for developing a knowledge-based CDSS in which data is formatted according to rules and then assessed to produce a final output.
- Expert Systems - These systems use a structured knowledge base and an inference engine to come up with ideas for diagnosis, recommendations, or treatments.
- Decision Trees systems - Decision tables are unique tables, which have conditions related to one or more decisions. One or more decisions or actions are linked to a set of conditions.
- Fuzzy Logic - Fuzzy logic systems are very important for clinical decision support systems because they can handle the ambiguity, imprecision, and vagueness that come with medical data and decision-making. This framework uses fuzzy sets, fuzzy rules, and linguistic variables to solve these problems.
- Ontology-Based Reasoning - Utilize organized medical knowledge representations to facilitate clinical thinking and decision making.

1.2.1. Non-knowledge-based systems

Non-knowledge-based CDSS still need a source of data, but instead of being programmed to follow expert medical knowledge, they use AI, ML, or statistical pattern recognition to make decisions. Non-knowledge-based CDSS are a quickly increasing way to employ AI in medicine; however, they come with a lot of issues, such as not being able to comprehend how AI makes suggestions (black boxes) and not having enough data.

Techniques used in Non-Knowledge-based systems**:**

- Logistic Regression - Logistic regression models look at how several independent variables (such a patient's age, lab findings, symptoms, and medical history) are related to a dependent outcome variable.
- Random Forest - Random Forest is a supervised ensemble machine learning algorithm widely used in Clinical Decision Support Systems.
- K-Nearest Neighbor - K-Nearest Neighbor is a way to classify data points based on how close they are to a set of other points.
- Support Vector Machine - It is also a classification algorithm that can detect the classes that are present in the data that is provided. During the training process, the algorithm is given data that has already been divided into two categories. With the help of this constructed model, the class identification of the new data point is carried out. Not only does it serve the purpose of classifying the items, but it also provides the margins between them on the plot with the greatest feasible width.

- Naïve Bayes- The naive Bayes classifier assumes that the presence of one feature in a class does not affect the presence of any other feature. This classifier just needs the class feature because the other class features don't have anything to do with each other.
- Gaussian Process - It is useful in statistical modeling and used to take benefits from the properties that are inherited from the normal distribution.

1.3. CDSS Operations

CDSS work in the background of the main application and give the physician information on the patient's condition, such as alarms, warnings, or predictions about what will happen next. CDSS has four operational inputs, namely [21]:

1. Triggers: Events that cause decision support rules to be used (Ex: prescribing a medicine).

2. Input data: Information that decision support functionality uses to draw conclusions about a patient, such as their demographics or lab findings.

3. Interventions: Various actions that the decision support function can take, like sending a reminder message to a doctor or showing a clinical practice guideline.

4. Offered choices: The options a clinician has after using the CDSS feature (Ex: picking between different suggested drugs or therapy).

The operational parameters defined above can be used to develop three principal categories of CDSS:

1. Passive systems: This is the most frequent type of CDSS. The user must ask the system for help in this mode.

2. Semi-active systems: These systems automatically send information, accepted knowledge, and guidelines on how to do things. They act as a watchdog, letting a doctor know about a certain clinical circumstance.

3. Active systems: These are also set off automatically and can make choices without the help of a doctor. For instance, orders for more tests based on health protocols, therapeutic tests (automatic control of a transfusion by a closed-loop system), or supervision systems (like smart control of a ventilator's parameters).

2. Literature Review

Aarav et al [2025] [5] developed a complete Heart Failure Prognostication System using the Django web development platform. The system uses a data-driven method for prognostic analysis that looks at a variety of patient characteristics and medical records. Django's ability to grow and change makes the web app easy for healthcare workers to use to securely enter and manage patient data. The backend has powerful machine learning algorithms that use big datasets to predict how heart failure will progress and how bad it will be. Some of the most important features of this system are real-time risk assessment, personalized treatment suggestions, and the ability to see prognostic insights. The Django framework makes it easy for the front-end and back-end to talk to each other, which guarantees a fun and responsive user experience. The answer also meets industry standards for protecting data and privacy. This program will help doctors and nurses find heart failure quickly, which will lead to better care and outcomes for patients. Not only does the Django web app make the process of predicting outcomes easier, it also sets the stage for future advances in cardiovascular health informatics.

Sreejith et al [2022] [6] proposed a classification model integrated with optimization techniques and machine learning algorithms. Having features that don't matter can make any classifier work less well. This study examines the influence of specific features on classification accuracy and automatically detects and eliminates irrelevant features from the dataset. It uses the Red Deer Algorithm (RDA) to find the best features and the random forest (RF) classifier to test them. RDA is an optimization algorithm that takes its cues from how red deer mate and roar. Made tests on the PCOS dataset, which you can find in the Kaggle dataset repository. An RF classifier with 50 estimators was used to train and test the best dataset. The reasons for using RDA as the search method were its better exploration and exploitation abilities. This method is new because it uses a new fitness function that takes into account both the accuracy of the classification and the best number of features. The suggested CDSS is 89.81% accurate. The results of the proposed work were juxtaposed with the efficacy of rival methodologies documented in the literature. The Logistic Regression classifier, k-Nearest Neighbour (k-NN), Decision Tree, Naïve Bayes, Support Vector Machine (SVM) classifier, RF-PSO, RF-Ant Colony Optimization, and RF-Genetic Algorithm have been shown to be better in terms of accuracy, sensitivity, and specificity.

Choi et al [2023] [7] developed a clinical decision support system for emergency rooms that uses machine learning and is based on how doctors make decisions. Using data on vital signs, mental status, lab results, and electrocardiograms from a stay in the emergency room, extracted 27 fixed features and 93 observation features. Some of the outcomes were intubation, admission to the intensive care unit, administration of an inotrope or vasopressor, and cardiac arrest while still in the hospital. eXtreme gradient boosting algorithm was used to figure out what would happen and predict it. Looked at the F1 score, the area under the receiver operating characteristic curve (AUROC), the area under the precision-recall curve, and the specificity, sensitivity, and precision. The models were able to accurately predict outcomes (AUROC>0.9), and the model with a lagging value of 6 and a leading value of 0 had the highest value. The AUROC curve for cardiac arrest in the hospital changed the least, and all outcomes became more delayed. When inotropic drugs were used, a person was intubated, or they were admitted to the intensive care unit, the AUROC curve changed the most with the leading 6 information (lagging). To improve how well the system works in this study, a human-centered approach was used to copy the way emergency doctors make clinical decisions. Clinical decision support systems that are based on machine learning and can be tailored to different clinical situations can help improve the quality of care.

Ibraheem et al [2024] [8] suggested a mixed RNN model that combines SimpleRNN, LSTM layers, and echo state cells to better handle long-term dependencies. We also present CG-Net, a new Convolutional Neural Network (CNN) framework for classifying gastrointestinal diseases that works better than previous CNN models. We improve model performance even more by adding more data and using transfer learning. This makes the model more general and less likely to break down when data is missing or not balanced. A lot of tests, like 5-fold cross-validation and measurements like accuracy, precision, recall, F1-score, and Area Under the Curve (AUC), show that the models are reliable. To make models easier to understand, SHapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are also used. Results showed that the suggested models greatly improve the accuracy and speed of diagnosis, making big steps forward in WBANs and CDSS.

Tutun et al [2023] [9] suggested the Network Pattern Recognition (NEPAR) algorithm to create the assessment tool and to figure out what questions users need to answer as part of the DSS development process. Then, the answers to these questions and other historical data are used to train different machine learning models that can guess if a person has a mental disease and what kind it is. This study uses advanced analytics and artificial intelligence to create a Decision Support System (DSS) that can quickly find and identify different mental illnesses. The findings indicate that the suggested DSS can accurately identify mental illnesses with just 28 questions, without any help from a person, 89% of the time. The suggested mental disorder diagnostic tool also has a lot of fewer questions than its competitors, which means that more people will take it and finish it. Mental health professionals can use this suggested DSS and the assessment tool that goes with it to make better clinical decisions and diagnoses.

Almazroi et al [2023] [10] proposed a Keras-based deep learning model to get results with a thick neural network in the suggested method. Different arrangements of hidden layers in the dense neural network, from 3 to 9 layers, are used to test the suggested model. The ReLu activation function is used by 100 neurons in each buried layer. Several heart disease datasets are used as standards for the research. The test evaluates both single models and groups of models, and it's run on all heart disease datasets. The dense neural network is also tested on all datasets using important metrics such as sensitivity, specificity, accuracy, and the F-measure. Different datasets have different attribute categories, so the success of different layer combinations varies. The results of the suggested framework are studied by doing a lot of experiments. The study's results show that the deep learning model suggested in this research paper is more accurate, sensitive, and specific when used on all heart disease datasets compared to single models and other ensemble methods.

Tanya et al [2023] [11] created and used a new cloud-based decision tree CDSS for on-call eye care consultations. Using current rules and the opinions of experts, a web-based decision tree algorithm was created. After getting specific details about the patient's eye problem, the algorithm gave them a preliminary diagnosis and a level of urgency before sending an electronic referral to the on-call eye clinic. Descriptive statistics were used to describe the data. Cohen's kappa coefficient and Spearman-rho correlations were used to describe the connections that were seen. Analysis of contingency tables and modified residuals were used for post hoc analysis. The CDSS gets a more accurate diagnosis and sense of urgency, makes it easier to collect information, and gets rid of the need for old-fashioned paper-based consultations.

Bernardini et al [2026] [12] showed a clinical decision support system based on machine learning that can use normal laboratory tests to figure out the risk of hepatic fibrosis in people with NAFLD. The framework is made from data from electronic health records that were gathered over 15 years and originally included 1,272,572 patients from general practice. Two groups of 12,960 and 25,478 patients were chosen based on clinical criteria and then used for model building and evaluation. Using a new screening method that preprocesses predictors by using well-established clinical indicators (e.g., hepatic steatosis index, fibrosis-4 index) along with a chosen minimal number of predictors, the proposed approach provides a strong foundation for monitoring fibrosis risk. It is also practical and cost-effective for wide clinical use. The study's results show that screening and keeping an eye on the risk of fibrosis in NAFLD patients can work well, with the best AUC of 92.97%, PRAUC of 75.44%, and Sensitivity of 79.63%.

Katib et al [2026] [13] proposed an approach called Artificial Intelligence with Deep Convolutional Neural Network Based Clinical Decision Making in Kidney Oncology (AIDCNN-CDMKO). The main goal of the AIDCNN-CDMKO methodological framework is to help doctors make decisions about how to accurately identify and classify kidney tumors. The AIDCNN-CDMKO algorithm given here uses the Gaussian filter (GF) to improve picture clarity by lowering noise and making features easier to find. Moreover, the integration of feature extraction models, including VGG16, MobileNetV1, and EfficientNetB5, is utilized to obtain comprehensive and complementary representations from multimodal imaging data. The attention mechanism-based CNN and bi-directional long short-term memory (CNN-BiLSTM-AM) classifier is used to find kidney cancer. To confirm the enhanced analytical outcomes of the AIDCNN-CDMKO methodology, comprehensive simulations are performed utilizing the CT Kidney and RCC Kidney Histopathology datasets. The comparative analysis of the AIDCNN-CDMKO shown an enhanced accuracy rate of 98.33% and 98.42% across the dual datasets.

Abugabah et al [2026] [14] introduced TransYOLO-GJO an explainable and optimized detection framework that integrates transformer-based attention mechanisms into the YOLOv9 architecture and leverages the Golden Jackal Optimization (GJO) algorithm for hyperparameter tuning. The transformer encoder enhances contextual feature extraction, particularly in dense breast regions, while GJO dynamically adjusts critical hyperparameters such as anchor sizes, learning rates, and attention configurations to maximize detection performance. The model was trained and evaluated on the CBIS-DDSM dataset, achieving a mean Average Precision (mAP) of 95.1% and an F1-score of 93.2%, outperforming traditional baseline models. Interpretability was incorporated through Grad-CAM heatmaps and SHAP-based feature attribution, enabling radiologists to visualize the decision-making process. The results confirm that the proposed framework not only enhances diagnostic accuracy but also strengthens trust in AI-assisted clinical decision support systems, making it a promising solution for real-world deployment in breast cancer screening.

Kehkashan et al [2026] [15] suggested a 1D CNN model for predicting cardiodiagnostics that is easy to understand and combines automated feature extraction with AI. Utilized a 1D CNN model with two convolutional layers, one with 64 filters and the other with 128 filters. The CNN will be trained on the Cleveland Heart Disease Dataset (Kaggle), which has 303 occurrences and 14 attributes. It will then be tested for accuracy, precision, recall, F1 score, and LIME-SHAP interpretability. The results show that the model did quite well, with an accuracy of 98.05%, a precision of 100%, a recall of 96.12%, an F1 score of 98.02%, an MCC of 0.963, and a Kappa coefficient of 0.961. Our findings surpass numerous contemporary methodologies presented in the literature. LIME and SHAP analyses elucidate the influence of individual features (sex, number of main vessels, thalassemia status) on model projections, hence improving interpretability and correlating with clinical insights into cardiac risk factors critical for precision medicine. This study illustrates the capacity of interpretable deep learning to revolutionize cardiovascular diagnostics via improved clinical decision support systems and reliable AI integration in precision medicine.

Singh et al [2023] [16] created a hybrid method for locating relevant features by combining two algorithms, ESO and the GSO algorithm, and getting rid of unimportant features and making things easier. Soft computing technologies and machine learning algorithms create a framework for prognostic research by sorting data examples into relevant and irrelevant categories based on the severity of cancer. So, this study showed a new way to sort breast cancer tumors. Integrated soft computing methodologies—our constructed algorithms are utilized for the first time in this context—with artificial intelligence-driven machine learning tactics to develop a predictive model. Tested our suggested method on WDBC breast cancer data sets, and the results demonstrate that our proposed hybrid algorithm works very well for breast cancer classification. Achieved remarkable results, with accuracy at 98.9578%, sensitivity at 0.9705, specificity at 1.000, precision at 1.000, F1-score at 0.9696, and an AUC of 0.9980 (approaching the maximum of 1.0000). Integrated our findings into a reliable clinical prediction system, enabling visual science experts to provide more precise and efficient decisions in the future. In addition, our proposed method could be employed to identify various disorders.

Niraula et al [2023] [17] created a comprehensive AI-based optimal decision-making system for DTR oncologists. We created an interactive software tool called Adaptive Radiotherapy Clinical Decision Support (ARCliDS) to demonstrate the proposed framework for KBR-ART applications. Artifcial RT Environment (ARTE) and Optimal Decision Maker comprise ARCliDS. ARTE is supervised learning-modeled Markov decision procedure. ODM uses reinforcement learning and ARTE training. ODM can optimize daily dosage modifications to promote tumor local control and minimize side effects. Graph Neural Networks (GNN) use inter-feature interactions to increase modeling performance, and a unique double GNN architecture avoids nonphysical treatment response. Two clinical trials on adaptive RT in NSCLC and adaptive stereotactic body RT (SBRT) in HCC patients provided datasets of 117 and 292. We generated 10,000 simulated patients using Generative Adversarial Networks for ODM training. The ODM was trained on synthetic patients and verified on the original dataset. Double GNN architecture corrected the nonphysical dose-response trend and improved ARCliDS recommendation. For NSCLC and HCC, ARCliDS with double GNNs reproduced 36% and 50% of good clinical judgments (local control and no side effects) and improved 74% and 30% of unfavorable clinical decisions. In conclusion, ARCliDS is the first web-based multi-omics data tool for KBR-ART. ARCliDS can learn from reported clinical decisions and encourage AI-assisted clinical decision-making to improve DTR outcomes.

Rehman [2026] [18] created and tested using 1298 type 2 diabetes and non-diabetic patients with training dataset of 650 and test dataset of 648. The system used BMI, plasma fasting glucose, and hemoglobin A1C to predict. A 105-patient clinical pilot trial compared the system's diagnostic accuracy to non-endocrinology specialists. At 99.8% accuracy, the AI-CDSS predicted diabetes, 99.3% prediabetes, 99.2% at-risk persons, and 98.8% no diabetes. In the test dataset, Endocrinologists and the AI-CDSS agreed 98.8%. Type 2 diabetes was found in 45% of 105 pilot research participants. The AI-CDSS exhibited a 98.5% concordance rate, compared to 85% for nonendocrinology specialists. The AI-CDSS may be effective for accurately detecting type 2 diabetes, especially in cases when diabetes specialists are unavailable.

Ertugrul et al [2025] [19] proposed the Pediatric Obesity and Weight Management (PedOWM) tool, a semantic rule-based Clinical Decision Support System (CDSS) intended to evaluate and address juvenile and adolescent obesity utilizing national anthropometric data. PedOWM was evaluated utilizing retrospective auxological data from 100 Turkish children, primarily consisting of overweight and obese persons, while also included cases from additional BMI categories, including underweight and normal weight. The algorithm looked at anthropometric measurements and made therapy recommendations based on its semantic principles. The examination encompassed visual plot comparisons, expert assessments by a pediatric endocrinologist, statistical analyses, and a performance comparison between PedOWM’s recommendations and those of the clinical expert. PedOWM's treatment suggestions were quite similar to those made by clinical experts. The system's accuracy was 99.5%, its precision was 97.1%, its recall was 97.5%, and its F1-score was 97.6%.

Aiosa et al [2023] [20] proposed a new Clinical Decision Support System (XAI-CDSS) based on eXplainable Artificial Intelligence. It is a whole tool with three main parts: prediction models, XAI interpretation, and a graph-based view of non-communicable diseases. Machine learning algorithms are suggested to forecast the risk variables associated with the direct correlation between obesity and comorbidities, including cardiovascular disease, heart disease, and diabetes. Multilayer perceptron and extreme gradient boosting from a group of machine learning techniques because they worked best for predicting the risk factors of the chosen comorbidities. They can predict diabetes with an accuracy of 0.72 and cardiovascular and heart disease with an accuracy of 0.73. The intuitive XAI interface helps the end user understand how the machine learning decision-making process works. The graph visualization shows how these co-occurring pathologies are related to other non-communicable diseases and gives healthcare professionals a global view that can be used to prevent obesity and related diseases and for long-term treatment and care.

Singh [2024] [21] developed an automated clinical decision support system (CDSS) that would help doctors make better decisions about patients and improve the way healthcare is given. This suggested method put a lot of weight on making changes that meet the needs of the patient, parent, and doctor. A flexible framework that can pick out hepatitis, skin problems, hepatic disease, and autism in adults and give people the results as advice was done. The unique thing about this CDSS is that it uses both rough set theory (RST) and machine learning (ML) to make healthcare decisions more accurate and useful. A rough set method was used for feature selection to get rid of elements that were highly redundant or not important. Then, different machine learning methods were used to look at four public medical datasets from the UCI repository and Kaggle. These methods included K nearest neighbors (KNN), LSVM, radial basis function support vector machine (RBF SVM), decision tree (DT), random forest (RF), and Naive Bayes (NB). The model was built, and its performance was evaluated using accuracy, recall, F1-score, and root mean square error (RMSE), among other validity metrics. The results showed that important features of hepatitis, skin conditions, hepatic disease, and autism found by RST and RF were 92.85%, 90.90%, 100%, and 80% similar respectively.

Nayaki [2024] [22] proposed a Clinical Decision Support System (CDSS) employing deep learning methodologies, with particular emphasis on Recurrent Neural Networks (RNNs) and Bidirectional Long Short-Term Memory (LSTM) networks. The algorithm is meant to guess medical diseases based on 132 clinical symptoms and target prognoses. We trained and tested a number of models, including Support Vector Machine, Decision Tree, K-Nearest Neighbors, deep learning architectures, and Logistic Regression. We used important measures like recall, precision, F1-score, and accuracy to measure their performance. The Bidirectional LSTM network surpassed conventional machine learning techniques, exhibiting a superior capacity for managing sequential clinical data with an accuracy of 90.16%. This study underscores the potential of deep learning models to enhance diagnostic accuracy and dependability, presenting exciting developments for clinical decision-making systems.

Islam [2023] [30] This model was created to be a clinical decision support system (CDSS) by using multiple machine learning techniques to guess who has type 2 diabetes. The publicly accessible Pima Indian Diabetes (PID) dataset was utilized for research purposes. We employed data preparation, K-fold cross-validation, hyperparameter tuning, and different machine learning classifiers, such as K-nearest neighbor (KNN), decision tree (DT), random forest (RF), Naïve Bayes (NB), support vector machine (SVM), and histogram-based gradient boosting (HBGB). To make the outcome more accurate, a few different scale methods were also applied. To improve the system's effectiveness for future study, a rule-based approach was adopted. After that, DT and HBGB were more than 90% accurate. Because of this outcome, the CDSS was put into place. Users can enter the necessary input parameters through a web-based user interface to gain decision help and some analytical data for each patient. The deployed CDSS will help doctors and patients make decisions about diabetes diagnosis and give real-time suggestions based on analysis to improve the quality of care. For future endeavors, the aggregation of daily data from diabetes patients could facilitate the development of an enhanced clinical support system for global daily decision-making assistance for patients.

Table 1: An overview of prediction models in different diagnosis/departments

Authors	Diagnosis/Departments	Methods	Merits	Demerits
Aarav et al [2025] [5]	Heart disease	Gradient Boosting and Django-based Web Frameworks	Simplifies the prognostication process	May be slower than lightweight frameworks for high-frequency
Sreejith et al [2022] [6]	Polycystic Ovarian Syndrome	CDSS using Red Deer algorithm and Random Forest classifier	Algorithm is superior in terms of accuracy, sensitivity, and specificity	High Computational Complexity, lack of Interpretability
Choi et al [2023] [7]	Emergency Department	CDSS with eXtreme gradient boosting algorithm	Improved the quality of care	Absence of a real-time patient information acquisition system limits the model's applicability in dynamic ED settings.
Ibraheem [2024] [8]	Real-time medical Query processing	Mixed RNN	Improved the accuracy and efficiency.	Have to reduce data imbalance issues.
Tutun [2023] [9]	Mental health disorder	Network Pattern Recognition (NEPAR) algorithm	It provides diagnostic accuracy.	Not fully optimal.
Almazroi [2023] [10]	Heart disease	Keras-based deep learning model	More accurate.	Limited Flexibility for Research.
Tanya [2023] [11]	Ophthalmology triage	Cloud-based decision tree CDSS	Fast Decision Making.	Medical data stored in cloud may be vulnerable to cyber-attacks.
Bernardini [2026] [12]	Hepatic Fibrosis Risk Prediction	ML-based CDSS	High transparency.	Risk of cyber-attacks or data breaches.
Katib [2026] [13]	Kidney disease	Artificial Intelligence with Deep Convolutional Neural Network-Based Clinical Decision Making	Shows a superior accuracy value.	Lacks validation on real-time or streaming medical data.

Abugabah et al [2026] [14]	Breast cancer	TransYOLO-GJO	Enhances diagnostic accuracy	High Computational Complexity
Kehkashan et al [2026] [15]	Heart disease	1D CNN model	Automatically extracts important features from clinical raw data	Works quickly with smaller dataset.
Singh et al [2023] [16]	Breast cancer	Eagle Strategy Optimization (ESO) and Glowworm Swarm Optimization	Simple implementation	Not suitable for highly complex problems
Niraula [2023] [17]	Radiotherapy	Adaptive Radiotherapy Clinical Decision Support	Clinicians understanding	Limited Handling of Continuous Data
Rehman [2026] [18]	Diabetes	AI-Driven Clinical Decision Support System	Predicts prediabetes using patient data	Lack of transparency
Ertugrul [2025] [19]	Pediatric obesity	Pediatric Obesity and Weight Management CDSS	Provide promising findings on the applicability, effectiveness, and efficiency of PedOWM	Difficult to integrate with existing Electronic Health Records
Aiosa et al [2023] [20]	General	eXplainable Artificial Intelligence (XAI-CDSS)	Transparency	Increased Computational Cost
Singh et al [2024] [21]	General	Rough Set Theory and ML-based CDSS	More accurate	Difficulty Handling continuous data
Nayaki et al [2024] [22]	General	Recurrent Neural Networks (RNNs) and LSTM (Bidirectional Long Short-Term Memory)	Reduces need for manual temporal feature engineering	Difficulty capturing long historical medical information
Islam et al [2023] [30]	Diabetes	ML-based CDSS	Improves medical quality by providing real-time analysis-based suggestions	Better CDSS have to be updated for daily decision support for patients worldwide.

3. Research Gap

Even though Clinical Decision Support Systems (CDSS) have come a long way, there are still some key research gaps in knowledge-based, non-knowledge-based, and hybrid approaches. Rule based and expert systems encounter difficulties in ongoing knowledge updating, scalability for multimorbidity management, and customization for varied patient demographics. Decision tree and ontology-based models frequently encounter difficulties in managing temporal, partial, or heterogeneous clinical data, hence constraining their applicability in real-world scenarios [22]. Data-driven methods like Machine Learning and Deep Learning are very good at making predictions, but they have problems with biased and retrospective datasets, not being able to be used by different institutions, not having enough large annotated medical datasets, and being hard to understand, which makes clinicians less likely to trust and use them. Natural language processing and Bayesian networks are two examples of technologies that still have trouble getting accurate and standardized information from unstructured electronic health records. This is especially true in large-scale healthcare settings where Bayesian networks have to deal with complex calculations and structural learning problems.

Also, hybrid CDSS models that mix knowledge-based reasoning with machine learning don't have standard frameworks or strong multi-center validation tests. New technologies like cloud-based CDSS, IoT-integrated systems, and explainable AI raise more issues around data protection, interoperability, cybersecurity, and following the rules. Another important gap is in workflow integration. To make CDSS solutions that are scalable, easy to understand, safe, and clinically validated, we need to fill all these gaps. These solutions can then be used reliably in modern healthcare settings.

4. CDSS Dataset

Clinical Decision Support Systems (CDSS) need high-quality clinical datasets to make accurate and trustworthy recommendations. These datasets usually come from Electronic Health Records (EHRs) and contain information about the patient's age, gender, race, and ethnicity, as well as their medical history, lab test results, vital signs, diagnosis codes, medication details, and treatment outcomes. AI-based CDSS uses big, well-organized datasets to teach and test machine learning models that can help with disease prediction, diagnosis, and treatment planning. Researchers in academia often use publicly available datasets like MIMIC-III, which has data on patients in Intensive Care Unit, and the Pima Indians Diabetes Database, which is often used for diabetes prediction research. Imaging datasets and genetic libraries also help specialized CDSS applications in precision medicine and radiology. But the quality, completeness, variety, and compliance of the dataset with data privacy laws are very important for the CDSS to work well. Bad or biased data can have a big impact on how well the system works and how reliable it is in clinical settings. In this paper, we utilized UCI dataset for comparing the algorithms.

5. Quantitative analysis

Quantitative analysis is essential for assessing the performance, reliability, and clinical efficacy of Clinical Decision Support Systems (CDSS). As Machine Learning (ML) and Deep Learning (DL) techniques grow more common in healthcare, it is more important than ever to use objective numbers to quantify how accurate, strong, and generalizable they are. Quantitative analysis employs statistical metrics, performance indicators, and validation methodologies in a systematic manner to evaluate the efficacy of a CDSS model in facilitating clinical decision-making.

$$\text{Accuracy} = \frac{Truenegatives+Truepositives}{positives+negatives}$$

$$\text{Precision} = \frac{Truepositives}{Falsepositives+Falsenegatives}$$

$$\text{Sensitivity} = \frac{Truenegatives}{Falsenegatives+Truenegatives}$$

F-Measure = 2 * $\frac{Sensitivity * Specificity}{Sensitivity + Specificity}$

Here, the Cleveland Heart Disease dataset and the Hungarian dataset were compared yet we know that comparisons between research have their restrictions. Results are specific to the Cleveland dataset and Hungarian dataset more comprehensive evaluations across multiple datasets would provide better insights into model performance.

The CDSS datasets for cardiac illness are sourced from the publicly accessible machine learning UCI data collection, which is endorsed by numerous academics. There are certain things about each dataset that will help figure out if the patient has heart disease or not. The label property (num), which is the output feature, has categorical values that are either healthy or sick. 1 has replaced healthy values, and 0 has replaced sick values. The detail of each dataset is mentioned below.

- **Cleveland dataset:** Cleveland dataset contains 14 features. The 13 features are input features, and they don't depend on any other. The last column is an output feature that is basically a label attribute. It depends on the input characteristics. For example, if it is 0, it signifies the patient has heart disease; if it is not, it means they don't. The dataset has 303 examples in it [28].
- **Hungarian dataset:** Hungarian dataset contains 294 occurrences and 12 features. The output feature "num" is dependent on the input characteristics; however, the thirteen input features are unrelated to one another. Each value from 0 to 4 can be found in the label attribute "num". The patient is sick with heart disease if the values are 0, otherwise, they are not [29].

Comparison of Heart Disease datasets in CDSS

Table 2: Cleveland Dataset variation attributes

Data variation	Multivariate	Count of samples	303
Type of Attribute	Categorial, Int, Real	Number of attributes	14

Table 3: Hungarian Dataset variation attributes

Data variation	Multivariate	Count of samples	294
Type of Attribute	Int, Decimal	Number of attributes	12

Table 2 and Table 3 outlines the dataset variation in each attribute, attribute characteristics and output attribute range.

Techniques	Accurate	Specificity	Sensitivity	F-score
Nearest Neighbors	80.54	80	80.58	80.31
Linear SVM	79.83	75.65	79.55	79.53
Decision Tree	72.59	71.97	72.54	72.44

Naïve Bayes	81.23	79.28	81.16	81.01
AdaBoost	74.52	60.54	73.54	73.07
Deep Learning	82.49	77.08	87.24	84.41

Table 4: Evaluation Results of Various CDSS Techniques using Cleveland dataset

Techniques	Accurate	Specificity	Sensitivity	F-score
Nearest Neighbors	76.89	62.63	73.8	73.43
Linear SVM	81.31	66.27	78.04	78.46
Decision Tree	75.8	75.54	75.68	74.04
Naïve Bayes	82.31	76.72	81.12	80.36
AdaBoost	81.29	66.18	78	78.69
Deep Learning	83.03	69.27	90.9	87.37

Table 5: Evaluation Results of Various CDSS Techniques using Hungarian dataset

The Table 4 and Table 5 analyses showed that different dataset gives different range of values. Moreover, it is also analyzed that deep learning performs better compared to individual techniques. The reason behind better results is that automatic feature extraction and model training are done without human intervention [24].

Performance graphs and insights

Performance graphs show how well a CDSS system finds true positives (like correctly identifying an illness) while reducing false positives and false negatives. Researchers and healthcare practitioners can use the information from these graphs to compare algorithms, find overfitting or underfitting, check how well a model generalizes, and figure out how safe it is for patients.

Here, compared the accuracy, sensitivity, specificity, and F-score of individual classifiers with deep learning. The described graph shows that the proposed deep learning method has done much better in terms of accuracy, specificity, sensitivity, and F-score.

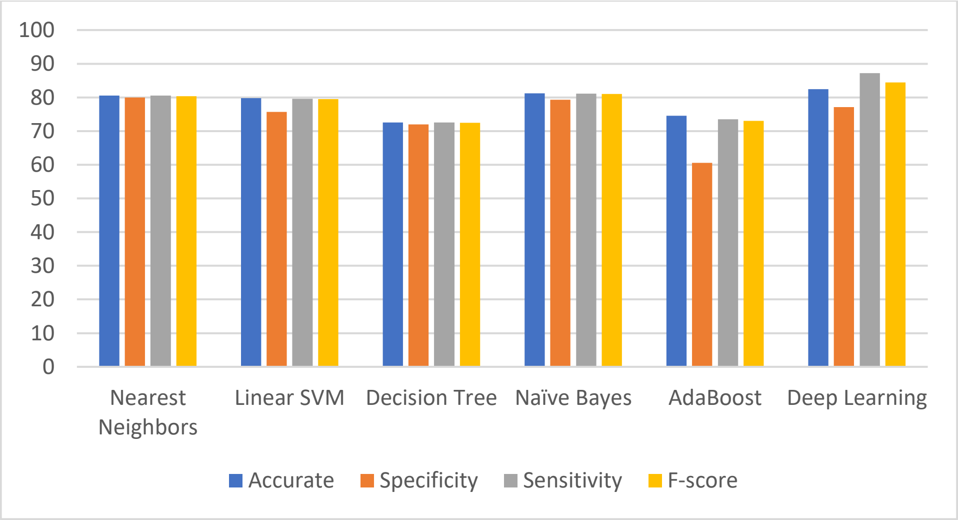

Figure 4: Graphical comparison of Results of Various CDSS Techniques using Cleveland dataset.

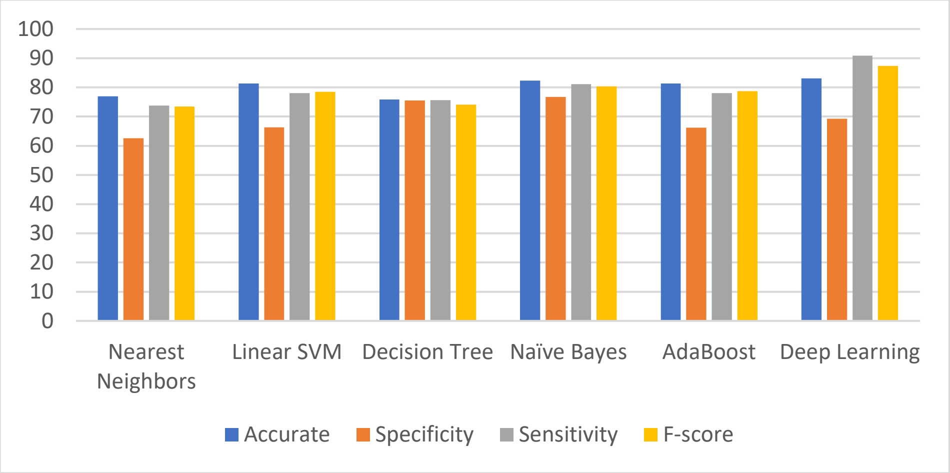

Figure 5: Graphical comparison of Results of Various CDSS Techniques using Hungarian dataset.

It is clear from the above Figure 3 and Figure 4 that, with different datasets, deep learning has performed significantly better in terms of accuracy, specificity, sensitivity and F-score.

Discussion

The main point of definition is to stress that CDSS is an active knowledge system that employs two or more classes of patient data to make medical suggestions that are customized to each instance. This indicates that CDSS is, indeed, a Decision Support System focused on the application of knowledge management in healthcare to derive medical recommendations by synthesizing various forms of contemporary options and information.

CDSS is a tool that helps therapists make better decisions about their patients by turning raw clinical data into meaningful information. CDSS is a piece of software that gives a healthcare system information so that it can deliver safe care. These details include standards and evidence-based instructions, actions and protocols, rules and ideas for care, medicine references and tools to figure out the right proportions, the future for connecting to a library, digital reference books, and/or online references.

The application of CDSS has the potential to provide significant assistance to doctors in the areas of early diagnosis, treatment planning, and risk assessment. In addition, the efficiency of the workflow was increased as a result of the implementation of automatic alerts and evidence-based suggestions. Despite the fact that these results are encouraging, there were a few obstacles that were discovered. These difficulties included data imbalance, missing values, and difficulties in integrating with the Electronic Health Record (EHR) systems that were already in place. As an additional point of interest, it was determined that in order to keep clinical dependability intact, continuous model updates and validation are required.

Taking everything into consideration, CDSS has the potential to improve the quality of decision-making and the outcomes for patients when it is backed by high-quality datasets and proper validation procedures. The focus of future research should be on enhancing the interpretability of models, minimizing bias, and ensuring that they can be seamlessly integrated into clinical settings that are based in the real world.

Conclusion

By giving real-time, evidence-based suggestions, CDSS helps lower the number of mistakes made in diagnosis and treatment. By giving healthcare providers evidence-based recommendations and alerts, it helps them make better decisions that lead to better patient outcomes. The CDSS was made as a tablet software that may be used without an internet connection for primary care professionals. It included a systematic decision-support system to help doctors figure out what was wrong with kids and how to treat them. The CDSS was customized to address local priority health issues, illness trends, available resources, and sociocultural factors affecting the resident and refugee populations. The design incorporated local terminology, language, and imagery for suitable clinical evaluation.

References

1. Bleher, H. and Braun, M., 2022. Diffused responsibility: attributions of responsibility in the use of AI-driven clinical decision support systems. AI and Ethics, 2(4), pp.747-761.
2. Thorakkattil, S.A., Sridhar, S.B., Abdulsalim, S., Karattuthodi, M.S., Chandra, P. and Unnikrishnan, M.K., 2025, September. Clinical Decision Support Systems in Indian Healthcare Settings: Benefits, Barriers, and Future Implications. In Healthcare (Vol. 13, No. 17, p. 2220). MDPI.
3. Elhaddad, M. and Hamam, S., 2024. AI-driven clinical decision support systems: an ongoing pursuit of potential. Cureus, 16(4), p.e57728.
4. Elgin, C.Y. and Elgin, C., 2024. Ethical implications of AI-driven clinical decision support systems on healthcare resource allocation: a qualitative study of healthcare professionals' perspectives. BMC Medical Ethics, 25(1), p.148.
5. J. Aarav Kannan, R. Rajalakshmi, A. V. A. Mary, S. Premalatha, R. J. Grace L K and S. Jancy, "Clinical Decision Support System for Heart Failure Prognosis Using Gradient Boosting and Django-based Web Frameworks," 2025 IEEE International Conference on Intelligent Signal Processing and Effective Communication Technologies (INSPECT), Gwalior, India, 2025, pp. 1-6
6. Sreejith, S., Nehemiah, H.K. and Kannan, A., 2022. A clinical decision support system for polycystic ovarian syndrome using red deer algorithm and random forest classifier. Healthcare Analytics, 2, p.100102.
7. Choi, A., Choi, S.Y., Chung, K. et al. Development of a machine learning-based clinical decision support system to predict clinical deterioration in patients visiting the emergency department. Sci Rep 13, 8561 (2023)
8. Ibraheem, I., Hashim, W., Thabit, R., Alrasheedy, M., Aljohan, A., Park, J. and Chang, B., 2024. Optimizing the Clinical Decision Support System (CDSS) by Using Recurrent Neural Network (RNN) Language Models for Real-Time Medical Query Processing. Computers, Materials, & Continua, 81(3), p.4787.
9. Tutun, S., Johnson, M.E., Ahmed, A., Albizri, A., Irgil, S., Yesilkaya, I., Ucar, E.N., Sengun, T. and Harfouche, A., 2023. An AI-based decision support system for predicting mental health disorders. Information Systems Frontiers, 25(3), pp.1261-1276.
10. A. A. Almazroi, E. A. Aldhahri, S. Bashir and S. Ashfaq, "A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning," in IEEE Access, vol. 11, pp. 61646-61659, 2023.
11. Tanya, S.M., Nguyen, A.X., Buchanan, S. and Jackman, C.S., 2023. Development of a cloud-based clinical decision support system for ophthalmology triage using decision tree artificial intelligence. Ophthalmology Science, 3(1), p.100231.
12. Bernardini, M., di Cosmo, M., Barone, G., Romeo, L. and Frontoni, E., 2026. Machine Learning-Based Clinical Decision Support System for Hepatic Fibrosis Risk Prediction in General Practice. ACM Transactions on Computing for Healthcare.
13. Katib, I., Ragab, M., Al-Hanawi, M.K., Alqurashi, M., Alghamdi, B.M., Alattas, S.G. and Al-Ghamdi, A.S.A., 2026. Artificial intelligence with deep convolutional neural network-based clinical decision-making on kidney Oncology using multimodal imaging. Scientific Reports.
14. Abugabah, A., Shukla, P.K., Shukla, P.K. et al. Enhancing breast cancer detection in mammographic imaging using explainable clinical decision support system and framework. Discov Artif Intell 6, 15 (2026)
15. Kehkashan, T., Abdelhaq, M., Al-Shamayleh, A.S., Riaz, R.A., Abdullah, M., Ahmed, A.I.A. and Akhunzada, A., 2026. Sustainable and interpretable heart disease prediction: a clinical decision support approach for biomedical healthcare applications.
16. Singh, L.K., Khanna, M. and Singh, R., 2023. Artificial intelligence based medical decision support system for early and accurate breast cancer prediction. Advances in engineering software, 175, p.103338.
17. Niraula, D., Sun, W., Jin, J., Dinov, I.D., Cuneo, K., Jamaluddin, J., Matuszak, M.M., Luo, Y., Lawrence, T.S., Jolly, S. and Ten Haken, R.K., 2023. A clinical decision support system for AI-assisted decision-making in response-adaptive radiotherapy (ARCliDS). Scientific Reports, 13(1), p.5279.

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18. Rehman, M.U., Rehan, I. and Khalid, S., 2026. AI-Driven Clinical Decision Support System for Enhanced Diabetes Diagnosis and Management. arXiv preprint arXiv:2602.11237.
19. Ertugrul, D.Ç., Akcan, N. and Bitirim, Y., 2025. Revolutionizing pediatric obesity intervention strategies: From traditional growth reference tools to AI-enabled pediatric obesity clinical decision support systems. International Journal of Medical Informatics, p.106109.
20. Aiosa, G.V., Palesi, M., Sapuppo, F. and Xibilia, M.G., 2023, October. Explainable AI-based clinical decision support system for obesity comorbidity analysis. In 2023 IEEE 19th International Conference on e-Science (e-Science) (pp. 1-6). IEEE.
21. Singh, K.N. and Mantri, J.K., 2024. A clinical decision support system using rough set theory and machine learning for disease prediction. Intelligent Medicine, 4(3), pp.200-208.
22. Nayaki, P., Ramana, A., SD, P.R., Thanabal, M.S. and NK, J., 2024, November. Clinical Decision Support System Using Recurrent Neural Network. In 2024 First International Conference on Data, Computation and Communication (ICDCC) (pp. 619-625). IEEE.
23. Wysocki, O., Davies, J.K., Vigo, M., Armstrong, A.C., Landers, D., Lee, R. and Freitas, A., 2023. Assessing the communication gap between AI models and healthcare professionals: Explainability, utility and trust in AI-driven clinical decision-making. Artificial Intelligence, 316, p.103839.
24. Paolo Fraccaro, Dympna O′Sullivan, Panagiotis Plastiras, Hugh O′Sullivan, Chiara Dentone, Antonio Di Biagio, Peter Weller, Behind the screens: Clinical decision support methodologies – A review,
25. Health Policy and Technology, Volume 4, Issue 1, 2015, Pages 29-38
26. Bain, A.P., Ngai, D. and Bernard, P.A., 2026. Clinical Decision Support Systems in Generalist Practice: Utilizing Clinical Decision Support Systems Tools to Improve Clinical Decisions and Patient Outcomes. Medical Clinics, 110(2), pp.191-207.
27. Almazroi, A.A., Aldhahri, E.A., Bashir, S. and Ashfaq, S., 2023. A clinical decision support system for heart disease prediction using deep learning. IEEE Access, 11, pp.61646-61659.
28. Suryawanshi, N.S., 2024. Accurate prediction of heart disease using machine learning: A case study on the cleveland dataset. Int. J. Innov. Sci. Res. Technol, 9(7), pp.1042-1049.
29. Bertalan, Á., Angyal, V., Domján, P., Sædder, E.A., Király, G., Erdélyi, L., Gyimesi, N. and Dinya, E., 2025. Development of an Artificial Intelligence Powered Medication Risk Score Calculator Application. Basic & Clinical Pharmacology & Toxicology, 137(4), p.e70109.
30. Islam, R., Sultana, A., Tuhin, M.N., Saikat, M.S.H. and Islam, M.R., 2023. Clinical decision support system for diabetic patients by predicting type 2 diabetes using machine learning algorithms. Journal of Healthcare Engineering, 2023(1), p.6992441.
31. Ouanes, K. and Farhah, N., 2024. Effectiveness of artificial intelligence (AI) in clinical decision support systems and care delivery. Journal of medical systems, 48(1), p.74.