

Explainable Deep Learning Models for Improved Clinical Decision Support Systems

Dr. Kavita K. Ahuja, Assistant Professor, Prime Institute of Computer and Management, VNSGU, Gujrat, India
prof.ahujakavita@gmail.com

Abstract: As electronic medical records proliferate and artificial intelligence advances, clinical decision support systems (CDSSs) aid healthcare providers in diagnostic and therapeutic choices. Conventional knowledge-driven CDSSs rely on curated medical databases and fixed inference rules, offering transparent reasoning but facing high costs for data curation and uniformity. Data-driven CDSSs leverage extensive datasets and machine learning algorithms for robust predictions, yet they suffer from opaque "black-box" operations that undermine reliability. CDSSs incorporating explainable AI (XAI) deliver interpretable justifications for outputs, fostering trust through visualization of decision pathways. Despite these benefits, current XAI-CDSS implementations are constrained by limited data scopes and insufficient model interpretability. This research introduces an innovative XAI-CDSS architecture to overcome these challenges, outlines applicable datasets, resources, and models, and establishes a versatile foundational model for decision support across diverse medical conditions. We conclude with prospective advancements in CDSS innovation and underscore critical societal considerations to unlock their full clinical potential.

Keywords: AI in Healthcare, Deep learning, Clinical decision support system

I. Introduction

Clinical decision support systems (CDSSs) aid healthcare professionals in disease diagnosis and management by analyzing patient-specific clinical data [1]. Recent progress in big data analytics and artificial intelligence (AI) has sparked significant interest in integrating these technologies into CDSSs. In particular, AI-powered CDSSs offer substantial benefits, enhancing clinical processes such as diagnosis, medication recommendations, outcome predictions, and therapeutic planning through sophisticated AI algorithms. Initially designed for image analysis, convolutional neural networks (CNNs) have expanded into diverse medical imaging tasks, including identifying abnormalities, delineating organs, and categorizing pathologies. CNN-driven CDSSs excel by employing layered feature learning and spatial relationships, enabling thorough examination of medical visuals—a marked advancement compared to conventional machine learning approaches in CDSSs. CDSSs traditionally divide into knowledge-driven types, which use pre-established rules, and non-knowledge-driven types, which operate without fixed rules [2].

Knowledge-driven CDSSs derive conclusions from established data patterns and conditional (if-then) logic. Their key strength lies in the clear visibility of the decision pathway due to reliance on explicit guidelines; however, a drawback is the necessity to anticipate and codify rules for every possible scenario upfront.

In contrast, non-knowledge-driven CDSSs derive decisions by identifying patterns in historical clinical data through machine learning or AI techniques, without relying on explicit rules. These systems have been widely explored across medical fields, including hypertension, heart failure, and pulmonary conditions [3,4]. They hold promise as a transformative approach, minimizing the expenses associated with knowledge curation while enabling tailored patient care. Nevertheless, the inherent "black-box" nature [5]—where the underlying mechanisms producing AI outputs cannot be elucidated—poses challenges for adoption in healthcare settings that demand full transparency.

To deploy such systems effectively, rigorous clinical testing and validation, or compelling supporting evidence, become essential. Put differently, knowledge-driven CDSSs require resource-intensive expert input to formalize evidence from literature, clinical practice, or patient data, whereas non-knowledge-driven CDSSs falter due to their opacity, rendering them impractical for real-world medical use. Explainable AI (XAI) [6] emerged to address this by demystifying the operations of AI systems. XAI encompasses techniques and procedures that empower users to interpret and rely on machine learning outcomes.

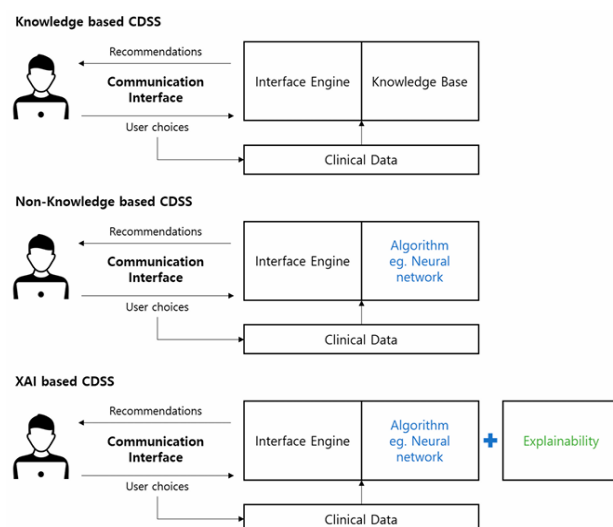


Figure 1: Difference between knowledge based, non-knowledge based, and XAI based CDSSs.

The key contributions of this work are outlined below:

- Conducting a thorough systematic analysis of explainable AI approaches that enhance reliability and clarity in medical applications, while outlining a prospective pathway for XAI-enhanced CDSSs.
- Organizing diverse research—from legacy CDSSs to advanced XAI-CDSSs—using suitable classification standards, and distilling the strengths and drawbacks of each type to advance a pioneering XAI-CDSS framework.
- Presenting a groundbreaking CDSS architecture built on contemporary XAI tools, illustrated by pinpointing domains where it offers the greatest utility and promise.

Core attributes of XAI include developing machine learning methods that (1) deliver interpretable models without sacrificing predictive efficacy (e.g., accuracy) and (2) allow effective comprehension, appropriate confidence, and efficient oversight of advanced AI collaborators. Variations among knowledge-driven, non-knowledge-driven, and XAI-driven CDSSs are illustrated in Figure 1 [7]. XAI renders AI decision processes and justifications accessible to users. Broadly, XAI methods fall into feature-centric, model-centric, complexity-reduction, and technique-oriented categories. In healthcare, where accountability is paramount, XAI-CDSSs combine superior AI capabilities with interpretability, paving the way for practical applications. Specifically, they clarify the logic and evidence supporting AI predictions within clinical workflows. For instance, in pathology detection, an XAI-CDSS analyzing an MRI scan for tumors would detail the image features triggering the alert and the substantiating indicators. This research outlines an XAI-CDSS framework and explores its implementations.

II. Related Work

This section classifies CDSSs into knowledge-driven, non-knowledge-driven, and XAI-driven variants. Each category reviews key studies, technologies, and approaches, with a summary depicted in Figure 2.

I. Knowledge-Driven CDSSs

To handle large-scale data effectively, knowledge bases have been developed as core architectures, integrating clinician expertise-derived correlations from historical records into CDSSs [8]. These qualify as knowledge-driven CDSSs, which employ inference engines to generate recommendations from structured rule repositories. Designing domain-specific knowledge structures and rule sets is thus crucial. Table 1 compiles the attributes, capabilities, and application areas of knowledge-driven CDSSs. It segments technologies underpinning these systems, delineating their traits, associated studies, primary roles (e.g., diagnosis/treatment or alerts/monitoring), and targeted medical fields. Tables 2 and 3 follow an identical structure. Knowledge-driven CDSSs formulate rules drawing from published literature, real-world practice, or patient-centered data [9], making them prevalent in guideline-adherent clinical settings and evidence-based medicine (EBM). A prominent rule-inference approach, evidential reasoning (RIMER), relies on belief rule base (BRB) systems [10–12]. BRB systems assign belief degrees to capture diverse uncertainties and broaden traditional if-then rules for knowledge representation. Typical BRB-CDSS architectures incorporate an interface tier, application logic tier, and data handling tier [13–15]. Such designs have demonstrated efficacy in domains like COVID-19 [16], heart failure [17], psychogenic pain [18], tuberculosis [19], acute coronary syndrome (ACS) [20], and lymph node metastasis [21]. Effective knowledge encoding in CDSSs can employ structures like decision trees, Bayesian networks, or k-nearest neighbors [22]. One

investigation using decision trees introduced a modeling technique where glaucoma guidelines were distilled into mind maps by experts and then transformed into recursive decision trees through collaboration between clinicians and developers [23]. A parallel effort converted clinician-generated mind maps of thyroid nodule management into recursive decision trees to derive operational rules [24], progressing from implicit knowledge to formalized explicit forms, and ultimately to deployable executable rules. Further, a decision tree-oriented CDSS for pediatric allergies integrated a specialized knowledge repository, ONNX inference capabilities, and tree-based logic to deliver diagnostic and therapeutic insights to practitioners [25].

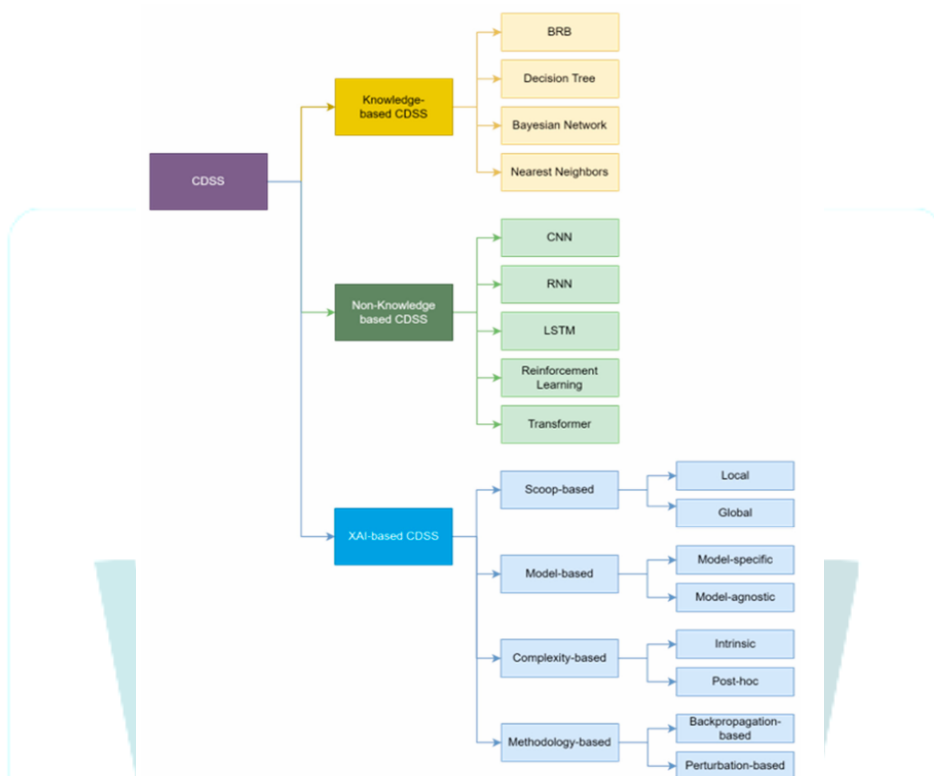


Figure 2: Overview of related work

Bayesian network CDSSs, applied across fields like liver disorders [26], breast cancer [27], infections [28], diabetes [29], angina [30], respiratory conditions [31], and lymph node metastases [32], incorporate what-if scenario simulations.

In oral health, Bayesian frameworks with expectation-maximization (EM) algorithms have identified anomalies in dental imagery [33]. Likewise, a fuzzy Bayesian network paired with fuzzy ontology addressed uncertainties in hepatitis C virus (HCV) outbreak diagnostics [34].

Knowledge-based clinical decision support systems (CDSSs) assist decision-making by utilizing structured knowledge bases, well-defined data models, and continuous domain-specific updates. In recent years, genomics has emerged as a prominent research area within knowledge-based CDSSs. Clinical genomic data models have been developed to support the analysis and interpretation of genomic information, enabling its integration into clinical workflows and applications [35].

Furthermore, several approaches have been introduced to enhance the updating of knowledge bases. These methods often rely on natural language processing (NLP) techniques to extract and analyze newly available textual information, which can then be transformed into decision rules [36].

A key advantage of knowledge-based CDSSs is the transparency of their decision-making processes, allowing outcomes to be easily interpreted and traced. However, these systems face significant challenges, particularly in terms of development and maintenance costs.

They depend heavily on domain experts and knowledge engineers for standardization, validation, and error correction, as maintaining high-quality data is essential for their effectiveness.

Table 1. Knowledge-based CDSSs.

Category	Features	Functions		Applied Domain
		Diagnosis and Treatment	Alert and Monitoring	
BRB	An extension of if-then rules utilizing confidence rules that include confidence levels to represent knowledge	✓		Tuberculosis
		✓		Heart Failure
		✓		Acute Coronary
		✓		Measles
		✓		Lymph Node Cancer
Decision Tree	Represent knowledge based on a tree structure with a hierarchy of knowledge relationships		✓	COVID-19
			✓	Psychogenic Pain
		✓		Glaucoma
		✓		Thyroid
		✓		Allergies
Bayesian Network	Utilizes probabilities based on Naïve Bayes to classify data	✓		Glaucoma
		✓		Liver Disease
		✓		Breast Cancer
		✓		Infectious Diseases
		✓		Angina Pectoris
		✓		Respiratory Diseases
		✓		Lymph Node Cancer
		✓		Dental Hygiene
		✓		Hepatitis
Nearest neighbors	Determines the class of a new instance using the attributes of the nearest neighbor		✓	Diabetes
		✓		Melanoma Diagnosis
		✓		Diagnostics

II. Non-Knowledge-Driven CDSSs

Amid surging volumes of data and domain expertise, the scope of information requiring analysis for clinical choices has expanded exponentially.

Autonomously from vast datasets akin to human cognition, deep learning and AI—rooted in artificial neural networks—facilitate clinical decision support. These techniques discern patterns within patient records to link symptoms with conditions. Furthermore, they process diverse inputs like text, imagery, videos, audio, and signals, fostering non-knowledge-driven CDSSs capable of grasping holistic clinical contexts. Initial efforts in non-knowledge-driven CDSSs focused on image processing for diagnostic purposes. Convolutional neural networks (CNNs) [37], which emulate human visual pathways to train on image motifs, have diagnosed obstructive sleep apnea via higher-order correlations in polysomnography visuals and annotations [38,39]. An automated analyzer combined CNNs with word embeddings to assess ambulance service experiences and enhance patient contentment [40]. Likewise, a standalone CNN trained on clinical images detected melanoma [41]. Recurrent neural networks (RNNs) suit sequential data analysis. Electronic health records (EHRs)—digitized patient histories with timelines—align well with RNNs [42].

One application leveraged RNNs on heart failure EHRs for superior prediction over alternatives like SVMs [44], MLPs [45], logistic regression [46], and KNNs [47] [43]. ECG signals, also temporal, benefit from RNNs in sleep apnea identification [48]. Clinical datasets' extended timelines risk overlooking historical context. Long short-term memory (LSTM) networks [49] mitigate this by forecasting via prior sequences. LSTMs have multitasked diagnostic labeling [50] and bidirectionally processed polysomnography metrics (e.g., oral-nasal airflow, nasal pressure, abdominal plethysmography) for sleep apnea detection [51]. Deep learning excels in radiographic interpretation, pinpointing lung nodules [52], cancers [53], and tuberculosis [54] on chest X-rays. Distinct from supervised or unsupervised paradigms, reinforcement learning (RL) [55] self-generates training via state observation and action selection. Conventional CDSSs, reliant on varying clinician judgments, sometimes neglect symptom interplay—a gap RL addresses in dynamic settings.

A deep RL CDSS optimized initial ICU dosing to avert errors and sequelae [56]. Privacy-aware RL enables secure, patient-focused decisions; an iterative secure computation framework delivered adaptive therapies sans data exposure [3]. RL-graph neural networks advanced conversational radiotherapy tools, boosting decisions amid variable responses and patient diversity [57].

III.XAI-Driven CDSSs

Explainable AI (XAI) [5] addresses the "black-box" opacity [6] inherent in deep learning models, which outperform rule-based or traditional machine learning alternatives yet sacrifice comprehensibility. This embodies the "performance–interpretability tradeoff," illustrated in Figure 3 [58,59]: deep learning leads in efficacy, trailed by machine learning (e.g., decision trees, nearest neighbours, Bayesian networks), and rule-based systems; interpretability inversely correlates. Integrating XAI into deep learning elucidates predictive rationales, bolstering transparency and trustworthiness of superior outputs. As XAI applications proliferate across domains [60], it emerges as a remedy for CDSS uncertainties, where precision and dependability are paramount [59].

Table 2. Non-knowledge-based CDSSs.

Category	Features	Functions		Applied Domain
		Diagnosis and Treatment	Alert and Monitoring	
CNN	Features extracted were analyzed by connecting them to convolutional layers	✓		Sleep Apnea
		✓		Sleep Apnea
		✓		Melanoma
			✓	Ambulance assignment
RNN	Process time series data to find sequential patterns in the data	✓		Heart Failure
		✓		Sleep Apnea
LSTM	Useful when dealing with long-term data and utilizing historical data to predict what to expect in the future.	✓		Diagnostics
		✓		Sleep Apnea
		✓		Lung nodules
		✓		Lung cancer
Reinforcement Learning	Trains software to make decisions to achieve the most optimal results	✓		Pulmonary tuberculosis
		✓		Medications
		✓		Protecting patient information
Transformer	Specializes in processing text data with large language models using transformers in an encoder–decoder structure	✓		Radiology
		✓		Diagnosis code categorization

The XAI explanation strategies broadly divide into scope-, model-, complexity-, and methodology-centric approaches [60]. Prevailing recent techniques encompass SHAP (Shapley additive explanations), LIME (local interpretable model-agnostic explanations) [61], post-hoc interpretability [62], and Grad-CAM (gradient-weighted class activation mapping) [63].

Scope-based methods gauge data contributions via feature salience in AI training. LIME [64], a prime instance, delivers instance-specific elucidations. It approximates model predictions locally; for emotion detection via deep neural networks, LIME spotlights contextually relevant neighboring words pivotal to a given forecast.

The proposed framework processes multimodal inputs across medical fields—text, audio, images, and genomics—while integrating explainable AI into exemplar deep learning architectures. It culminates in application blueprints showcasing viable deployment scenarios. Conventional AI-driven CDSSs predominantly rely on textual inputs, occasionally incorporating a single supplementary biometric or visual modality. Yet, to capture elusive elements like dynamic patient states, expressions, and behaviors beyond structured records, multimodal strategies prove essential.

XAI-based CDSS framework. Multimodal CDSSs synergize disparate data streams for nuanced patient profiling (e.g., vitals, labs, visuals, notes), elevating bedside surveillance or intraoperative tumor spotting. As depicted in Figure 2, a knowledge graph emerges from inter-feature links extracted via large language models, VATT, and

audio processors on text, images, and signals. Reinforcement or continual learning further auto-expands this graph, accommodating novel insights without historical loss.

Table 3. XAI-based CDSSs.

XAI	Techniques	Features	Functions		Applied Domain
			Diagnosis and Treatment	Alert and Monitoring	
Scoop Based	Local	Considers the model as a black box and focus on the local variables that contribute to the decision	✓		Depression
			✓		Parkinson
			✓		Gait classification
			✓		Alzheimer's disease
			✓		Alzheimer's disease
			✓		Chronic kidney disease
				✓	COVID-19
				✓	Malnutrition and heart disease
				✓	Adverse
		Global	Explains the contribution that relates to the output by getting an understanding of the interaction mechanism of the model variables	✓	
✓				COVID-19	
✓				Alzheimer's disease	
✓				Chronic kidney disease	
				✓	Surgical event

IV. Dataset

A. Clinical Datasets

Large-scale clinical datasets play a crucial role in developing and evaluating artificial intelligence models in healthcare. One of the most prominent multimodal datasets is the UK Biobank, which has been collecting data since 2006 from over 500,000 participants. This dataset includes a wide range of hierarchical data types such as lifestyle information, physical measurements, biological samples, electrocardiogram (ECG) recordings, and electronic health records (EHRs). In addition to standard clinical data, it also provides advanced biomedical information, including genomic sequencing, mutation analysis, and various imaging modalities such as brain MRI, cardiac MRI, abdominal imaging, and vascular ultrasound data.

Similar large-scale biobanks have been developed in other regions, including the China Kadoorie Biobank and Biobank Japan, which further contribute to population-level health research and AI model training.

Another widely used dataset in clinical AI research is the MIMIC (Medical Information Mart for Intensive Care) dataset developed by the Massachusetts Institute of Technology. Currently available in its fourth version (MIMIC-IV), it is an open-access dataset containing detailed electronic health records of intensive care unit (ICU) patients from Beth Israel Deaconess Medical Center. This dataset includes demographic details, diagnostic codes, medication records, and clinical notes. It also integrates multimodal data such as laboratory results, physiological signals, and medical imaging like chest radiographs. Due to its richness and accessibility, MIMIC-IV is extensively used for predictive modeling, including disease progression and hospital readmission analysis.

In addition to large multimodal datasets, several domain-specific datasets are available. For example, the Alzheimer's Disease Neuroimaging Initiative (ADNI) provides detailed brain imaging data for neurodegenerative disease research. Similarly, datasets focusing on physical activity and behavioral patterns are used to study mental health conditions such as schizophrenia and depression.

Overall, these datasets enable the construction of both multimodal and unimodal AI models, allowing researchers to combine diverse data sources or focus on specific clinical domains depending on the application. A summary of such datasets is typically presented in tabular form for comparative analysis.

V. Discussion and Conclusions

This paper's principal advancement lies in taxonomizing CDSS studies—from legacy systems to cutting-edge XAI variants—via apt criteria, distilling their attributes and shortcomings. It advances a novel XAI-infused CDSS paradigm, scrutinizes explainable techniques fostering healthcare trust and lucidity via optimal deployment niches, and charts a resilient trajectory for XAI-CDSS evolution.

Field- and feature-based curation of reviewed CDSSs unveils individual merits, demerits, and forward imperatives. Prevailing systems falter on narrow data scopes, AI opacity, and inscrutable reasoning—deficits untenable in reliability-centric medicine, where interpretive decision trails are imperative. Addressing black-box pitfalls in knowledge-opaque CDSSs, we proffer an XAI-grounded framework yielding substantiated rationales for outputs, complemented by curated datasets, models, and assets.

Digital medical records streamline research yet remain gated by privacy safeguards for sensitive profiles, necessitating public education campaigns. Even with disclosed data origins, decision transparency, and outcomes, human oversight persists as the default trust anchor. As remote care proliferates, regulatory streamlining is crucial. With societal buy-in and infrastructural bolstering, XAI-CDSS innovations—harnessing expansive multimodal datasets, knowledge graphs, and explainability—promise transformative clinical tools. Ongoing work applies this framework to hospital-sourced post-laparotomy data, validating real-world viability for abdominal surgery cohorts.

References

- [1] M. Khalifa, "Clinical decision support: Strategies for success," *Procedia Computer Science*, vol. 37, pp. 422–427, 2014.
- [2] S. R. Simon, D. H. Smith, A. C. Feldstein, N. Perrin, X. Yang, Y. Zhou, R. Platt, and S. B. Soumerai, "Computerized prescribing alerts and group academic detailing to reduce the use of potentially inappropriate medications in older people," *Journal of the American Geriatrics Society*, vol. 54, pp. 963–968, 2006.
- [3] X. Liu, R. H. Deng, K. K. R. Choo, and Y. Yang, "Privacy-preserving reinforcement learning design for patient-centric dynamic treatment regimes," *IEEE Transactions on Emerging Topics in Computing*, vol. 9, pp. 456–470, 2019.
- [4] J. De Fauw et al., "Clinically applicable deep learning for diagnosis and referral in retinal disease," *Nature Medicine*, vol. 24, pp. 1342–1350, 2018.
- [5] Y. Liang, S. Li, C. Yan, M. Li, and C. Jiang, "Explaining the black-box model: A survey of local interpretation methods for deep neural networks," *Neurocomputing*, vol. 419, pp. 168–182, 2021.
- [6] F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," arXiv preprint arXiv:1702.08608, 2017.
- [7] R. T. Sutton, D. Pincock, D. C. Baumgart, D. C. Sadowski, R. N. Fedorak, and K. I. Kroeker, "An overview of clinical decision support systems: Benefits, risks, and strategies for success," *NPJ Digital Medicine*, vol. 3, p. 17, 2020.
- [8] T. Syeda-Mahmood, "Role of big data and machine learning in diagnostic decision support in radiology," *Journal of the American College of Radiology*, vol. 15, pp. 569–576, 2018.
- [9] I. Sim, P. Gorman, R. A. Greenes, R. B. Haynes, B. Kaplan, H. Lehmann, and P. C. Tang, "Clinical decision support systems for the practice of evidence-based medicine," *Journal of the American Medical Informatics Association*, vol. 8, pp. 527–534, 2001.
- [10] J. B. Yang and M. G. Singh, "An evidential reasoning approach for multiple-attribute decision making with uncertainty," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 24, pp. 1–18, 1994.
- [11] J. B. Yang, "Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties," *European Journal of Operational Research*, vol. 131, pp. 31–61, 2001.
- [12] J. B. Yang, J. Liu, J. Wang, H. S. Sii, and H. W. Wang, "Belief rule-base inference methodology using the evidential reasoning approach RIMER," *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, vol. 36, pp. 266–285, 2006.
- [13] S. Rahaman, M. M. Islam, and M. S. Hossain, "A belief rule based clinical decision support system framework," in *Proc. 17th Int. Conf. Computer and Information Technology (ICCIT)*, Dhaka, Bangladesh, 2014, pp. 165–169.
- [14] G. Kong, D. L. Xu, X. Liu, and J. B. Yang, "Applying a belief rule-base inference methodology to a guideline-based clinical decision support system," *Expert Systems*, vol. 26, pp. 391–408, 2009.
- [15] M. S. Hossain, K. Andersson, and S. Naznin, "A belief rule based expert system to diagnose measles under uncertainty," in *Proc. Int. Conf. Health Informatics and Medical Systems*, Dallas, TX, USA, 2015, pp. 17–23.
- [16] F. Ahmed, M. S. Hossain, R. U. Islam, and K. Andersson, "An evolutionary belief rule-based clinical decision support system to predict COVID-19 severity under uncertainty," *Applied Sciences*, vol. 11, p. 5810, 2021.
- [17] S. Rahaman and M. S. Hossain, "A belief rule based clinical decision support system to assess suspicion of heart failure," in *Proc. Int. Conf. Informatics, Electronics and Vision (ICIEV)*, Dhaka, Bangladesh, 2013, pp. 1–6.
- [18] G. Kong et al., "A belief rule-based decision support system for clinical risk assessment of cardiac chest pain," *European Journal of Operational Research*, vol. 219, pp. 564–573, 2012.
- [19] M. S. Hossain, F. Ahmed, and K. Andersson, "A belief rule based expert system to assess tuberculosis under uncertainty," *Journal of Medical Systems*, vol. 41, p. 43, 2017.
- [20] M. S. Hossain, S. Rahaman, R. Mustafa, and K. Andersson, "A belief rule-based expert system to assess suspicion of acute coronary syndrome (ACS) under uncertainty," *Soft Computing*, vol. 22, pp. 7571–7586, 2009.
- [21] Z. G. Zhou et al., "A bi-level belief rule based decision support system for diagnosis of lymph node metastasis in gastric cancer," *Knowledge-Based Systems*, vol. 54, pp. 128–136, 2013.
- [22] B. Silva, F. Hak, T. Guimaraes, M. Manuel, and M. F. Santos, "Rule-based system for effective clinical decision support," *Procedia Computer Science*, vol. 220, pp. 880–885, 2023.
- [23] H. Y. Hyungwon, "Clinical knowledge modeling for thyroid nodule surgical treatment CDSS using mind maps and iterative decision trees," *Journal of the Korean Institute of Communications and Information Sciences*, vol. 37, pp. 28–33, 2020.
- [24] H. W. Yu et al., "Use of mind maps and iterative decision trees to develop a guideline-based clinical decision support system for routine surgical practice: Case study in thyroid nodules," *Journal of the American Medical Informatics Association*, vol. 26, pp. 524–536, 2019.
- [25] H. W. Yu, "Design and implementation of a clinical decision support system for supporting allergy diagnosis and treatment decision making for pediatricians," *Journal of Knowledge and Information Technology Systems*, vol. 18, 2023.
- [26] H. Wasyluk, A. Onisko, and M. Druzdzel, "Support of diagnosis of liver disorders based on a causal Bayesian network model," *Medical Science Monitor*, vol. 7, pp. 327–331, 2001.
- [27] N. Cruz-Ramirez et al., "Diagnosis of breast cancer using Bayesian networks: A case study," *Computers in Biology and Medicine*, vol. 37, pp. 1553–1564, 2007.

- [28] P. J. Lucas, N. C. De Bruijn, K. Schurink, and A. Hoepelman, "A probabilistic and decision-theoretic approach to the management of infectious disease at the ICU," *Artificial Intelligence in Medicine*, vol. 19, pp. 251–279, 2000.
- [29] S. Andreassen et al., "A probabilistic approach to glucose prediction and insulin dose adjustment," *Computer Methods and Programs in Biomedicine*, vol. 41, pp. 153–165, 1994.
- [30] J. Vila-Francés et al., "Expert system for predicting unstable angina based on Bayesian networks," *Expert Systems with Applications*, vol. 40, pp. 5004–5010, 2013.
- [31] E. O. Edye et al., "Applying Bayesian networks to help physicians diagnose respiratory diseases in the context of COVID-19 pandemic," in *Proc. IEEE URUCON*, Montevideo, Uruguay, 2021, pp. 368–371.
- [32] C. Reijnen et al., "Preoperative risk stratification in endometrial cancer (ENDORISK) by a Bayesian network model," *PLoS Medicine*, vol. 17, p. e1003111, 2020.
- [33] B. Thanathornwong, S. Suebnukarn, and K. Ouivirach, "Clinical decision support system for geriatric dental treatment using a Bayesian network and a convolutional neural network," *Healthcare Informatics Research*, vol. 29, p. 23, 2023.
- [34] I. Riali, M. Fareh, M. C. Ibañssa, and M. Bellil, "A semantic-based approach for hepatitis C virus prediction and diagnosis using a fuzzy ontology and a fuzzy Bayesian network," *Journal of Intelligent & Fuzzy Systems*, vol. 44, pp. 2381–2395, 2023.
- [35] S. Cao, W. Lingao, R. Ji, C. Wang, L. Yao, L. Kai, and A. N. Abdalla, "Clinical decision support system based on KNN/ontology extraction method," in *Proc. 3rd Int. Conf. Signal Processing and Machine Learning (SPML)*, Beijing, China, Oct. 2020, pp. 56–62.
- [36] W. Abbes, D. Sellami, S. Marc-Zwecker, and C. Zanni-Merk, "Fuzzy decision ontology for melanoma diagnosis using KNN classifier," *Multimedia Tools and Applications*, vol. 80, pp. 25517–25538, 2021.
- [37] L. O. Chua, "CNN: A vision of complexity," *International Journal of Bifurcation and Chaos*, vol. 7, pp. 2219–2425, 1997.
- [38] L. Cen, Z. L. Yu, T. Kluge, and W. Ser, "Automatic system for obstructive sleep apnea events detection using convolutional neural network," in *Proc. 40th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC)*, Honolulu, HI, USA, Jul. 2018, pp. 3975–3978.
- [39] D. Dey, S. Chaudhuri, and S. Munshi, "Obstructive sleep apnoea detection using convolutional neural network based deep learning framework," *Biomedical Engineering Letters*, vol. 8, pp. 95–100, 2018.
- [40] J. Cerqueiro-Pequeño, M. Casal-Guisande, A. Comesaña-Campos, and J. B. Bouza-Rodríguez, "Conceptual design of a new methodology based on intelligent systems applied to the determination of the user experience in ambulances," in *Proc. 9th Int. Conf. Technological Ecosystems for Enhancing Multiculturality (TEEM)*, Salamanca, Spain, Oct. 2021, pp. 290–296.
- [41] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, pp. 115–118, 2017.
- [42] L. R. Medsker and L. Jain, "Recurrent neural networks," *Design and Applications*, vol. 5, pp. 64–67, 2001.
- [43] E. Choi, A. Schuetz, W. F. Stewart, and J. Sun, "Using recurrent neural network models for early detection of heart failure onset," *Journal of the American Medical Informatics Association*, vol. 24, pp. 361–370, 2017.
- [44] S. Suthaharan, "Machine learning models and algorithms for big data classification," *Integrated Series in Information Systems*, vol. 36, pp. 1–12, 2016.
- [45] H. Taud and J. F. Mas, "Multilayer perceptron (MLP)," in *Geomatic Approaches for Modeling Land Change Scenarios*, Berlin, Germany: Springer, 2018, pp. 451–455.
- [46] M. P. LaValley, "Logistic regression," *Circulation*, vol. 117, pp. 2395–2399, 2020.
- [47] B. Mahesh, "Machine learning algorithms—A review," *International Journal of Scientific Research (IJSR)*, vol. 9, pp. 381–386, 2020.
- [48] M. Cheng, W. J. Sori, F. Jiang, A. Khan, and S. Liu, "Recurrent neural network based classification of ECG signal features for obstruction of sleep apnea detection," in *Proc. IEEE Int. Conf. Computational Science and Engineering (CSE) and Embedded and Ubiquitous Computing (EUC)*, Guangzhou, China, Jul. 2017, vol. 2, pp. 199–202.
- [49] R. DiPietro and G. D. Hager, "Deep learning: RNNs and LSTM," in *Handbook of Medical Image Computing and Computer Assisted Intervention*, Amsterdam, Netherlands: Elsevier, 2020, pp. 503–519.
- [50] Z. C. Lipton, D. C. Kale, C. Elkan, and R. Wetzell, "Learning to diagnose with LSTM recurrent neural networks," *arXiv preprint arXiv:1511.03677*, 2015.
- [51] H. ElMoqet, M. Eid, M. Glos, M. Ryalat, and T. Penzel, "Deep recurrent neural networks for automatic detection of sleep apnea from single channel respiration signals," *Sensors*, vol. 20, p. 5037, 2020.
- [52] K. H. Lee, J. M. Goo, C. M. Park, H. J. Lee, and K. N. Jin, "Computer-aided detection of malignant lung nodules on chest radiographs: Effect on observers' performance," *Korean Journal of Radiology*, vol. 13, p. 564, 2012.
- [53] P. J. Mazzone et al., "Lung cancer screening with computer aided detection chest radiography: Design and results of a randomized, controlled trial," *PLoS ONE*, vol. 8, p. e59650, 2013.
- [54] T. Pande, C. Cohen, M. Pai, and F. Ahmad Khan, "Computer-aided detection of pulmonary tuberculosis on digital chest radiographs: A systematic review," *International Journal of Tuberculosis and Lung Disease*, vol. 20, pp. 1226–1230, 2016.
- [55] M. A. Wiering and M. Van Otterlo, "Reinforcement learning," in *Adaptation, Learning, and Optimization*, Berlin, Germany: Springer, 2012, vol. 12.
- [56] X. Qiu, X. Tan, Q. Li, S. Chen, Y. Ru, and Y. Jin, "A latent batch-constrained deep reinforcement learning approach for precision dosing clinical decision support," *Knowledge-Based Systems*, vol. 237, p. 107689, 2022.
- [57] K. Gade, S. C. Geyik, K. Kenthapadi, V. Mithal, and A. Taly, "Explainable AI in industry," in *Proc. 25th ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, New York, NY, USA, Aug. 2019, pp. 3203–3204.
- [58] T. Hulsén, "Explainable artificial intelligence (XAI): Concepts and challenges in healthcare," *AI*, vol. 4, pp. 652–666, 2023.
- [59] A. Sajid, A. Tamer, E. S. Shaker, M. Khan, M. A. M. Jose, C. Roberto, G. Riccardo, D. S. Javier, D. R. Natalia, and H. Francisco, "Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence," *Information Fusion*, vol. 99, p. 101805, 2023.
- [60] F. Gabbay, S. Bar-Lev, O. Montano, and N. Hadad, "A LIME-based explainable machine learning model for predicting the severity level of COVID-19 diagnosed patients," *Applied Sciences*, vol. 11, p. 417, 2021.
- [61] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, San Francisco, CA, USA, Aug. 2016, pp. 1135–1144.
- [62] M. R. Zafar and K. Naimul, "Deterministic local interpretable model-agnostic explanations for stable explainability," *Machine Learning and Knowledge Extraction*, vol. 3, pp. 525–541, 2021.
- [63] A. Adadi and B. Mohammed, "Peeking inside the black-box: A survey on explainable artificial intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.