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A Review of Intelligent System for Predicting Complications in Hemodialysis Patients Using Machine Learning Techniques

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ABSTRACT

Anesthesiology patients have CKD/ESRD as one of the comorbid condition and burdened with associated morbidity; despite continuous evolution in dialysis technology including mechanics, blood purification principle, membrane science, fluid therapy with but advances in long-term outcomes however remains meager especially during intra-dialysis period where patient may experience few abnormalities like hypotension/hypertension/arrhythmias/fluid overload/anemia instability due to vascular access damage potential contributory for morbidly predicable state and thus affecting outcome. Machine learning (ML) has the potential to enhance early detection of hemodynamic and biochemical deterioration with multidimensional clinical, laboratory, and statistical data from foreign agencies. The evidence from published machine learning research on dialysis-related complications, including blood pressure swings, dry weight monitoring, quality-of-life prediction, hospitalization risk, cardiac arrest, anemia management, and mortality prediction, is compiled in this review. In more than 30 studies, gradient boosting models (XGBoost/LightGBM) and deep learning architectures performed best, especially in predicting low and high systolic blood pressure [50–56]; simple_ linear statistical models performed worse, indicating that it is unrealistic to expect these models to capture complex nonlinear physiological relationships. Despite this compelling evidence, most studies have methodological shortcomings, such as retrospective single-center training sets. variable feature sets, a lack of external validation, poor interpretability, and underrepresentation of time-series signals. Multicenter cohorts, explainable AI, real-time streaming analytics, federated learning, and the integration of the Internet of Things in Healthcare. Platforms for providing Individualized adaptive hemodialysis therapy should be the focus of future research.

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1. Introduction

Chronic kidney disease (CKD) is an increasingly recognized global health challenge [1-4], with millions of patients surviving on chronic hemodialytic therapy as their only means to sustain life. [5, 6]. Hemodialysis, despite its vital role, is often associated with both short-term and long-term complications[3]. Lack of donors means that for many patients with ESRD (end-stage renal disease), dialysis continues to be the main treatment modality, but without complications during and after sessions**[7].** as headaches (HDH)[8-10], hypotension intradialytic[11-13],

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hypertension[13-15], cardiovascular instability[16-18] sudden cardiac death[19], sudden cardiac arrest,[19-21], Anemia [22-25], Post-dialysis fatigue [6] .fluid overload[26-28], electrolyte imbalance[29, 30], Bloodstream infection[31-33]Reduced skeletal muscle mass in HD patients [34], attributable to changes in muscle mass and measurement differences. Estimating kidney function in older adults is difficult work[35]. and poor quality of life[36, 37]. These complications are major contributors to hospitalizations, morbidity, and mortality in hemodialysis patients[38, 39]. The first 90 days after commencement are a high-risk period for this patient cohort [40]. In the hospital, cardiac arrest (IHCA) is a grave event for healthcare professionals and patients alike[41]. Women also have a higher resting heart rate than men[42]. Conventional clinical monitoring approaches do not adequately reflect the complex and evolving physiology of patients undergoing hemodialysis [43-45]. Therefore, the early detection and forecast of complications are still a huge clinical challenge [46, 47]. Recent developments in big data analytics and machine learning now make it possible to model such complex dynamics by mining the real-time hemodynamic parameters, dialysis machine variables, and large-scale EMR [46, 48]. Several ML models – such as Random Forest [44-46], Support vector machine [44-46], Gradient boosting technique [30, 45], and deep learning techniques [13, 48]—have been applied to predict complications such as blood pressure variability[11, 13], have been used to predict complications like blood pressure variability [11-13], dry weight changes [26-28], and cardiac events [20, 21]. The promising accuracy of these models in predicting at-risk patients and improving clinical decision-making has been shown by the above-mentioned models [13, 48]. Despite the growing interest in this type of research, the studies that have already been published vary widely in terms of the methods used, data sources, prediction objectives, and evaluation measures[2]. Thus, the goal of this narrative review is to classify and evaluate. The Various machine learning (ML) and forecasting models used in this context, current constraints, and future research trends focused on deploying reliable real-time and clinically applicable prediction systems.

1.1Clinical Background: Hemodialysis Complications

Intradialytic patient characteristics. Unstable hemodialysis patients are on hemodialysis routinely (as a consequence of rapid fluid transfer, osmotic load, and cardiovascular stress). Common complications include:

- **Intradialytic hypotension (IDH):** From 8% (literature data) up to >40% of sessions; correlated with volume depletion, and autonomic dysfunction[49]
- **Intradialytic hypertension (IDHTN):** -related to endothelial dysfunction, arterial stiffness, and volume overload[50].
- **Cardiac arrhythmias & sudden cardiac arrest:** Account for almost 40% of HD-related deaths[18, 51].
- **Fluid overload and inaccurate dry weight:** Fluid overload and non-measurement of dry weight: Leading causes of hypertension and heart failure.[52, 53].
- **Anemia and ESA resistance:** Anemia and resistance to ESA: management made difficult by highly varying hemoglobin response[54, 55].
- **Vascular access failure:** Vascular access dysfunction: AV fistula thrombosis and line sepsis[56, 57].
- **Neurological: including dialysis headache and disequilibrium syndrome**[10, 22].
- **Diminished quality of life and fatigue, frequently due to metabolic stress and inflammation**[6, 58].

Table 1 summarizes common hemodialysis-related adverse events, including the mechanisms and clinical implications

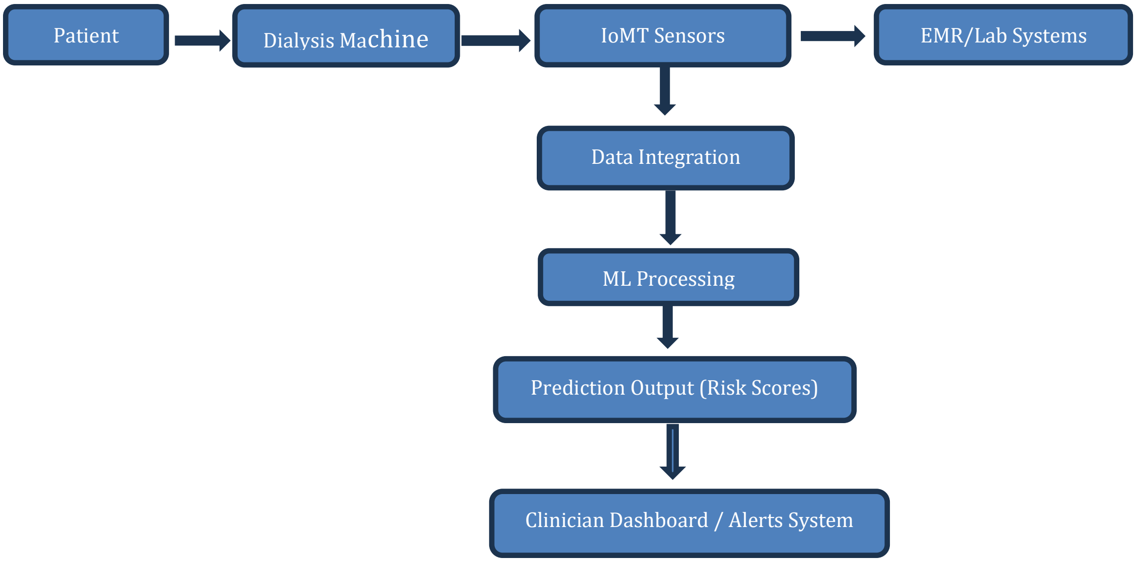
Complication	**Key Pathophysiological Mechanisms**	**Clinical Impact**
Intradialytic Hypotension (IDH)	Hypotension is caused by ultrafast filtration, decreased cardiac output, autonomic nervous system insufficiency, and delayed refill.	Lightheadedness, N&V, cramping, syncope, premature termination of session, excess hospital admissions
Intradialytic Hypertension (IDHTN)	Sympathetic hyperactivity, arterial stiffness, endothelial dysfunction, and volume overload	Stroke risk, cardiovascular stress, inadequate volume control, and high mortality
Cardiac Arrhythmias	Disturbance of electrolytes (K^+, Ca^{2+}), swallowed stress, LV hypertrophy, and autonomic imbalance	Tachycardia, RACE Cardiovascular: Cardiac arrest, sudden emergency, Palpitations
Fluid Overload	Incorrect dry weight, excessive interdialytic weight gain, and sodium imbalance	High blood pressure, Fluid in the lungs (pulmonary edema), Heart failure, Hospitalization

Complication	**Key Pathophysiological Mechanisms**	**Clinical Impact**
Anemia Instability / ESA Resistance	In the setting of inflammation, iron deficiency, poor ESA toxicity, reduced responsiveness, and shortened RBC lifespan.	Fatigue, reduced quality of life, transfusion need, and higher mortality
Vascular Access Failure	Stenosis of the fistula, thrombosis, failure of the catheter, and infection, unhygienic practices, and the use of longer time periods	Denial of access, emergent interventions, and increased mortality
Catheter-Related Bloodstream Infection (CRBSI)	Biofilm production, unhygienic practices, and catheter use for longer time periods	Fever, sepsis, hospitalization, mortality
Symptoms Neurological (Dialysis Disequilibrium Syndrome, Headache)	rapid osmotic shifts, cerebral edema	Headache, confusion; in serious cases, seizures
Muscle Cramps and Fatigue	Change of fluids, electrolytes, and diminished perfusion	Pain, session intolerance, reduced QOL

2. Previous Studies

Hemodialysis treatment produces diverse physiological (hemodynamic, metabolic), biochemical, and device signals that require application of real-time data into a single computational pipeline before machine learning algorithms can output clinically meaningful predictions. (**Figure 1)** provides an overview of how clinical data are transformed into analytic inputs and ultimately risk predictions, which we describe as the broad Clinical-to-ML Data Integration Pipeline.

This workflow illustrates the transfer of information from bedside patient data (dialysis machine outputs and IoMT sensor readings)—collected through successive layers of data integration and preprocessing—to machine learning models, which generate risk scores and alerts to support clinical decision-making**.**



2. 1-Predicting Intradialytic Hypotension and Hypertensive Event

The vast majority of studies aim to predict blood pressure instability due to its association with hospital admissions and mortality.

Key findings include:

XGBoost and LightGBM consistently obtaining AUC0.82–0.92 for IDH.

-Important predictors:

-Recent systolic BP trends

-Ultrafiltration rate

-Interdialytic weight gain

-Age and comorbidities

-Hematocrit and electrolytes

-Models generated from continuous sensor measurements in real-time supersede the models created using static pre-dialysis values.

Limitations:

Definitions of IDH differ in the various studies.
The majority of datasets are retrospective and from single-center studies.[60, 61]

2.2-Prediction of Dry Weight and Fluid Overload

- Accurate guesses of the dry weight are important to prevent hypotension and fluid overload.
- Regarding 4, ML models (Random Forest, XGBoost, and RVFL) are moderate to good with higher accuracy when Δ congruent to 0.5–1 kg is required.
- Deep learning- and hybrid-based approaches are superior to traditional bioimpedance methods.
- CRP, albumin, and BPV are important predictors of changes in dry weight.

Limitations:

- Rare proxy metrics, so limit real-time predictions
- Low accuracy for heavy deviations (>2 kg).[52]

2.3 Prediction of Arrhythmias and Sudden Cardiac Arrest

Research using ECG and EMR data reveals that:

- Patients with an increased risk of SCA can be identified using ML models.
- Predictors are K+, MAP, oxygen saturation, and acidosis.
- Performance varying $0.75 \le AUC \le 0.85$, depending on dataset quality.[21, 51]

2.4 Quality of Life and Fatigue Prediction

Results of the analysis performed with decision trees, Naïve Bayes, and MLP were

- QOL scores are associated with income, albumin, dose of iron, age, and emotional health.
- ML can predict length of stay in ICU, AUC 0.77[62].

2.5 Prediction of Hemodialysis Mortality:

Large databases (e.g., USRDS) show:

- XGBoost for 90-day mortality post-dialysis initiation achieves AUC ~0.83.
- Significant predictors: age, albumin, recent hospitalization, type of vascular access, and CRP.[63].

2.6 Prediction of Bloodstream Infection and Vascular Access Failure

ML models with IoMT + EMR data demonstrate the following:

- Accuracy 93% for IDH and
- 99% for the prediction of AV fistula obstruction.

The main risk factors are catheterization, previous infection, and inflammatory markers[59].

2.7 Risk Prediction Schematic

To illustrate how machine learning models combine multidimensional physiological, biochemical, and hemodialysis-related parameters to predict the risk of complications **(Figure 2**), the diagram provides a schematic representation of the prediction process. It illustrates the key features of the inputs, including blood pressure trends, ultrafiltration rate, weight gain between hemodialysis sessions, electrolyte concentrations, hemoglobin levels, and inflammatory markers for the ML model, which generates risk probabilities for major HD complications.

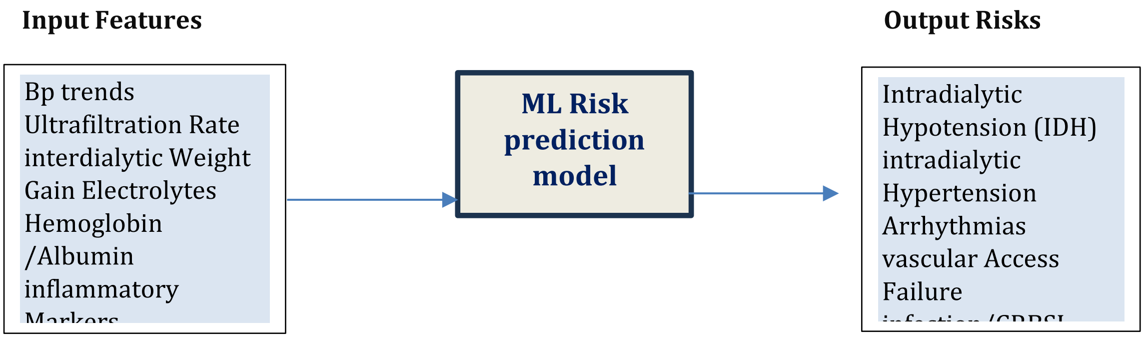


Table 2 - Summary of previous studies for hemodialysis

Ref.	Year	Method	Datasets	Limitation	accuracy	Precision	recall	F1_ score	ROC_ AUC
[50]	2025	XGBoost, KNN, Cat Boost, SVM, Decision Tree, Logistic Regression, Naive Bayes, Random Forest, LightGBM	A total of 67,524 Hemodialysis sessions were analyzed in 258 patients.	Limited generalizability, insufficient data, lack of treatment interventions, variation in recording data, and a small dataset.	IDH 0.84 IDHTN 0.85	IDH 0.87 IDHTN 0.77	IDH 0.93 IDHTN 0.64	IDH 0.90 IDHTN 0.70	IDH 0.89 IDHTN 0.89
[11]	2023	XGBOOST RNN	Data from 42,656 dialysis sessions and 693 patients were used.	Dynamic input-output changes and the black box of the model, high risk of bias, low generalizability, and some IDH patients were excluded from the sensitivity analysis.	-	0.734	-	-	0.887
[60]	2023	IDH_A Light GBM, LDA, MLP Tab Net, IDH_B LKIGHTGBM, XGB, LDA, MLP, TABNET, SVM.	IDH-A dataset: 62,227 sessions, IDH-B dataset: 64,870 sessions;	There are several limitations: the study was retrospective and included only a small number of Asian patients; baseline blood pressure was not taken into account. Although there was significant variation among centers, the model's performance remained consistent.	-	-	-	-	IDH_A 0.82 IDH_B 0.68
[53]	2023	Random Forest	Number of dialysis sessions: 69,375, OF 14 patients	Retrospective, single-center data. Retrospective, single-center data.	DW-UP_ MODEL 0.0656. DW-DOWN-MODEL	0.045	0.676	0.084	0.70

					0.618	0.055	0.751	0.102	0.74
[27]	2021	Slap RVFL, Linear regression, LR, ANN, MKRR, MKSVR, BCM devise.	using 476 clinical measurements	Limitations included a small sample size of only two hospitals, the use of clinical dry weight as a reference (rather than the gold standard), the need for additional or more comprehensive clinical data, and the need to improve the model through deep learning.	RM 0.3136, RMS 1.9694, RMSE 1.3136, and R^2 0.9501.	-	-	-	-
[52]	2021	XGBoost	Study Population Dataset: 69,375 dialysis sessions 314 patients	Limitations included a small sample size of only two hospitals, the use of clinical dry weight as a reference (rather than the gold standard), the need for additional or more comprehensive clinical data, and the need to improve the model through deep learning.	DW<1kg: ~83%, DW<2 kg: ~72%. All data: <40%,	-	-	-	-
[64]	2022	SVM, SVCR, MLP, KNN, DT, Random Forest, Gradient boosting ‹Voting.	215 patients were studied, 6000 sessionsand 50 , factors	The study was conducted at a single center, and some potentially relevant features were not recorded; the model's performance may depend on the clinical context.	0.97%	-	-	-	-
[51]	2021	Cox regression with backward selection, β coefficients.	A total of 257 patients were included (190 in the derivation cohort, 67 in the validation cohort.	Data imbalance, fixed window selection, and missing patient data all affect the model's accuracy.	-	-	-	-	**0.78 and 0.75**
[65]	2025	LR, KNN, Decision tree, Naïve Bayes, SVM, XGBoost, ANN.	Used dataset 2181 rows And 14 features	Class imbalances, compatibility issues, privacy concerns, biases, and the longitudinal data available.	0.739 0.889 0.941 0.709 0.839 0.956 0.894	0.074 - - - - - -	0.073 - - - - - -	0.074 - - - - - -	- - - - - - -
[66]	2025	KNN ,XGBoost, Random Forest, Extra Trees, AdaBoost, Decision Tree.	Database of the 240 hemodialysis patients.	Limitations regarding sample size, population representation, follow-up duration, and the absence of changes in treatment.	0.92	0.86	0.96	0.91	-

3 .Methodology

The complete workflow adopted in the reviewed machine learning studies is a multi-stage pipeline that processes raw clinical data and dialysis Data in predictive models that forecast high-risk events. It typically begins with the collection of multidimensional patient profiles, followed by a series of preprocessing steps, including feature generation, model training, and performance evaluation. The final step involves deploying the predictive model in healthcare settings, where point-of-care risk alerts can be generated.

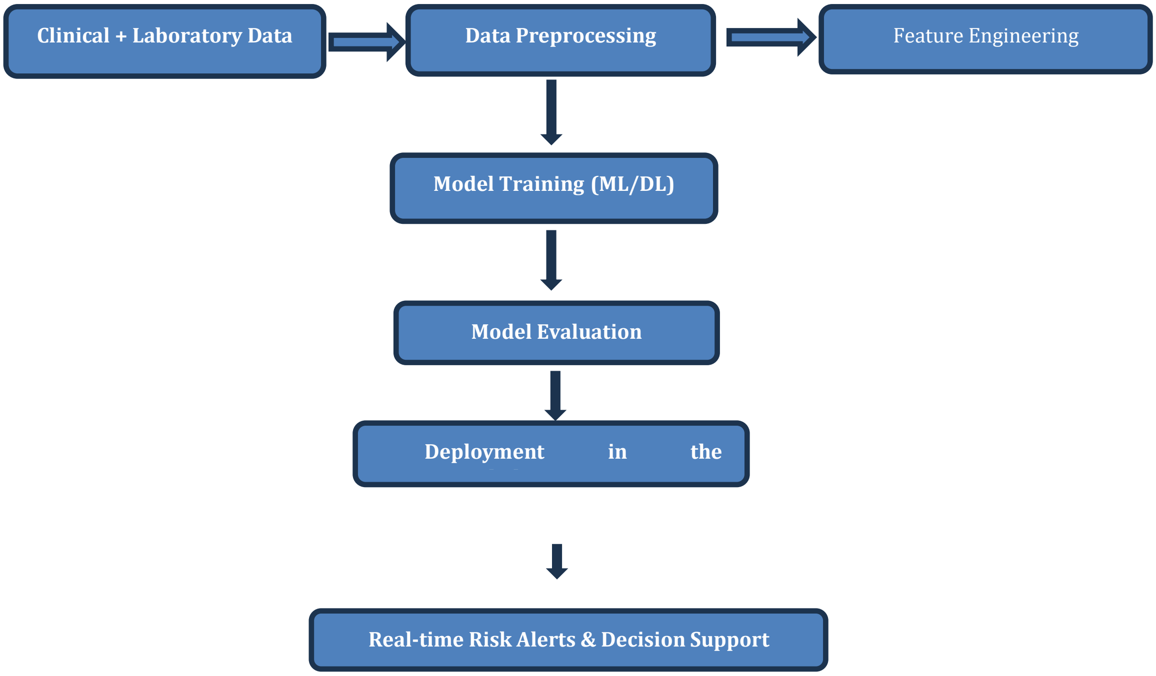


Figure 3 shows a workflow diagram. This summarizes machine learning as a complete pipeline used in hemodialysis research, including feature engineering, data collection, preprocessing, model training, assessment, and clinical implementation.

3.1-Search Strategy

To identify pertinent research on hemodialysis patient problems and the use of machine learning algorithms for prediction, a thorough literature search was conducted. Mendeley was used to access open medical research databases, including studies that were indexed in Scopus between 2015 and 2024, for the search. Several keywords related to hemodialysis complications served as the basis for the search strategy. "Hemodialysis," "hypotension," "Dry weight," and "Cardiac arrest were among the primary search terms. These keywords were combined, and pertinent studies were retrieved using Boolean operators like "AND" and "OR". The structure of the search query was as follows: “Dry weight" OR ("Hemodialysis" AND "Hypotension") OR "Cardiac arrest". Studies on hemodialysis problems and machine learning-based prognostic methods were the main focus of the search.

3.1.1-Dataset

Sources of Data and Machine Learning Techniques. Sources of Dialysis-Related Data: Studies typically utilize:

Electronic medical records (EMR)[59, 60].

- Dialysis machine parameters (blood flow rate, ultrafiltration, conductivity)[11].
- Laboratory examination (electrolytes, hemoglobin, CRP, albumin)[52, 63].
- Demographic and comorbidity information[30, 67].
- IoMT (Internet of Medical Things) RT sensors[11, 59].
- Quality of life[62, 68].
- Physiological time-series signals (BP trends, HRand ECG ,)[21].
- Sizes of datasets range across the spectrum of medicine—from small single-center collections (~200 patients) to national registries (>1 million).

3.1.2 Types of Machine Learning Models

The most frequently used techniques in the studies included are

- Supervised Learning
- Random Forest
- Gradient boosting (XGBoost, LightGBM, CatBoost)
- Support Vector Machines
- Logistic Regression
- K-Nearest Neighbors
- Deep learning (MLP, LSTM, CNN). [69]

Unsupervised Learning

Clustering for patient stratification [69]

- Anomaly detection
- Feature extraction and dimensionality reduction

Time-Series Models

- LSTM networks
- RNN-based architectures
- Temporal convolutional models[11]

Explainability Tools

- SHAP (widely used)
- LIME
- Feature importance rankings

3.2-Criteria for Inclusion and Exclusion

To guarantee the quality and applicability of the chosen literature, the studies included in this review were chosen using predetermined inclusion and exclusion criteria. Criteria for Inclusion: research on patients receiving hemodialysis. Studies that concentrate on hemodialysis-related problems such as hypotension, anemia, cardiac arrest, and problems with dry weight. Studies that used machine learning methods to analyze or predict medical outcomes. Papers published in scientific publications that have undergone peer review.

Exclusion Standards: tidies unrelated to dialysis problems or hemodialysis. Articles that lack adequate methodological or clinical details. Publications that are not scientific, like comments, editorials, or unfinished reports. Duplicate research or publications that share data.

3.3- Study Selection Process

A systematic study selection process was conducted to ensure the inclusion of relevant, high-quality studies. Initially, 45 studies related to dialysis complications and machine learning applications were identified using the specified search strategy. After removing duplicate studies, 38 studies remained for the screening phase. Titles and abstracts were then reviewed to exclude irrelevant studies, resulting in the selection of 20 studies for full-text review. The studies were then evaluated according to predefined inclusion and exclusion criteria, which included studies focusing on dialysis patients and addressing complications such as hypotension, anemia, cardiac arrest, or dry weight management using machine learning techniques or intelligent systems. Studies unrelated to dialysis, those not using machine learning techniques, those lacking sufficient methodological information, or those that were duplicates were excluded. Ultimately, 10 studies were selected for detailed analysis and comparison in the “Related Work” section.

3.4- Risk of Bias Assessment

To ensure the reliability of the studies included in this review, a risk of bias assessment was conducted. Each selected study was evaluated based on several criteria, including methodological clarity, the quality of the data used, the machine learning techniques applied, and the validity of the reported results. Studies characterized by unclear methodology, insufficient data description, or unreliable results were considered to have a higher risk of bias. This assessment helped ensure that the review focused on high-quality studies relevant to the research topic**.**

3.5-performance metric extraction

To ensure a consistent comparison among the reviewed studies, the performance metrics reported in each selected study were extracted and systematically analyzed. These metrics included common evaluation indicators such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC). These metrics were then summarized and compared to evaluate the performance of the machine learning models used in studies related to dialysis complications.

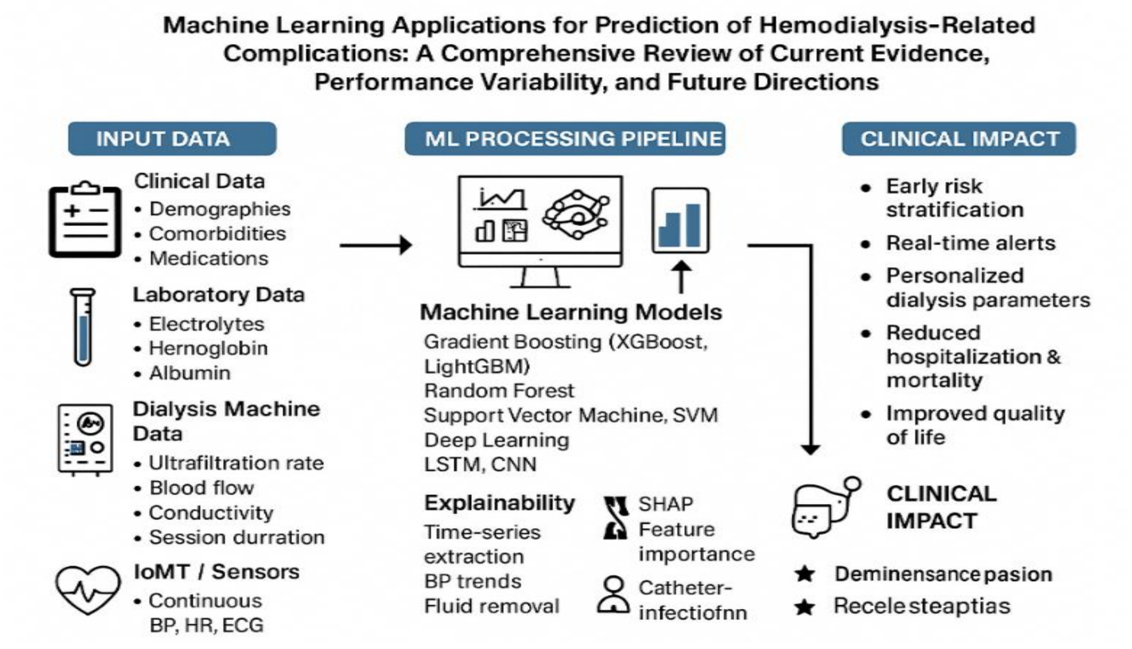


Figure 4. Synopsis of the Machine Learning Pipeline Used for Predicting Hemodialysis Complications. This diagram summarizes the main data sources (clinical data, lab data, dialysis machine, and IoMT sensors) as well as the ML processing pipeline, model types, and clinical impact on patient management of these studies

4. Critical Evaluation of Current Literature

Strengths

1. Machine learning models achieve higher predictive accuracy compared to traditional statistical methods.
2. The integration of Internet of Medical Things (IoMT) and cloud computing technologies enables real-time data analysis and continuous monitoring of patient status.
3. Explainable AI techniques, such as SHAP, contribute to improving model interpretability and increasing their acceptance in clinical applications.

Key Limitations

1. Many studies rely on retrospective data from a single center, which may limit the generalizability of the results.
2. The developed models may not be applicable in different geographic regions, among diverse ethnic groups, or with different types of dialysis machines.
3. Longitudinal time-series data are not sufficiently utilized, even though dialysis treatment is a dynamic process that changes over time.
4. Any published studies lack external validation of the models, which may affect the reliability of the results.
5. The effect of certain medications, such as erythropoiesis-stimulating agents (ESAs) and antihypertensive drugs, is not adequately accounted for in many models.
6. The integration of data from wearable devices remains limited, although such data could significantly improve the predictive ability of models.

5. Clinical Implications

Predictive models based on machine learning have the potential to revolutionize hemodialysis care by enabling earlier, more accurate, and personalized clinical decisions. By integrating multidimensional data—including blood pressure trends, ultrafiltration rates, laboratory values, and sensor-based physiological measurements—doctors can be proactive rather than reactive to complications.

Intradialytic hypotension and hypertension, which continue to be common and clinically disruptive events, can be forecast minutes to hours before their occurrence, enabling preemptive changes in ultrafiltration rate, dialysate composition ,orsession length. Likewise, early recognition of patients at risk for arrhythmias, fluid overload, vascular access complications, or infection may lead to earlier intervention, avoidance of hospitalization, and improved survival.

Explainable AI techniques, such as SHAP, can increase confidence in clinical decision-making by providing information about the specific features that are important for predicting each patient's outcome. This enables personalized treatment planning and promotes shared decision-making. When integrated into dialysis machines, information displays, or IoMT-connected monitoring systems, the risk scores derived from RCT-SML-Ch can provide immediate alerts to reduce the cognitive burden on healthcare workers and nursing staff.

Finally, the clinical impact of multi-modal learning in hemodialysis goes beyond mere prediction: These devices help reduce incidents such as

fatigue and achieve better fluid balance management by minimizing treatment variability (and agitation), thereby improving patients' quality of life while undergoing chronic dialysis.

6. Future Directions

6.1 Federated Learning in Collaboration Among Medical Centers

Federated learning enables collaborative model training among multiple hospitals without the need to share raw patient data.

6.2 Explainable AI (XAI)

for clinical use. In terms of clinical application, the ability to interpret and explain results from medical devices is a highly desired feature.

Integration of SHAP with graph neural networks and causal modeling is necessary.

6.3 Continuous Monitoring through IoMT and Wearables

EKG patches, blood pressure monitors, hydration sensors, and live alerts.

6.4 Personalized Dialysis Based on Digital Twin Models

Patient-stratification before the session begins.

6.5 Integration of Multi-Modal Data Combining

- ECG
- Dialysis pump data
- Imaging
- Laboratory markers
- Patient-reported outcomes.[21].

6.6 Prospective Clinical Trials

To establish real effectiveness and evaluate changes in mortality and hospitalization.

7. Conclusion

Gradient boosting and deep learning outperform traditional statistical models for predicting instability of blood pressure, fluid overload, mortality, vascular access issues, and patient-reported outcomes. Methodological inconsistencies, lack of rigorous external validation, and difficulties regarding data quality and interpretability, however, limit their widespread use in routine clinical practice. In the future, rigorous multicenter databases, standardized outcome definitions, and registries with real-time systems may be necessary to evaluate the effectiveness of algorithms across multiple data sources. Additionally, artificial intelligence and future clinical validation will be of paramount importance. When carefully integrated into clinical practice, machine learning tools can achieve significant improvements in safety, patient-tailored treatment, and quality of life for hemodialysis patients. Machine learning has recently shown great potential for predicting hemodialysis (HD)-related complications from complex clinical and physiological data.

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