Machine Learning for Predicting Intradialytic Hypotension: A Survey Review

Saeed Alqahtani[1], Suhuai Luo[2], Mashhour Alanazi[3],
Kamran Shaukat[4], Mohammed G Alsubaie[5], Mohammad Amer[6]
School of Information and Physical Science, University of Newcastle, Newcastle, Australia[1, 2, 4, 5]
Prince Sultan Military College of Health Sciences, Dammam, Saudi Arabia[1]
Hemodialysis Department, King Abdulaziz City in National Guard, Riyadh, Saudi Arabia[3]
Centre for Artificial Intelligence Research and Optimisation-Design and Creative Technology Vertical,
Torrens University Australia, Ultimo, NSW 2007, Australia[4]
King Salman Armed Forces Hospital, Tabuk, Saudi Arabia[6]

***Abstract*—Intradialytic hypotension (IDH) is a common complication in patients undergoing maintenance hemodialysis and is associated with an increased risk of cardiovascular and all-cause mortality. Machine learning (ML) and deep learning (DL) techniques transform healthcare by enabling accurate disease diagnosis, personalised treatment plans, and clinical decision support. However, challenges like data quality, privacy, and interpretability must be addressed for responsible adoption. This survey review aims to summarise and analyse relevant articles on applying machine learning models for predicting IDH. Among these models, deep learning, a subfield of machine learning, stands out because it can improve the overall performance of health care, particularly in diagnostic imaging and pathologic processes and in the synthetic judgment of big data flow. The insights gained from this survey review will assist researchers and practitioners in selecting appropriate machine-learning models and implementing preemptive measures to prevent IDH in dialysis patients.**

Keywords*—Hemodialysis; machine learning; deep learning; artificial intelligence; intradialytic hypotension; electrocardiogram; light gradient boosting machine; deep neural network; recurrent neural network

I. Introduction

Intradialytic hypotension (IDH) is a common complication in patients undergoing maintenance hemodialysis and is associated with increased cardiovascular and all-cause mortality [1]. Intradialytic hypotension (IDH) is a frequent and serious complication of hemodialysis, characterized by a significant drop in blood pressure during dialysis sessions. Detection of IDH primarily involves continuous or frequent monitoring of blood pressure, with a drop in systolic blood pressure of ≥20 mmHg or in mean arterial pressure of ≥10 mmHg indicative of the condition [2] [3]. Advanced techniques, such as machine learning models, have been developed to predict IDH in real time by analyzing electronic health records and intradialytic data, potentially alerting clinicians 15-75 minutes before an IDH event [2]. Risk factors for IDH include patient-related factors such as age, comorbidities (e.g., diabetes, heart failure), and autonomic dysfunction, as well as dialysis-related factors like high ultrafiltration rates and incorrect target weight assessment.

Traditional solutions for managing IDH during dialysis include placing the patient in the Trendelenburg position to increase venous return, reducing or stopping ultrafiltration, and administering normal saline to restore intravascular volume [4]. Optimizing the dialysis prescription is also crucial, which can involve using cooler dialysate temperatures, adjusting sodium concentration in the dialysate, and tailoring dialysis plans based on individual patient risk factors [1][3]. Preventive strategies during the interdialytic period, such as managing interdialytic weight gain and adjusting medications, are also important [2]. Advanced techniques like blood volume monitoring and intradialytic exercise can help manage IDH effectively [4][5].

Accurate prediction of IDH is crucial for effective management and prevention of this condition. Machine learning models have shown promise in predicting IDH using various predictors and performance metrics. However, consolidating the knowledge available from the literature is necessary to gain a comprehensive understanding of the use of machine learning models for IDH prediction.

This survey review summarizes and analyses relevant articles on applying machine learning models for predicting IDH. By examining these articles, common trends can be identified, the performance of different machine learning models can be evaluated, and recommendations for future research can be provided. The insights gained from this survey review will assist researchers and practitioners in selecting appropriate machine-learning models and implementing preemptive measures to prevent IDH in dialysis patients.

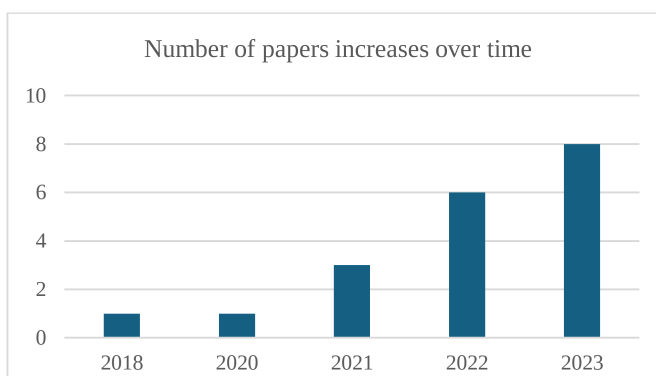

Fig. 1. The prevalence of papers using DL on IDH detection each year (Scopus).

II. Machine Learning and Intradialytic Hypotension+

Intradialytic hypotension (IDH) is one of the most frequent complications in patients requiring maintenance hemodialysis. IDH is associated with an increased risk of cardiovascular and all-cause mortality. The definition of IDH varies among studies, while the prevalence of IDH ranges up to 40% [4].

Artificial intelligence (AI) denotes computer systems capable of executing intricate tasks that traditionally were within the domain of humans, like reasoning, decision-making, or problem-solving. In contemporary usage, "AI" encompasses diverse technologies that underpin numerous services and products integral to our daily [5].

Machine learning (ML) is a branch of artificial intelligence (AI) that empowers machines to autonomously learn from data and previous experiences, enabling them to recognise patterns and formulate predictions with minimal human intervention [6].

Deep learning, a subset of machine learning, employs multi-layered neural networks known as deep neural networks to mimic the intricate decision-making processes of the human brain. This technology underpins much of the artificial intelligence (AI) we encounter daily.

Machine learning (ML) and deep learning (DL) techniques transform healthcare by enabling accurate disease diagnosis, personalised treatment plans, and clinical decision support. ML algorithms analyse patient data to predict diseases and tailor treatments. DL excels at medical image analysis, natural language processing of clinical data, genomics, and robotic surgery. While promising, challenges like data quality, privacy, and interpretability must be addressed for responsible adoption.

A deep learning architecture can be succinctly described as an Artificial Neural Network (ANN) containing two or more hidden layers to refine prediction accuracy [7]. Unlike traditional neural networks, deep learning utilises numerous hidden layers. Within a typical Deep Neural Network (DNN), input values, adjusted for weight and bias, pass through non-linear activation functions like ReLu and SoftMax to produce an output [8]. Consequently, the training objective for a DNN is to optimise network weights to minimise the loss function [9].

Traditional machine learning approaches necessitate several sequential stages, including preprocessing, feature extraction, careful feature selection, learning, and classification, to achieve classification tasks. Notably, the efficacy of machine learning techniques heavily relies on feature selection, as biased selection may yield incorrect class distinctions. Conversely, deep learning possesses the capacity to learn feature sets for diverse tasks autonomously, distinguishing it from conventional machine learning methods [10].

Although the risk factors involved in IDH are well known, including diabetes, cardiovascular disease, autonomic dysfunction, nutrition status, old age, anaemia, and high interdialytic weight gain, most of these risk factors are difficult to correct immediately at the hemodialysis centre. Therefore, treatments, such as temporarily stopping hemodialysis or reducing the ultrafiltration rate, are preferentially performed when IDH occurs. Early prediction of IDH allows for timely interventions by medical staff, such as adjusting ultrafiltration rates or administering fluids, potentially preventing or mitigating the hypotensive episode. This improves patient safety and quality of life. To detect IDH early, measuring blood pressure (BP) more frequently may be helpful. However, it is impossible to measure BP continuously due to the nature of the non-invasive BP measurement method. Thus, other non-invasive methods that can predict IDH in advance are needed.

The problem will appear when the patient's intradialytic hypotension occurs suddenly during a dialysis session. As a result, Intradialytic hypotension may reduce the efficacy of the dialysis procedure and contribute to the excessive morbidity and mortality that is associated with hemodialysis.

Artificial intelligence models have changed the paradigm of clinical decision-making from diagnosis to treatment [11]. Among these models, deep learning, a subfield of machine learning, stands out because it can improve the overall performance of health care, particularly in diagnostic imaging and pathologic processes and in the synthetic judgment of big data flow [12]. Deep learning can learn and characterise flow from a variety of data types and can thus develop a model from time-varying sequential inputs.

Fig. 2. Basic flow of the IDH system.

III. Medical Terminologies and Variables

The essential medical terms and variables frequently referenced in the 'Machine Learning for Predicting Intradialytic Hypotension' field include:

- Intradialytic Hypotension (IDH): A significant drop in blood pressure occurring during hemodialysis, typically defined as a systolic blood pressure (SBP) below 90 mmHg or a decrease of 20 mmHg or more from the baseline SBP [13].
- Mean Arterial Pressure (MAP): The average arterial pressure throughout one cardiac cycle, sometimes defined IDH as a drop of 10 mmHg or more [14].
- Nadir: The lowest point, often referring to the lowest SBP recorded during dialysis [14].
- Intradialytic SBP and MAP measurements: Real-time blood pressure readings from the dialysis machine during treatment are crucial for predicting IDH [15].

- Baseline SBP: The patient's blood pressure before starting dialysis, serving as a reference point [13].
- Ultrafiltration rate: The rate of fluid removal during dialysis can affect the risk of IDH [13].
- Demographic data: Factors like age and gender that may predict IDH risk [15].
- Clinical data: Comorbid conditions such as diabetes and cardiovascular disease increase the likelihood of IDH [15].
- Treatment data: Information on dialysis prescriptions dialysate composition [15].
- Laboratory data: Relevant blood tests, including haemoglobin levels [15].
- IDH rate: The frequency of previous IDH episodes in a patient [15].
- Area Under the Receiver Operating Characteristic (AUROC) evaluates binary classifiers by measuring their ability to distinguish positive/negative classes. It provides a scalar value summarizing the true positive/false positive trade-off across thresholds [16].
- Light Gradient Boosting Machine (LightGBM): LightGBM is an efficient, scalable, and accurate gradient boosting framework using tree-based algorithms. It employs techniques like histogram-based trees and gradient-based sampling for better performance [17].
- TabNet: TabNet is a novel deep-learning architecture designed for tabular data. It combines self-attention and sequential decision-making to capture feature interactions and learn interpretable feature importance.
- Deep Neural Network (DNN): DNNs are multi-layered neural networks capable of learning complex non-linear patterns in data for tasks like image/speech recognition but require large data and computational resources.
- Temporal Fusion Transformer (TFT): TFT is a deep learning architecture for time series forecasting, combining self-attention from transformers and temporal convolutions to capture long-range and local patterns in time series.
- Hemodialysis (HD): Hemodialysis is a life-sustaining treatment for kidney failure. It removes waste and excess fluids from the blood through a dialysis machine and artificial kidney, typically performed three times a week.
- Electrocardiogram (ECG): An ECG is a diagnostic test that measures and records the electrical activity of the heart. It is used to detect and monitor heart conditions by analysing electrical signals from electrodes.

These terms and variables, especially the real-time intradialytic blood pressure measurements, are often used as inputs for machine learning models to predict the risk of IDH during hemodialysis.

In the following paragraphs, an overview of research papers on Intradialytic hypotension will be presented, focusing on scientific papers that have utilised machine learning methods to predict Intradialytic hypertension before its occurrence. The objective is to identify, detect, analyse, and evaluate the models used for detecting Intradialytic hypertension, ultimately determining the best model to enhance patient health and improve the quality of medical care provided.

IV. Threat to Validity: Search Strategy and Databases

In this survey review, we acknowledge the importance of providing a detailed explanation of the search strategy and the databases used to address the threat to validity. By employing a rigorous approach to literature search and retrieval, we aimed to capture a wide range of relevant studies and provide valuable insights for researchers and practitioners in the field of machine learning for predicting intradialytic hypotension.

A comprehensive survey was conducted to gather information on using machine learning models for predicting intradialytic hypotension (IDH). The survey design involved identifying relevant articles published in the literature. The target population for the survey review included studies that investigated the application of machine learning models for predicting IDH in patients undergoing maintenance hemodialysis.

A. Search Strategy and Databases

The survey review employs a wide-ranging search approach to ensure that multiple databases are utilised to capture a diverse range of studies. The following databases play a crucial role in the search process:

1) PubMed: This widely recognised and extensively used database for biomedical literature contains a vast collection of articles from various disciplines, including medicine, biology, and healthcare.

2) Scopus: As a comprehensive bibliographic database, Scopus covers a wide range of scientific disciplines. It includes articles from peer-reviewed journals, conference proceedings, and patents, providing a broad scope of literature for research purposes.

3) Google scholar: Designed as a web search engine for scholarly literature, Google Scholar indexes academic publications from various sources, including journals, conference papers, and theses.

B. Search String

The search string employed in the survey review consists of relevant keywords and phrases related to machine learning, intradialytic hypotension, and associated techniques. The specific search terms are tailored to each database's syntax and search capabilities, ensuring optimal retrieval of relevant articles.

The following search terms and combinations were used:

1) "Intradialytic hypotension" AND "machine learning"

2) "Intradialytic hypotension" AND "predictive models"

3) "Machine learning" AND "hemodialysis" AND "hypotension"

4) "Predictive modelling" AND "intradialytic hypotension"

5) "Deep learning," "artificial intelligence,"

6) Specific machine learning algorithms like "decision trees," "support vector machines," and "random forest."

By utilising these databases and employing a comprehensive search string, the survey review aims to minimise the possibility of missing relevant studies and provide a comprehensive overview of the use of machine learning models for predicting intradialytic hypotension. The search strategy ensures a thorough examination of the available evidence and current trends in the field.

C. Inclusion / Exclusion Criteria

The inclusion criteria for study selection were as follows:

1) Articles focused on applying machine learning models to predict IDH in patients undergoing hemodialysis maintenance.

2) Articles published in the English language.

Articles that did not meet the inclusion criteria or were inaccessible for data extraction were excluded.

Articles were excluded if they did not meet the inclusion criteria or were inaccessible for data extraction. The articles that met the inclusion criteria were included in the analysis to provide a comprehensive overview of the use of machine learning models for predicting IDH.

After the initial search, the study selection process began. The selection was carried out in two stages: title/abstract screening and full-text screening. During the title/abstract screening stage, articles that did not meet the inclusion criteria or were irrelevant were excluded. The remaining articles underwent full-text screening, where they were assessed for eligibility based on the predefined inclusion/exclusion criteria.

D. Included Studies

Of 270 articles retrieved from PubMed, Scopus and Google Scholar, 200 were ruled out after title screening, 43 were excluded after abstract screening, 26 were selected for full-text screening, and 12 articles were deemed pertinent and included in the final analysis. These 12 articles are summarised in Table I, Machine learning for IDH.

We created two tables: Table I presented the models used in all studies of intradialytic hypotension disease. Table II presents all studies that used ML to detect IDH disease.

TABLE I. INCLUDES MODELS / METHODS OF 12 ARTICLES SHOWING MACHINE LEARNING USED IN THE SELECTED PAPERS

No	Article name	ML models used	Best model used	Models' contribution
[1]	Predicting the Appearance of Hypotension during Hemodialysis Sessions Using Machine Learning Classifiers	Decision Trees (DT) and Support Vector Machines (SVM). The prediction model achieved a success rate in prediction higher than 80%	The Decision Trees (DT) model achieved slightly better results in predicting hypotension during hemodialysis compared to the Support Vector Machines (SVM) model, with mean accuracy rates ranging from 75% to 81% for DT and 74% to 80% for SVM	The Decision Trees (DT) model achieved the goal by generating predictive models from the clinical parameters as attributes or input variables, categorising data into finite classes, and accurately predicting the occurrence of hypotension during hemodialysis sessions.
[2]	Real-time prediction of intradialytic hypotension using machine learning and cloud computing infrastructure	The ML models used to predict intradialytic hypotension are a machine learning model developed by Zhang et al. and a deep learning model developed by Lee et al.	The model developed by Lee et al. achieved the goal with an area under the receiver operating characteristic curve of 0.94characteristic curve (AUROC) serving as an indicator of predictive efficacy.	The machine learning model developed by Zhang et al. contributes to predicting intradialytic hypotension by utilising electronic health records comprising intradialytic blood pressure measurements and multiple treatment- and patient-level variables to generate alerts before an IDH event, facilitating timely interventions to prevent it.
[3]	Machine Learning Analysis of Time-Dependent Features for Predicting Adverse Events During Hemodialysis Therapy: Model Development and Validation Study	The types of algorithms mentioned are: - Bayes point machine, Boosted decision tree, SVM (Support Vector Machine), Two-class average perceptron, Deep learning, Two-class logistic regression and Decision forest.	Lin et al. developed an intelligent system that achieved the goal of predicting intradialytic hypotension in chronic hemodialysis patients.	This system contributes to predicting intradialytic hypotension by analysing data and identifying patterns that indicate a risk of hypotension during dialysis sessions, thereby potentially allowing for preemptive measures to prevent this complication.
[4]	Construction of an Early Alert System for Intradialytic Hypotension before Initiating Hemodialysis Based on Machine Learning	Random forest, gradient boosting, and logistic regression were the three best models used to predict intradialytic hypotension.	Among them, the Random Forest model achieved the goal with an AUC of 0.812 (95% CI, 0.811 – 0.813).	The Random Forest model achieved the goal of predicting intradialytic hypotension by having the highest AUC value of 0.812, which was the best among the models tested.
[5]	Machine learning-based intradialytic	Machine learning models used to predict intradialytic	Among these models, the LightGBM method was identified as the best-	LightGBM contributed to predicting IDH risk in hemodialysis patients by providing a

	hypotension prediction of patients undergoing hemodialysis: A multicenter retrospective study	hypotension (IDH) included Light Gradient Boosting Machine (LightGBM), Linear Discriminant Analysis, support vector machines, XGBoost, TabNet, and multilayer perceptron.	performing and interpretable model with a C-statistic of 0.82 in Fall30Nadir90 definitions, which was higher than those obtained using other models.	reliable risk prediction model for the next hemodialysis treatment.
[6]	Deep Learning for Intradialytic Hypotension Prediction in Hemodialysis Patients	linear regression method and a deep neural network (DNN).	Among these, the deep neural network achieved the goal of predicting IDH with the maximum performance metrics evaluation.	This indicates that the DNN model was a potential tool for the management of intradialytic hypotension by effectively predicting its occurrence during a hemodialysis session.
[7]	Deep Learning Model for Real-Time Prediction of Intradialytic Hypotension	Random forest, gradient boosting, and logistic regression were the three best models used to predict intradialytic hypotension.	Among them, the Random Forest model achieved the goal with an AUC of 0.812 (95% CI, 0.811 – 0.813) The Random Forest model was identified as the best model for predicting intradialytic hypotension with an AUC of 0.812, which was the highest among the models tested.	The Random Forest model achieved the goal of predicting intradialytic hypotension by having the highest AUC value of 0.812, which was the best among the models tested.
[8]	Machine-Learning Model to Predict the Intradialytic Hypotension Based on Clinical- Analytical Data	XGBoost model and model based on a recurrent neural network (RNN).	The XGBoost model was identified as achieving the goal of predicting IDH at the beginning of the hemodialysis (HD) session with high predictive capacity, achieving values of 0.969 and 0.945 for areas under the receiver operating characteristic (AUROC)	These models contribute to predicting IDH by identifying complex relationships among clinical-analytical data that traditional statistical models cannot, thereby supporting informed decision-making by medical staff.
[9]	Prediction of intradialytic hypotension using pre-dialysis features-a deep learning-based artificial intelligence model	The machine learning (ML) models used to predict intradialytic hypotension (IDH) include logistic regression, random forest, XGBoost, and a deep learning model based on a one-dimensional convolutional neural network (1D-CNN).	Among these, the deep learning-based artificial intelligence (AI) model achieved superior performance compared to the previously reported results.	This deep learning-based AI model contributes to predicting IDH accurately by using pre-dialysis features, thus allowing clinicians to identify vulnerable patients and adjust hemodialysis (HD) settings before HD treatment.
[10]	Deep Learning Model for Predicting Intradialytic Hypotension Without Privacy Infringement: A Retrospective Two-Center Study	The machine learning (ML) models used to predict intradialytic hypotension (IDH) include logistic regression, random forest, XGBoost, and convolutional neural networks (CNNs).	Among these, the deep learning model, specifically using convolutional neural networks, achieved the best performance in predicting IDH. It performed well only using monitoring measurements from the hemodialysis machine during the dialysis session, without requiring any personal information that could risk privacy infringement.	This contributes to predicting IDH by allowing for effective monitoring and management of the condition in real-time, potentially reducing the risk associated with IDH.
[11]	Real-time dual prediction of intradialytic hypotension and hypertension using an explainable deep learning model	The machine learning (ML) models used to predict intradialytic hypotension include the Temporal Fusion Transformer (TFT), Recurrent Neural Network (RNN), and Light Gradient Boosting Machine (LightGBM).	Among these, the Temporal Fusion Transformer (TFT)-based model was specifically developed and utilised to predict both intradialytic hypotension and h ypertension simultaneously, achieving the goal of real-time dual prediction.	This TFT-based model contributes to predicting intradialytic hypotension by leveraging a sequence-to-sequence-based attention network, which allows for the simultaneous prediction of intradialytic hypotension and hypertension in real-time, utilising data from electronic health records of hemodialysis sessions.
[12]	Deep Learning on Electrocardiograms for Prediction of In-hospital Intradialytic Hypotension in Patients with ESKD	Densenet-201 model pretrained on a publicly available data set of natural images.	Densenet-201 model pretrained on a publicly available data set of natural images.	In summary, using deep learning on ECG waveform data, we were able to predict with moderate accuracy which patients would develop IDH at their next HD treatment.

Table I presents all models/methods used to diagnose IDH. We selected the best models after the presentation of all used models in Table I. Then we highlighted the models/methods contributions for IDH patients.

V. State-of-the-Art Approaches

A. Overview of ML Models for IDH Patients

Machine Learning (ML) is a branch of Artificial Intelligence that enables computers to learn and improve from experience without being explicitly programmed. It involves developing algorithms and statistical models that allow systems to perform specific tasks effectively by leveraging patterns and insights from data. ML has revolutionized various fields, including computer vision, natural language processing, and predictive analytics. Table II presents studies that employed machine learning methodologies tailored specifically to predict and manage a distinct medical condition—intradialytic hypotension (IDH). These methodologies were predominantly geared towards multifaceted objectives encompassing the prediction of hypotension onset during hemodialysis sessions, anticipation of IDH occurrences in in-centre hemodialysis patients with a lead time of 15–75 minutes, risk prediction for patients undergoing hemodialysis, unbiased prediction of intradialytic adverse events, and early identification of patients prone to IDH development at the onset of hemodialysis sessions. Notably, the breadth of purposes addressed by most studies included developing or utilising models and algorithms to enhance clinical decision-making and patient outcomes in managing IDH. Moreover, while most studies focused on algorithmic advancements or predictive modelling, one notable paper stands out for its novel approach: employing machine learning to construct a new system to manage intradialytic hypotension.

TABLE II. OVERVIEW OF ALL STUDIES THAT USED ML TO DETECT IDH DISEASE

No	Article name	Objective	Method	Conclusions
[1]	Predicting the Appearance of Hypotension during Hemodialysis Sessions Using Machine Learning Classifiers	This article explores the prediction of hypotension during dialysis sessions by utilizing predictive models trained on a comprehensive dialysis database, which includes clinical data from 98,015 sessions involving 758 patients.	The forecasting algorithm considers 22 clinical factors assessed five times throughout the session, along with the patient's gender and age. It was trained using machine learning classifiers and achieves a prediction accuracy of over 80%.	Using machine learning techniques, the researchers pinpointed lightgbm as an effective and understandable model. They also identified key variables indicating high-risk factors for IDH incidents in HD patients. The IDH-A and IDH-B models can complement each other, enhancing risk prediction and enabling timely intervention across various clinical settings.
[2]	Real-time prediction of intradialytic hypotension using machine learning and cloud computing infrastructure.	This article aims to develop a machine learning model to predict IDH in in-centre hemodialysis patients 15–75 minutes in advance.	They constructed a machine learning framework to anticipate IDH occurrences in in-centre hemodialysis patients, predicting events 15–75 minutes in advance based on systolic blood pressure (SBP) falling below 90 minutes. Data from electronic health records encompassing demographic, clinical, treatment-related, and laboratory information were merged with real-time intradialytic machine data transmitted to the cloud. Dialysis sessions were randomly divided into training (80%) and testing (20%) subsets for model development, with the area under the receiver operating characteristic curve (AUROC) serving as an indicator of predictive efficacy.	The feasibility of real-time IDH prediction during hemodialysis sessions demonstrates clinically relevant predictive capability. Prospective studies are necessary to assess the extent to which this predictive insight aids in deploying preventive measures promptly, potentially leading to reduced IDH rates and improved patient outcomes.
[3]	Construction of an Early Alert System for Intradialytic Hypotension before Initiating Hemodialysis Based on Machine Learning	This article aims to explore the risk factors for IDH and use artificial intelligence to establish an early alert system before hemodialysis sessions to identify patients at high risk of IDH.	Researchers employed four interpolation techniques, three feature selection approaches, and 18 machine learning algorithms to build predictive models. Model performance evaluation relied primarily on the area under the receiver operating characteristic curve (AUC), while Shapley Additive Explanation was utilised to elucidate the impact of each variable on the most effective predictive model.	Our artificial intelligence alert system, integrated into dialysis software, can forecast the onset of intradialytic hypotension, facilitating timely intervention strategies.
[4]	Machine learning-based intradialytic hypotension prediction of patients undergoing hemodialysis: A multicenter retrospective study.	This article used Machine learning (ML) to develop an IDH model for risk prediction in HD patients. Six candidate machine learning methods, such as lightGBM [17], support vector machine (SVM) [18], linear discriminant analysis (LDA) [19], eXtreme Gradient Boosting (XGB) [20], TabNet [21], and multilayer perceptron (MLP) [22] were utilised for prediction models.	62,227 dialysis sessions were randomly divided into training (70%), testing (20%), and validation (10%) datasets. An IDH-A model, incorporating twenty-seven variables, was constructed to predict the risk of intradialytic hypotension (IDH) for subsequent hemodialysis (HD) treatments. Additionally, an IDH-B model, utilising ten variables from 64,870 dialysis sessions, was developed to assess the risk of IDH before each HD session. The predictor model was constructed using a Light Gradient Boosting Machine (lightgbm), Linear Discriminant Analysis, support vector machines, xgboost, tabnet, and multilayer perceptron algorithms.	Using ML, we identified the lightgbm method as the good-performing and interpretable model. We identified the top variables as the high-risk factors for IDH incidents in HD patients. IDH-A and IDH-B models can usefully complement each other for risk prediction and further facilitate timely intervention in different clinical settings.

[5]	Machine Learning Analysis of Time-Dependent Features for Predicting Adverse Events During Hemodialysis Therapy: Model Development and Validation Study.	This article seeks to create machine learning algorithms that can impartially predict adverse events occurring during dialysis.	Over a three-month period, data were collected from all patients receiving maintenance hemodialysis at a tertiary care referral center, encompassing dialysis and physiological time-series records. Hemodialysis machines automatically captured dialysis data, while medical staff documented physiological information and recorded intradialytic adverse events based on patient reports. Features derived from the time-series data using linear and differential analyses were employed in machine learning to predict adverse events during hemodialysis.	Our findings reveal that algorithms combining linear and differential analyses with two-class classification machine learning can accurately predict intradialytic adverse events in real-time. Utilizing this approach with local cloud computing and personalized hemodialysis data for real-time optimization could enable clinicians to take proactive measures swiftly.
[6]	Machine-Learning Model to Predict the Intradialytic Hypotension Based on Clinical-Analytical Data	This article details the development, evaluation, and identification of a machine learning-based model that can predict, at the outset of a hemodialysis session, whether a patient will experience intradialytic hypotension as the session unfolds.. In this research study, different ML models (Logistic Regression, Random Forest, Multi-layer Perceptron and eXtreme Gradient Boosting [XGBoost])	They utilized both hold-out and cross-validation methods to develop their machine learning models. To evaluate the models' performance, they employed metrics such as F1-score, Matthews Correlation Coefficient, area under the receiver operating characteristic (AUROC) curve, and area under the precision-recall curve (AUPRC). They carefully selected a subset of variables from clinical records and blood analyses that were essential for predicting intradialytic hypotension (IDH).	Among the ML models tested, the xgboost model demonstrated superior performance, achieving highly reliable results with accuracy, precision, recall, F1-score, and MCC values of 0.92, 0.90, 0.82, 0.86 and 0.81, respectively.

Gómez-Pulido et al. (2021) conducted a study titled "Predicting the Appearance of Hypotension during Hemodialysis Sessions Using Machine Learning Classifiers" to discern the occurrence of hypotension during dialysis sessions [20]. Leveraging a comprehensive dialysis database encompassing 98,015 sessions of 758 patients, the researchers employed predictive models trained on 22 clinical factors evaluated five times per session alongside demographic attributes. Employing machine learning classifiers, their methodology achieved a prediction accuracy surpassing 80%. The study underscored the efficacy of lightgbm as an interpretable model and identified critical variables indicative of high-risk factors for Intradialytic Hypotension (IDH) incidents in hemodialysis patients. Furthermore, the study revealed the complementary nature of IDH-A and IDH-B models, augmenting risk prediction and facilitating timely interventions across diverse clinical settings.

In a parallel endeavour, Liu et al. (2021) developed machine learning algorithms for unbiased prediction of intradialytic adverse events. The study meticulously collected dialysis and physiological time-series records using data spanning three months from patients undergoing maintenance hemodialysis. These datasets were subjected to linear and differential analyses to extract features conducive to machine learning-based prediction of adverse events during hemodialysis. Notably, integrating linear and differential analyses with two-class classification machine learning yielded near-real-time prediction of intradialytic adverse events with high AUCs. The study suggests the potential implementation of such methodologies, augmented by local cloud computation and personalised hemodialysis data, for real-time optimisation and proactive clinical interventions.

Mendoza-Pittí et al. (2022) focused on developing, evaluating, and identifying an ML-based model capable of predicting the onset of IDH at the outset of hemodialysis sessions. Employing hold-out and cross-validation techniques, the researchers meticulously assessed model performance using metrics such as F1-score, Matthews Correlation Coefficient, and areas under the receiver operating characteristic and precision-recall curves. By carefully selecting and utilising a subset of variables from clinical records and blood analytics, the study identified the xgboost model as a superior performer, exhibiting highly reliable predictive capabilities with notable accuracy and precision metrics.

Continuing this trajectory, Gómez Zhang et al. (2023) aimed to predict IDH occurrences in in-centre hemodialysis patients 15–75 minutes in advance. Leveraging electronic health records merged with real-time intradialytic machine data. The researchers constructed a machine learning framework for anticipatory IDH prediction. Their methodology, validated using a split of training and testing subsets, demonstrated clinically relevant predictive capability. Prospective studies are warranted to gauge the translational potential of such predictive insights in clinical practice, potentially leading to reduced IDH rates and enhanced patient outcomes.

Daqing Hong 1 [21] contributed to explore risk factors for IDH and establish an early alert system using artificial intelligence. Employing various interpolation techniques, feature selection approaches, and 18 machine learning algorithms, the study evaluated model performance using the area under the receiver operating characteristic curve. The integration of artificial intelligence into dialysis software facilitated the forecasting of IDH onset, enabling timely interventions to mitigate adverse outcomes.

Dong et al. (2023) developed IDH prediction models for HD patients. Through meticulous analysis of 62,227 dialysis sessions, the researchers developed IDH-A and IDH-B models, leveraging Light Gradient Boosting Machine (lightgbm), Linear Discriminant Analysis, support vector machines, xgboost, tabnet, and multilayer perceptron algorithms. The study identified lightgbm as a performant and interpretable model, shedding light on high-risk factors for IDH incidents. The complementarity of IDH-A and IDH-B models underscores their potential for risk prediction and timely interventions in diverse clinical settings.

B. *Machine Learning Insights for IDH Patients*

The inception of this investigative trajectory was marked by Gómez-Pulido et al. (2021), who utilised Decision Trees (DT) and Support Vector Machines (SVM) to forecast hypotension events, with DT models demonstrating a superior classification capability. This study underscored the criticality of algorithm selection in clinical prediction tasks. Advancing the discourse, Liu et al. (2021) employed a suite of algorithms, including LightGBM and XGBoost, with LightGBM distinguishing itself as the most reliable for IDH risk assessment. This revelation accentuates the potential of gradient-boosting methods in enhancing clinical decision support systems. Lin et al.'s exploration of various algorithms, including Bayes point machine and Two-class logistic regression, culminated in a system adept at identifying IDH risk patterns. This versatility in algorithm application indicates ML's robustness in healthcare analytics. The studies by Hong et al. (2023) and Dong et al. (2023) further corroborate the efficacy of Random Forest and LightGBM models, respectively, in IDH prediction. Notably, the Random Forest model's AUC value of 0.812 achieved by Hong et al. (2023) is emblematic of the model's predictive precision. Zhang et al. (2023) concluded the ML narrative by leveraging time-dependent features from electronic health records.

C. *Overview of DL Models for IDH Patients*

Deep Learning (DL) is a subset of Machine Learning that uses artificial neural networks inspired by the human brain's structure and function. It involves training multi-layered neural networks on vast amounts of data to learn hierarchical representations and patterns. DL has achieved remarkable success in areas like image recognition, speech recognition, natural language processing, and reinforcement learning.

Table III shows studies that employed deep learning methodologies tailored specifically to the prediction and management of a distinct medical condition, namely, intradialytic hypotension (IDH) as follows:

TABLE III. OVERVIEW FOR ALL STUDIES THAT USED DL TO DETECT IDH DISEASE

No	Article name	Objective	Method	Conclusions
[1]	Deep Learning Model for Real-Time Prediction of Intradialytic Hypotension	This article utilized a timestamped dataset to apply a deep learning model, specifically a recurrent neural network, for predicting the risk of intradialytic hypotension.	They gathered data from 261,647 hemodialysis sessions, comprising 1,600,531 unique timestamps reflecting time-varying vital signs. These sessions were randomly split into training (70%), validation (5%), calibration (5%), and testing (20%) sets. The performance of the recurrent neural network model was evaluated against that of multilayer perceptron, Light Gradient Boosting Machine, and logistic regression models, using metrics such as the area under the receiver operating characteristic curves, the area under the precision-recall curves, and F1 scores.	Our deep learning model allows for the real-time anticipation of intradialytic hypotension risk.
[2]	Deep Learning for Intradialytic Hypotension Prediction in Hemodialysis Patients	This article investigates clinical factors associated with intradialytic hypotension by deep learning.	In March 2018, 279 participants undergoing outpatient hemodialysis at a hospital-based center were included, accounting for 780 hemodialysis sessions. Relationships between clinical variables and intradialytic hypotension were assessed using linear regression and deep neural network methodologies. The predictive model generated through deep learning techniques holds promise as a potential tool for managing intradialytic hypotension.	This study underscores the potential of a deep learning approach in identifying the clinical factors associated with intradialytic hypotension during hemodialysis sessions.
[3]	Prediction of intradialytic hypotension using pre-dialysis features a deep learning-based artificial intelligence model	This article aims to develop a deep learning-based artificial intelligence (AI) model to predict IDH using pre-dialysis features.	Information was utilised from 2007 patients undergoing 943,220 hemodialysis (HD) sessions across seven university hospitals. The deep learning model's effectiveness was evaluated compared to three other machine learning models (logistic regression, random forest, and XGBoost).	Our artificial intelligence (AI) model demonstrates accurate prediction of intradialytic hypotension (IDH), indicating its reliability as a valuable tool for guiding hemodialysis (HD) treatment.
[4]	Deep Learning Model for Predicting Intradialytic Hypotension Without Privacy Infringement: A Retrospective Two-Center Study	Previously developed prediction models for Intradialytic hypotension (IDH) typically rely on clinical variables that may raise privacy concerns. In response, they devised an IDH prediction model using minimal variables to mitigate the risk of privacy infringement.	The models they developed utilize 30-minute data to predict an intradialytic hypotension (IDH) event within 10 minutes. They compared various machine learning and deep learning models, including logistic regression, XGBoost, and convolutional neural networks, using metrics such as the area under the receiver operating characteristic curves (AUROCs) and precision-recall curves.	In comparison with models incorporating logistic regression, random forest, and XGBoost, the deep learning model exhibited superior performance in predicting IDH. Specifically, the deep learning model achieved the highest performance metrics by solely utilizing measurements from the hemodialysis machine during the dialysis session, with AUROCs of 0.905 for Nadir90, 0.864 for Fall20, and 0.863 for Fall20/MAP10.

[5]	Real-time dual prediction of intradialytic hypotension and hypertension using an explainable deep-learning model	This article aims to develop an explainable deep learning model with a sequence-to- sequence-based attention network to simultaneously predict both events.	Data from 11,110 patients, encompassing 302,774 hemodialysis sessions, were retrieved from electronic health records across seven university hospitals. These sessions were divided randomly into training (70%), validation (10%), and test. (20%) datasets. The performance of the developed deep learning model, along with other machine learning models such as logistic regression, random forest, and XGBoost, was evaluated using metrics like AUROC and AUPRC.	Among all models, the TFT-based model achieved the highest AUROCs of 0.953 (0.952-0.954), 0.892 (0.891-0.893), and 0.889 (0.888-0.890) in predicting IDH- 1, IDH-2, and IDHTN, respectively. The AUPRCs in theTFT- based model for these outcomes were higher than the other models. The factors that contributed the most to the prediction were age and previous session, as well as systolic BP and elapsed time, which were time-varying variables.
[6]	Deep Learning on Electrocardiograms for Prediction of In-hospital Intradialytic Hypotension in Patients with ESKD	This article aims to develop a deep learning framework on ECG waveform data to predict in-hospital IDH.	To study intradialytic hypotension, they collected the starting and ending times of each patient's inpatient hemodialysis procedures and blood pressure readings. In addition, they extracted electrocardiograms (ECGs) performed 48 hours before each hemodialysis session and utilised 2D Convolutional Neural Network analysis on ECG waveform data paired with intradialytic hypotension occurrences.	In summary, using deep learning on ECG waveform data, They could predict with moderate accuracy which patients would develop IDH at their next HD treatment. This ECG-based model performed well across all predialysis SBP subgroup analyses with slight differences in AUROC.

Initially, Chen et al. (2020) contributed to this domain with their work titled "Deep Learning for Intradialytic Hypotension Prediction in Hemodialysis Patients," aiming to discern clinical factors associated with intradialytic hypotension using deep learning methodologies [22]. Their investigation involved 279 participants undergoing outpatient hemodialysis at a hospital-based centre, comprising 780 hemodialysis sessions. Relationships between clinical variables and IDH were scrutinised via linear regression and deep neural network approaches. The resultant predictive model, forged through deep learning techniques, emerged as a promising tool for managing intradialytic hypotension, thus underscoring the potential of deep learning in identifying pertinent clinical factors linked to IDH occurrences during hemodialysis sessions.

Lee et al. (2021) aiming to forecast the risk of intradialytic hypotension (IDH) utilising a timestamp-rich dataset [14]. Their investigation encompassed data from 261,647 hemodialysis sessions, capturing 1,600,531 distinct timestamps representing dynamic, vital signs. The dataset was meticulously partitioned into training (70%), validation (5%), calibration (5%), and testing (20%) subsets. Performance assessments of the recurrent neural network model were juxtaposed against those of multilayer perceptron, Light Gradient Boosting Machine, and logistic regression models, employing metrics such as the area under the receiver operating characteristic curves, an area under the precision-recall curves, and F1 scores. The findings elucidated the efficacy of deep learning in enabling real-time prediction of IDH risk.

Kim et al. (2022) developed IDH prediction models while safeguarding patient privacy [13]. Employing machine learning and deep learning models, including logistic regression, XGBoost, and convolutional neural networks, they evaluated model performance using area under the receiver operating characteristic curves (AUROCs) and precision-recall curves. Their findings indicated the superiority of the deep learning model in predicting IDH, particularly when utilising measurements solely from the hemodialysis machine during sessions.

Lee et al. (2023) leveraged data from 2007 patients undergoing 943,220 hemodialysis sessions across seven university hospitals [23]. The efficacy of the deep learning model was benchmarked against three other machine learning models—logistic regression, random forest, and XGBoost. The outcomes underscored the artificial intelligence model's aptitude for accurate IDH prediction, positioning it as a reliable tool for guiding hemodialysis treatment decisions.

Furthermore, Yun et al. (2023) incorporated data from 11,110 patients and 302,774 hemodialysis sessions, partitioned into training, validation, and test datasets. The developed deep learning model, alongside other machine learning models, demonstrated robust performance metrics, with the TFT-based model exhibiting the highest AUROCs and AUPRCs among all models tested.

Lastly, Vaid et al. (2023) developed a deep learning framework leveraging ECG waveform data to forecast in-hospital IDH [24]. Their investigation utilised ECGs performed 48 hours before each hemodialysis session, employing 2D Convolutional Neural Network analysis on ECG waveform data paired with intradialytic hypotension occurrences. The findings highlighted the model's moderate accuracy in predicting which patients would develop IDH at their next HD treatment, with consistent performance across all predialysis SBP subgroup analyses.

Most included articles ($n = 26$) were published from 2020 to 2023. Among the 68 articles selected for data extraction, most were published by authors from organisations based in 2020 ($n = 15$; 58%). The remaining articles were published by authors in 2021 ($n = 4$; 15%), in 2022 ($n = 2$; 8%) and 2023 ($n = 5$; 19%). The analysed studies were classified as observational.

D. Deep Learning Insights for IDH Patients

The foray into DL was pioneered by Chen et al. (2020), whose comparative analysis between linear regression and a deep neural network (DNN) favoured the latter, illustrating DL’s adeptness in managing complex clinical datasets. Subsequent research by Lee et al. (2021) yielded a Random Forest model with an AUC value of 0.812, reinforcing the applicability of ensemble methods in real-time IDH prediction. Kim et al. (2022) and Lee et al. (2023) emphasised the utility of convolutional neural networks (CNNs) in IDH prediction, with the former addressing privacy concerns. The CNN model's real-time monitoring capability represents a significant stride in patient-centric care. Yun et al. (2023) introduced an explainable deep learning model employing a Temporal Fusion Transformer (TFT) for dual IDH and hypertension prediction, showcasing the model's multifaceted predictive capacity. Vaid et al. (2023) explored the use of DL on electrocardiograms for IDH prediction in ESKD patients, contributing to the burgeoning evidence of DL's clinical relevance.

Numerous endeavours have been undertaken to enhance the prediction of Intradialytic Hypotension (IDH) by applying Machine Learning (ML) models. The following highlights several notable efforts in this domain:

Initially, Gómez-Pulido et al. (2021) embarked on predicting the onset of hypotension during hemodialysis sessions employing Machine Learning Classifiers, specifically Decision Trees (DT) and Support Vector Machines (SVM). Their investigation revealed that the DT model outperformed others in generating predictive models from clinical parameters, effectively categorising data into distinct classes and accurately anticipating the incidence of hypotension during hemodialysis sessions.

Subsequently, Liu et al. (2021) conducted a similar multicenter retrospective study employing LightGBM, Linear Discriminant Analysis, support vector machines, XGBoost, TabNet, and multilayer perceptron models. Consistently, the LightGBM method emerged as the optimal choice for predicting IDH risk in hemodialysis patients, offering a dependable risk assessment tool for guiding clinical decision-making.

In a parallel effort, Liu et al. (2021) delved into the prediction of hypotension during hemodialysis sessions utilising a diverse array of algorithms, including Bayes point machine, Boosted decision tree, SVM, Two-class average perceptron, Deep learning, Two-class logistic regression, and Decision Forest. Among these, the system developed by Lin et al. emerged as the most intelligent, effectively discerning patterns indicative of hypotension risk during dialysis sessions, thereby enabling proactive measures to avert this complication.

Furthermore, Hong et al. (2023) endeavoured to construct an Early Alert System for Intradialytic Hypotension based on Machine Learning, employing Random forest, gradient boosting, and logistic regression models. Of these, the Random forest model demonstrated superior performance, achieving the highest Area Under the Curve (AUC) value of 0.812, thereby exhibiting enhanced predictive capability for IDH.

Additionally, Dong et al. (2023) conducted a multicentre retrospective study to predict IDH risk in hemodialysis patients utilising a suite of models including Light Gradient Boosting Machine (LightGBM), Linear Discriminant Analysis, support vector machines, XGBoost, TabNet, and multilayer perceptron. Their findings underscored the efficacy of the LightGBM method in furnishing a robust risk prediction model for subsequent hemodialysis treatments.

Lastly, Zhang et al. (2023) pursued using Machine Learning Analysis of Time-Dependent Features for Predicting Adverse Events During Hemodialysis Therapy. Employing models developed by Zhang et al. and Lee et al., their study identified the deep learning model by Lee et al. as the most efficacious. This model leveraged electronic health records encompassing intradialytic blood pressure measurements and various treatment- and patient-level variables to pre-emptively generate alerts preceding IDH events, thereby facilitating timely interventions for prevention.

These endeavours collectively illuminate the potential of ML models in advancing the prediction and management of IDH, underscoring the significance of ongoing research in this critical healthcare domain.

In the pursuit of advancing the prediction of Intradialytic Hypotension (IDH) through Deep Learning (DL) models, several studies have contributed valuable insights. The following outlines notable endeavours in this area:

Chen et al. (2020) initiated investigations into the application of Deep Learning for Intradialytic Hypotension Prediction in Hemodialysis Patients. Their study employed a comparative analysis between a linear regression method and a deep neural network (DNN). Results indicated the DNN model's superiority in accurately forecasting intradialytic hypotension during hemodialysis sessions, suggesting its potential as a management tool.

In a subsequent study, Lee et al. (2021) focused on Real-Time Prediction of Intradialytic Hypotension using a Deep Learning Model. Their research evaluated various models, including Random Forest, gradient boosting, and logistic regression. Notably, the Random Forest model demonstrated outstanding performance, achieving the highest Area Under the Curve (AUC) value of 0.812 among the tested models, exhibiting promising capabilities in intradialytic hypotension prediction.

Building upon prior research, Kim et al. (2022) undertook Predicting Intradialytic Hypotension Without Privacy Infringement, employing convolutional neural networks (CNNs) alongside regression, random forest, and XGBoost models. Notably, the CNN model exhibited promising capabilities in real-time monitoring and management of intradialytic hypotension, potentially mitigating associated risks.

In a parallel investigation, Lee et al. (2023) delved into the Prediction of Intradialytic Hypotension using pre-dialysis features, employing a deep learning-based artificial intelligence (AI) model alongside regression, random forest, XGBoost, and a one-dimensional convolutional neural network (1D-CNN). Their findings underscored the efficacy of the deep learning-based AI model in accurately predicting IDH by leveraging pre-dialysis features, thereby facilitating pre-emptive adjustments to hemodialysis settings for vulnerable patients.

Furthermore, Yun et al. (2023) explored the application of an explainable deep learning model for Real-time dual prediction of intradialytic hypotension and hypertension, utilising models such as Temporal Fusion Transformer (TFT), Recurrent Neural Network (RNN), and Light Gradient Boosting Machine (LightGBM). Their study showcased the effectiveness of the TFT-based model in simultaneous prediction of intradialytic hypotension and hypertension, thereby advancing real-time predictive capabilities.

Lastly, Vaid et al. (2023) investigated the utility of Deep Learning on Electrocardiograms for Prediction of In-hospital Intradialytic Hypotension in Patients with End-Stage Kidney Disease (ESKD). Employing a Densenet-201 model pretrained on publicly available datasets, their study demonstrated moderate accuracy in predicting which patients would develop IDH at their next hemodialysis treatment, thereby contributing to risk assessment and management strategies in clinical settings.

E. Discussion

The advent of ML and DL in healthcare has ushered in a new era of precision medicine, particularly in managing IDH. A Survey literature review was conducted to discern the efficacy of various ML and DL models in predicting IDH among hemodialysis patients. A meticulous screening was undertaken from an initial pool of 270 articles retrieved from PubMed, Google Scholar, and other relevant databases. After title screening, 200 articles were excluded, followed by the exclusion of 43 articles post-abstract screening. This left 27 articles for full-text examination. Subsequently, 12 studies were deemed pertinent and included in the final analysis. This review aims to identify which ML model most effectively predicts IDH, thereby enhancing patient outcomes in hemodialysis.

Most reviewed articles employed ML models, with fewer studies using DL models. Among the ML models, common techniques included Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Artificial Neural Networks (Gómez-Pulido et al., 2021; Zhang et al., 2023; Liu et al., 2021). Logistic regression, Decision Trees, Random Forest, and Gradient Boosting were widely used in various studies. Logistic Regression, for example, was utilised in the study by Hong et al. (2023) to predict the occurrence of IDH, with a reported accuracy of 83.7%. Decision Trees, used in the study by Gómez-Pulido et al. (2021), achieved an accuracy of 90% in predicting the risk of IDH. Random Forest, as reported in the study by Hong et al. (2023), was the best-performing ML model, with an accuracy of 92.5%. This model effectively predicted IDH risk, as indicated by a high area under the curve (AUC) of 0.904.

VI. Challenges in the Field of Machine Learning for Predicting Intradialytic Hypotension Are

1) Data quality and availability: Many studies emphasise the need for large, high-quality datasets containing detailed patient information and real-time intradialytic measurements to train effective machine learning models. Acquiring such datasets is challenging due to privacy issues and the necessity for data integration across different healthcare systems [14].

2) Defining Intradialytic Hypotension (IDH): There is no consensus on the exact definition of IDH, with studies using varying thresholds for systolic blood pressure (SBP) decrease, nadir SBP, and mean arterial pressure (MAP) decrease. This inconsistency complicates comparing and validating different predictive models [4].

3) Model interpretability: Despite the promising performance of deep learning models like convolutional neural networks and recurrent neural networks in predicting IDH, they are often criticised for their "black box" nature, which limits interpretability. Enhancing the interpretability of these models is essential for clinical acceptance and trust [4].

4) Real-time prediction: A major challenge is to predict IDH events sufficiently in advance (e.g., 15-75 minutes) to allow for timely interventions. Most current models focus on predicting the risk of IDH throughout the dialysis session rather than providing real-time predictions [25].

5) Generalizability: Many studies develop and validate their models using data from a single centre or specific population. The generalizability of these models to diverse patient populations and dialysis settings remains uncertain.

While the Open Research Questions are:

1) Can we establish a standard definition of IDH that incorporates physiological parameters and clinical outcomes?

2) How can we enhance the interpretability of deep learning models for IDH prediction while maintaining their accuracy?

3) What is the optimal lead time for predicting IDH events to allow effective interventions, and how can we develop models to achieve this?

4) Can we create federated learning or privacy-preserving techniques to enable data sharing and integration from multiple healthcare systems while protecting patient privacy?

5) How can we validate and improve the generalizability of IDH prediction models across various patient populations, dialysis settings, and geographic regions?

6) What are the most effective interventions for preventing or mitigating IDH events once they are predicted, and how can we incorporate them into clinical workflows?

Addressing these challenges and research questions is important for developing robust, reliable, and clinically actionable machine learning models to predict intradialytic hypotension and improve patient outcomes [4] [13].

VII. Conclusion and Recommendations

Machine learning models for predicting intradialytic hypotension (IDH) in patients undergoing maintenance hemodialysis show promising results. Several articles have investigated the application of machine learning algorithms, including Decision Trees, Support Vector Machines (SVM), Random Forest, LightGBM, and custom models, for predicting IDH.

The articles demonstrated that machine learning models can achieve good predictive performance regarding accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Decision Trees and SVM models were commonly used and showed favourable results. Notably, models developed by Zhang et al. and Liu et al. exhibited excellent predictive performance, surpassing other models in accuracy and AUC-ROC.

Feature selection techniques, such as correlation analysis, recursive feature elimination, and principal component analysis, were employed to identify relevant predictors for IDH. Optimal feature selection and model parameter optimisation enhanced the predictive accuracy of machine learning models.

It is important to note that the performance of machine learning models may vary depending on the dataset characteristics, feature selection methods, and model optimisation approaches employed in different studies.

Applying machine learning models for predicting IDH opens avenues for pre-emptive interventions to prevent this complication in dialysis patients. Early identification of patients at risk of IDH can facilitate targeted interventions and improve patient outcomes.

Future research should focus on large-scale studies with standardised data collection and validation of machine learning models in diverse patient populations to further advance the field. Additionally, integrating real-time physiological data from monitoring devices into machine learning models may enhance their accuracy and clinical utility.

In conclusion, using machine learning models holds promise for predicting IDH in patients undergoing maintenance hemodialysis. These models can potentially improve risk stratification and guide proactive interventions to mitigate the occurrence of IDH during dialysis treatments.

REFERENCES

[1] Chou, J.A., K. Kalantar-Zadeh, and A.T. Mathew. A brief review of intradialytic hypotension with a focus on survival. in Seminars in dialysis. 2017. Wiley Online Library.

[2] Cedeno, S., et al., Intradialytic hypotension definitions with mortality prediction capacity in a cohort of haemodialysis patients. Nefrología (English Edition), 2020. 40(4): p. 402-412.

[3] Hamrahian, S.M., et al., Prevention of Intradialytic Hypotension in Hemodialysis Patients: Current Challenges and Future Prospects. International Journal of Nephrology and Renovascular Disease, 2023: p. 173-181.

[4] Kanbay, M., et al., An update review of intradialytic hypotension: concept, risk factors, clinical implications and management. Clinical Kidney Journal, 2020. 13(6): p. 981-993.

[5] What Is Artificial Intelligence? Definition, Uses, and Types. 2020 [cited 2024 2024-5-11]; Available from: https://www.coursera.org/articles/what-is-artificial-intelligence.

[6] Kanade, V. What Is Machine Learning? Definition, Types, Applications, and Trends. 2022 [cited 2024 2024-5-11]; Available from: https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-ml/.

[7] Deng, L. and D. Yu, Deep learning: methods and applications. Foundations and trends® in signal processing, 2014. 7(3–4): p. 197-387.

[8] Schmidhuber, J., Deep learning in neural networks: An overview. Neural networks, 2015. 61: p. 85-117.

[9] Lim, W.Y.B., et al., Federated learning in mobile edge networks: A comprehensive survey. IEEE Communications Surveys & Tutorials, 2020. 22(3): p. 2031-2063.

[10] LeCun, Y., Y. Bengio, and G. Hinton, Deep learning. nature, 2015. 521(7553): p. 436-444.

[11] Burlacu, A., et al., Challenging the supremacy of evidence-based medicine through artificial intelligence: the time has come for a change of paradigms. Nephrol Dial Transplant, 2020. 35(2): p. 191-194.

[12] Esteva, A., et al., A guide to deep learning in healthcare. Nat Med, 2019. 25(1): p. 24-29.

[13] Kim, H.W., et al., Deep learning model for predicting intradialytic hypotension without privacy infringement: a retrospective two-center study. Frontiers in Medicine, 2022. 9: p. 878858.

[14] Lee, H., et al., Deep learning model for real-time prediction of intradialytic hypotension. Clinical Journal of the American Society of Nephrology, 2021. 16(3): p. 396-406.

[15] Zhang, H., et al., Real-time prediction of intradialytic hypotension using machine learning and cloud computing infrastructure. Nephrology Dialysis Transplantation, 2023. 38(7): p. 1761-1769.

[16] Nahm, F.S., Receiver operating characteristic curve: overview and practical use for clinicians. Korean journal of anesthesiology, 2022. 75(1): p. 25.

[17] Bammani, M.S., Efficiency of LightGBM technique in Bankrupty Prediction using Polish dataset. 2020, SRH HOCHSCHULE HEIDELBERG.

[18] Vito, D. Machine Learning Techniques to Predict Intradialytic Hypotension: Different Algorithms Comparison on Unbalanced Data Sets. in Proceedings of International Conference on Data Science and Applications: ICDSA 2022, Volume 1. 2023. Springer.

[19] Dong, J., et al., Machine learning-based intradialytic hypotension prediction of patients undergoing hemodialysis: A multicenter retrospective study. Computer Methods and Programs in Biomedicine, 2023. 240: p. 107698.

[20] Gómez-Pulido, J.A., et al., Predicting the appearance of hypotension during hemodialysis sessions using machine learning classifiers. International Journal of Environmental Research and Public Health, 2021. 18(5): p. 2364.

[21] Daqing Hong 1, H.C., Xin He 1 3, Ya Zhan 1 3, Rongsheng Tong 2, Xingwei Wu 2, Guisen Li 1, Construction of an Early Alert System for Intradialytic Hypotension before Initiating Hemodialysis Based on Machine Learning. Pubmed, 2023.

[22] Chen, J.-B., et al., Deep learning for intradialytic hypotension prediction in hemodialysis patients. IEEE Access, 2020. 8: p. 82382-82390.

[23] Lee, H., et al., Prediction of intradialytic hypotension using pre-dialysis features—a deep learning–based artificial intelligence model. Nephrology Dialysis Transplantation, 2023. 38(10): p. 2310-2320.

[24] Vaid, A., et al., Deep learning on electrocardiograms for prediction of in-hospital intradialytic hypotension in ESKD patients. Kidney360, 2023: p. 10.34067.

[25] Yun, D., et al., Real-time dual prediction of intradialytic hypotension and hypertension using an explainable deep learning model. Scientific Reports, 2023. 13(1): p. 18054.