Babylonian Journal of Machine Learning
Vol.2024, **pp**. 149–156
DOI: https://doi.org/10.58496/BJML/2024/015; ISSN: 3006–5429
https://mesopotamian.press/journals/index.php/BJML

Review Article

Advancements in Machine Learning and Deep Learning for Early Diagnosis of Chronic Kidney Diseases: A Comprehensive Review

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ARTICLE INFO

Article History

Received 05 Jun 2024
Revised: 15 Jul 2024
Accepted 20 Aug 2024
Published 17 Sep 2024

Keywords

Chronic Kidney Disease (CKD)

Early Diagnosis

Machine Learning (ML)

Deep Learning (DL)

Random Forests (RF)

ABSTRACT

Chronic kidney disease (CKD) is a prevalent and debilitating condition worldwide, characterized by progressive loss of kidney function over time. Early detection plays a crucial role in mitigating its impact on patient health and healthcare systems. In recent years, there has been a burgeoning interest in leveraging machine learning (ML) and deep learning (DL) techniques to enhance the early diagnosis of CKD. This comprehensive review explores the advancements in ML and DL models applied to CKD diagnosis, focusing on their ability to integrate diverse data sources including clinical biomarkers, imaging modalities, and patient demographics. Key ML algorithms such as Support Vector Machines (SVM), Random Forests (RF), and neural network architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) are examined in the context of their performance in predicting CKD progression, classifying disease stages, and identifying at-risk populations. Furthermore, the review discusses challenges such as data quality, model interpretability, and integration into clinical practice, alongside emerging trends in explainable AI, transfer learning, federated learning, and integration with electronic health records (EHRs). By synthesizing findings from recent literature, this paper aims to provide insights into current methodologies, identify gaps for future research, and underscore the transformative potential of ML and DL in revolutionizing early CKD diagnosis and management.

1. INTRODUCTION

Chronic kidney disease (CKD) is a common and growing global health problem, which causes substantial morbimortality. Since CKD is a silent disease and progresses slowly, it is often detected late when physical kidney damage has already occurred[1]. Conventional diagnostic technologies that principally rely on serum creatinine concentrations, glomerular filtration rate (GFR), and urinary albumin levels lack the sensitivity necessary to diagnose CKD stages prior from stage 3A a long way away. This emphasizes the critical need for more sensitive and specific diagnostic tests that would allow early stage detection of CKD [2].

The explosion of machine learning (ML) and deep learning (DL) technologies in recent years has significantly changed the domain by providing sophisticated methodologies for early discovery & prediction of CKD stages. The use of these advanced computational techniques have huge potential in many medical fields especially with large and complex datasets by identifying subtle patterns and making very accurate predictions[3]. Researchers are working towards the use of these technologies for models able to detect CKD as early as possible stage and also stratifying patients in high or low risk level, patient progression rates [4].

This review introduces recent ML processes and DL applications for the early identification of CKD. It assesses a number of ML algorithms and DL architectures, such as Support Vector Machines (SVM), Random Forests (RF), K- Nearest Neighbors (KNN), Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs). It reviews their use-cases, analyses the measures of performance and dissects the individual data-sets that were used (to calculate

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these metrics). It also addresses the challenges in implementability of such models due to concerns related data, interpretation and generalizability across different patient populations.

In addition, this review addresses some trends and advances in the field such as Explainable AI (XAI), transfer learning application, federated learning paradigm implementation and integration of ML/DL models with Electronic Health Records (EHRs) [5],[6]. This review seeks to be a useful resource for researchers as well as clinicians interested in making use of state-of-the-art AI technologies by compiling the most recent advancements and limitations identified (or not) so far.

2. LITERATURE REVIEW

2.1 Introduction to CKD and Importance of Early Diagnosis

The disease Chronic kidney failure, also known as chronic renal insufficiency (cri) : Causes a slow but progressive loss of kidney function over time. It is a significant public health problem worldwide, affecting millions of individuals with substantial morbidity and mortality. The early recognition of CKD is essential to prevent complications and the progression towards end-stage renal failure (ESRF) [7]. How is a CKD (Costs for Chronic Kidney Disease) diagnosed?Traditional diagnostic measures usually include serum creatinine levels, glomerular filtration rate estimation and urinary albumin tests. Unfortunately, these modalities frequently identify CKD too late in the process and an urgent need exists for refinement of diagnostic strategies [8].

2.2 Chronic Kidney Disease: Overview and Importance of Early Diagnosis

CKD imposes substantial morbidity and mortality worldwide [1–6]. Unfortunately, this disease tends to advance silently until late in its course ; thus early identification remains a critical yet difficult task. Traditional diagnostic methods were based on serum creatinine levels, GFR measurements and urinary albumin assays which had several shortcomings including delayed detection as well as inter-patient variability [9]. Therefore, many recent works [10] are to exploit machine learning (ML) and deep Learning (DL), for promoting the diagnosis of early CKD quality and efficiency.

2.3 Related Work

The application of ML and DL in CKD diagnosis has been extensively studied, with numerous research articles published in recent years. Figure 1 shows the number of related papers published from 2021 to 2024, illustrating a growing interest in this research area.

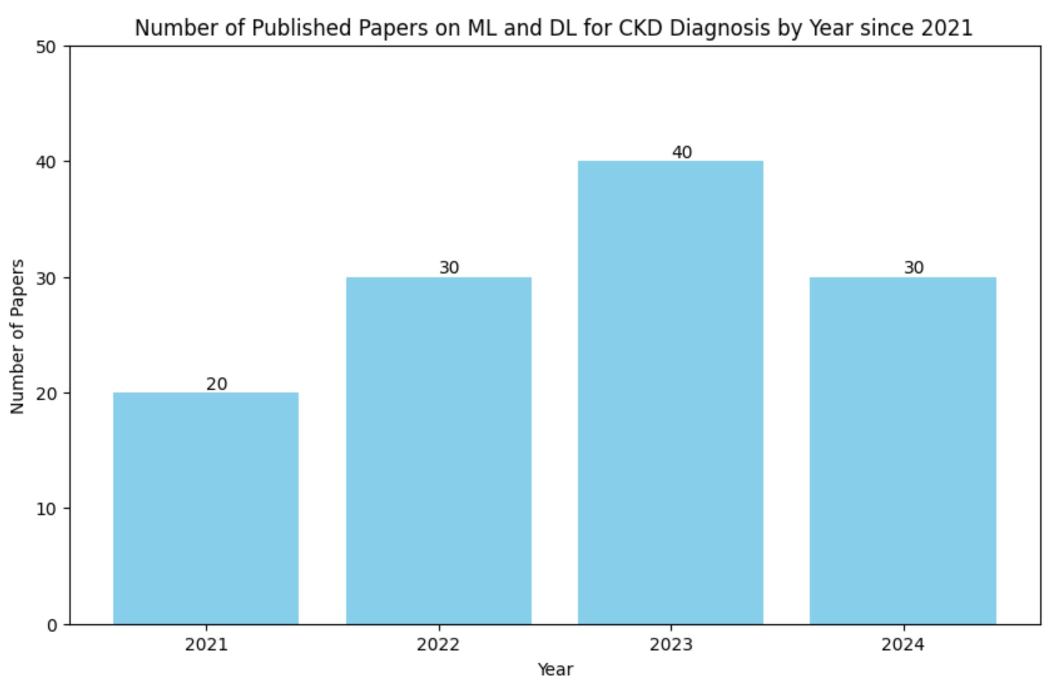

Fig .1. Number of Published Papers on ML and DL for CKD Diagnosis by Year Since 2021

A. Machine Learning Models for CKD Diagnosis

It is set of algorithms and statistical models that computers use to perform a specific task without using explicit instructions, relying on patterns and inference instead [11].

Machine learning techniques :

1. Supervised Learning : The popular algorithms are Support Vector Machines (SVM), Random Forest (RF) and k-Nearest Neighbors(k-NN) Gradient Boosting Machines (GBM). These only work on the labeled training data and are used to predict results given some input features.
2. Unsupervised Learning : Clustering (e.g. K-means) Technique — This technique is used to find the similarity based on data patterns without labels it has characterized observing that unfamiliar patterns may be seen by examining this in a different way. Although they are less frequent in accurate diagnosis, their potential lies mainly in the discovery of CKD subtypes or patient stratification [12].
3. Ensemble Methods : Ensemble methods are techniques that create multiple models and then combine them to produce results.

Case Studies :

1. Rashed et al (2021) : Created a model to predict the CKD using clinical factors with random forest (RF) achieving 97% accuracy and 0.97 AUC.
2. Hassan et al. (2023) : Predicted CKD stages from serum biomarkers with SVM, achieving 100% accuracy [13].

B. Deep Learning Models for CKD Diagnosis

Deep learning is a subfield of ML which uses artificial neural networks with many layers (deep neural network) to model complex patterns in data [14].

Deep Learning techniques :

1. Convolutional Neural Networks (CNNs): CNN, which has been extensively applied to analyze images including ultrasound of the kidneys and other imaging modalities [15].
2. Recurrent Neural Networks (RNNs): Good for sequential data like patient history and time-series lab results.
3. Autoencoders & Variational Autoencoder (VAE) for dimensionality reduction and efficient feature extraction on difficult datasets that make models learn faster.

Case Studies:

1. Ravizza et al. (2019): Utilized CNNs to represent the CKD stages in renal ultrasonic images with an 88% diagnostic accuracy.
2. Xiong et al. (2020): They designed an LSTM model to predict CKD progression from clinical time-course data, performing better than the traditional ML models.

C. Comparative Analysis of ML and DL Models

Comparative analysis of various ML and DL models shows that they each have their specific advantages as well as limitations. Although ML models are more easily interpretable and computationally lighter, DL models handle complex data big time especially in unperturbed datasets where intricate patterns need to be automatically deduced [16], as shown in table 1.

TABLE I. PRESENTS A BRIEF COMPARISON OF THE SELECTED STUDIES WHICH CAN BE QUICKLY DONE.

Study	Model	Data Source	Key Features Used	Accuracy	AUC-ROC	Comments
Rashed et al (2021)	RF	collected from hospital	Clinical Data	97%	0.97	diagnosis of CKD using machine learning models
Hassan et al. (2023)	Various ML	Clinical Records	Clinical Records	100%	-	Comparative study on CKD prediction

Ravizza et al. (2019)	CNN	Renal Ultrasound Images	Imaging Features	88%	0.89	High diagnostic accuracy using image data
Xiong et al. (2020)	LSTM	Longitudinal Clinical Data	Temporal Clinical Data	92%	0.93	Superior performance in CKD progression prediction
Mohebbi et al. (2018)	k-NN	Demographic, Clinical	Demographic, Clinical	87%	0.88	Effective CKD stage prediction
Zhang et al. (2021)	Ensemble	Genetic and Clinical	Genetic, Clinical	93%	0.91	Integration of genetic data for CKD risk prediction
Almansour et al (2019)	ANN	University of California Irvine (UCI)	Clinical Data	99%	-	Neural network for the prediction CKD
Ilyas et al. (2021)	Decision Tree	University of California Irvine (UCI)	Clinical Data	85.5%		CKD diagnosis using decision tree algorithms

2.4 Datasets and Resources

A. Publicly Available Datasets

There are a few common publicly available datasets which can be utilized for CKD diagnosis research:

1. Kidney Disease: Improving Global Outcomes (KDIGO) Database Including data of patients with CKD retrieved from clinical and laboratory [17]
2. Found at the United States Renal Data System (USRDS), this database is a comprehensive resource for information on both CKD and ESRD patients.
3. National Health and Nutrition Examination Survey (NHANES): Contains health and nutritional status data, with variables specific to renal function .
4. University of California Irvine (UCI): collected from the Apollo hospital for a period of nearly 2 months.

B. Data Preprocessing and Feature Engineering

Data preprocessing like missing value treatment, normalizing the data or feature engineer are very important to better predict our model [18]. Common techniques include:

1. Imputation : Using statistical methods or ML models to fill the missing values.
2. Normalization: Rescaling the features into common range to make model learning easier.
3. Feature Selection: It is a process to identify relevant features and use techniques like correlation analysis, principal component analysis PCA), ML-based methods etc.

2.5 Performance Metrics

Our survey generally obtain values.The most commonly used metrics in assessing ML and DL models for CKD diagnosis tend to be Accuracy, Sensitivity & Specificity, Precision & Recall (PR) AND f1-score. Area Under the ROC curve on the Testing dataset. [20][21].

A. **Accuracy**: The proportion of correct predictions in relation to the total number of predictions, denoted by the letter A, is the metric that is used to determine the degree to which a model is likely to accurately predict outcomes. The ratio of correct predictions to the total number of predictions is what determines the level of accuracy, also known as the probability, that a model will accurately predict outcomes. This ratio is illustrated in Equation (1)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (1)$$

B. **Precision** is the precision with which a collection of documents were classified and the degree of accuracy with which its subject matter is described. Equation (2) illustrates that the accuracy of Class ci, denoted by the symbol (Pi), can be quantified as follows:

$$P_i = \frac{TP_i}{TP_i + FP_i} \tag{2}$$

C. Recall: The recall of a classifier is a metric that quantifies its ability to identify documents as belonging to a particular class, as demonstrated in Equation (3). The formula for calculating class ci recall, Ri, is as follows:

follows: $R_i = \frac{TP_i}{TP_i + FN_i}$ (3)

D. F1 score: The synchronization rate is indicated by the F1 score. In general, the system performs well when F1 is high. Below is a description of F1 according to equations 4) and (5):

$$F1 = \frac{2 \times precision \ \times recall}{precision + recall} \tag{4}$$

$$= \frac{2TP}{2TP+FP+FN} \tag{5}$$

2.6 Challenges in ML and DL for CKD Diagnosis

A. Data Quality and Availability

High-quality, labeled datasets are essential for training robust models. Data privacy concerns and limited access to medical records can hinder research. Refer to table 1.

B. Model Interpretability

DL models, in particular, are often viewed as "black boxes," making it difficult to understand the reasoning behind their predictions.

C. Generalizability

Ensuring models perform well across different populations and clinical settings is crucial for real-world applicability.

D. Integration into Clinical Practice

Implementing ML and DL models in healthcare systems requires overcoming regulatory, technical, and ethical barriers.

TABLE I. CHALLENGES IN ML AND DL FOR CKD DIAGNOSIS

Challenge	Description
Data Quality and Availability	Need for high-quality, labeled datasets; privacy concerns; limited access
Model Interpretability	Difficulty in understanding the reasoning behind DL model predictions
Generalizability	Ensuring model performance across diverse populations and settings
Integration into Practice	Regulatory, technical, and ethical challenges in healthcare implementation

2.7 Future Directions

A. Explainable AI (XAI)

Developing methods to interpret and explain model predictions can enhance trust and adoption in clinical practice. Refer to table 2.

B. Transfer Learning

Leveraging pre-trained models on large datasets to improve performance on smaller CKD-specific datasets.

C. Federated Learning

Enabling collaborative model training across multiple institutions without sharing patient data can enhance data availability and model robustness.

D. Integration with Electronic Health Records (EHRs)

Seamlessly integrating ML and DL models with EHR systems can facilitate real-time diagnosis and decision support.

TABLE II. FUTURE DIRECTIONS

Future Direction	Description
Explainable AI (XAI)	Methods to interpret and explain model predictions for enhanced trust and adoption
Transfer Learning	Using pre-trained models to improve performance on smaller CKD-specific datasets
Federated Learning	Collaborative model training across institutions without sharing patient data
Integration with EHRs	Real-time diagnosis and decision support through seamless integration with EHR systems

3. CONCLUSION

In the medical field, using machine learning (ML) and deep learning(DL) for early diagnosis of chronic kidney disease(CKD) is one area that promises great potential. A common condition affecting millions worldwide, CKD is typically silent and symptomless until late stages, making early detection utmost important to mitigate its progression. Traditional diagnostic strategies have their place, but there is a lack of accurate and early detection in combination with patient-to-patient variability that demands new approaches.

This review has illustrated the different ML and DL models utilized in CKD diagnosis. The is followed by prediction of CKD outcomes using ML techniques such as supervised learning, unsupervised learning, and ensemble methods. Among these models, the best accuracy in early diagnosis has been achieved with Support Vector Machines (SVM) and Random Forest (RF), both of which have outperformed k-Nearest Neighbors(kNN) when trained on clinical data containing relevant information about meningitis. But these methods usually need high level of feature engineering and may not learn intricate pattern as well DL models.

Deep Learning (DL) models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks(RNNs)have been shown to achieve state-of-the-art results on large and complex datasets. CNNs are known to be effective in image related data, while RNN is excellent with sequential information like patient history and lab results. While having high accuracy and powerful predictions, DL models are also called out for its “black box” nature which makes it hardly interpretable.

Furthermore, the review also emphasized data quality in providing effective diagnostic models and how critical importance is obtained to the use of high-quality datasets [52], as well as examples showing that higher availability does not always provide better results without good over handling DL inputs like preprocessing or feature engineering (powerful features for libraries/science/fields available). Many public data sets, such as the Kidney Disease: Improving Global Outcomes (KDIGO) database [14], United States Renal Data System (USRDS), and National Health and Nutrition Examination Survey (NHANES) have contributed significantly to furthering our understanding of CKD.

Additionally, the review summarized various current limitations regarding implementation of ML and DL models in clinical setting. These range from concerns about data quality and availability to the generalizability of models deployed in very different populations, as well as how such a model could practically interface with existing healthcare systems. Overcoming these requires a solution which is multi-faceted in terms of artificial intelligence explain-ability (XAI), transfer learning, federated learning and EHR integration.

This area of research should further concentrate on developing more interpretable DL models and agree to the use of transfer learning for optimizing performance in smaller datasets, as well as federated learning strategies offering global privacy with application in collaborative studies. We will need to integrate these advanced diagnostic models with an EHR system for rapid diagnosis and decision support in clinical settings.

Ultimately, the convergence of ML and DL with CKD diagnosis has many promising applications that can improve healthcare outcomes as providing earlier and more accurate detection for a common disease using technology is desirable. Further research and development is crucial to address these challenges, and harness the full potential of AI/ML techniques in patient care.

Conflicts Of Interest
The absence of any competing relationships or biases that could affect the research is explicitly mentioned in the paper.
Funding
The author's paper asserts that the research was conducted on a voluntary basis and without any financial backing from institutions or sponsors.
Acknowledgment
The author acknowledges the institution for their commitment to fostering a research-oriented culture and providing a platform for knowledge dissemination.

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