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Early Chronic Kidney Disease Identification Using ML and DL Methods

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Abstract
Chronic diseases are diseases which tend to last for a longer period. And have substantial growth over a period of time. While Chronic kidney disease is one of the chronic diseases it is caused due to gradual loss of kidney functioning over time. Kidney is crucial organ in human body as it filters out waste products and unnecessary fluids through urine. By using glomerular filtration rate Aka GFR a method which measure kidneys ability to filter blood. There are many factors which are contributing to CKD among them diabetes and hypertension plays a significant role. It is observed that Machine learning algorithms such as Random forests and SVM able to classify a person having CKD or not but Deep learning models like vgg16 and deep neural networks have higher accuracy this is due to employing feature selection techniques to deep learning models give neural networks to capture most important features which improves classification accuracy much better than ML models. Identifying this at an early stage reduces the risk of getting more severe as already millions of people getting suffering from CKD. The primary goal of this study is to make extensive review on identifying CKD at an early stage by using ML and deep learning based neural networks.

Keywords: Chronic kidney disease, glomerular filtration, deep learning, chronic disease

INTRODUCTION

Chronic kidney diseases are a type of disease which occurs when kidney's ability to filter waste products from blood fail. According to National institute of health (NIH) one in every seven Americans are getting affected with this disease and spending huge amount of their fortune in getting medicated. While there are many factors which contribute to CKD diabetes and hypertension are most contributing to CKD. This is because hypertension increases blood flow through vessels much faster as a result pressure increases in glomeruli (a blood vessel in kidneys which are responsible to filter blood) if this on a continuous scale causing glomeruli to damage by damaging its capability to filter blood and waste products gets accumulated. High blood sugar levels directly affect blood vessels as glucose in sugar binds to protein in blood vessels which results in failure of kidney. There are many symptoms which are identified like fatigue, breathing shortness and urinary colour changes, swelling in legs. Below are the different types of kidney diseases identified and they are described below: Diabetic Nephropathy: This disease occurs when there is high level of sugar in human body, mainly affecting people who are suffering form type 1 and type 2 diabetes. High levels of sugar results in protein leak into urine as a result kidneys become less efficient at filtering waste. Identifying at early is necessary as it lead to end-stage renal disease (ESRD). Excessive Hypertension: Prolonged hypertension over a extended period of time damages blood vessels, leading to scarring where some parts of the kidney tissue are damaged and reduced filtering capacity. Moreover, if it becomes more extreme it leads ischemia where there is reduced blood flow to the kidneys as a result there is a lack of oxygen and nutrients to kidney tissues finally resulting in damage or dysfunction. Glomerulonephritis: It is a condition which affects Glomeruli (a tiny structure which filters blood in kidneys) as a result of Inflammation can damage glomeruli so retention of waste products and fluids. Due to damaged glomeruli, it allow proteins to leak into urine causing proteinuria resulting in swelling in various parts of the body. Renal Artery Stenosis: It is condition where renal arteries get narrowed which leads to reduced blood flow to the kidneys. As a result, renal artery gets affects which in terms causes reduced blood to the kidneys and waste secretion Glomerular Filtration Rate (GFR): GFR describes kidney ability to filter blood and remove waste, specifically the rate at which blood is filtered through the glomeruli. Based on filtering capacity and chronic kidney disease is classified into five stages and they are described below:

Stage 1: GFR ≥ 90 mL/min
Stage 2: GFR 60-89 mL/min
Stage 3: GFR 30-59 mL/min
Stage 4: GFR 15-29 mL/min
Stage 5: GFR < 15 mL/min

Below in the Fig.1. detailed pictorial representation of the Glomerular Filtration Rate severity and its effect on the body.

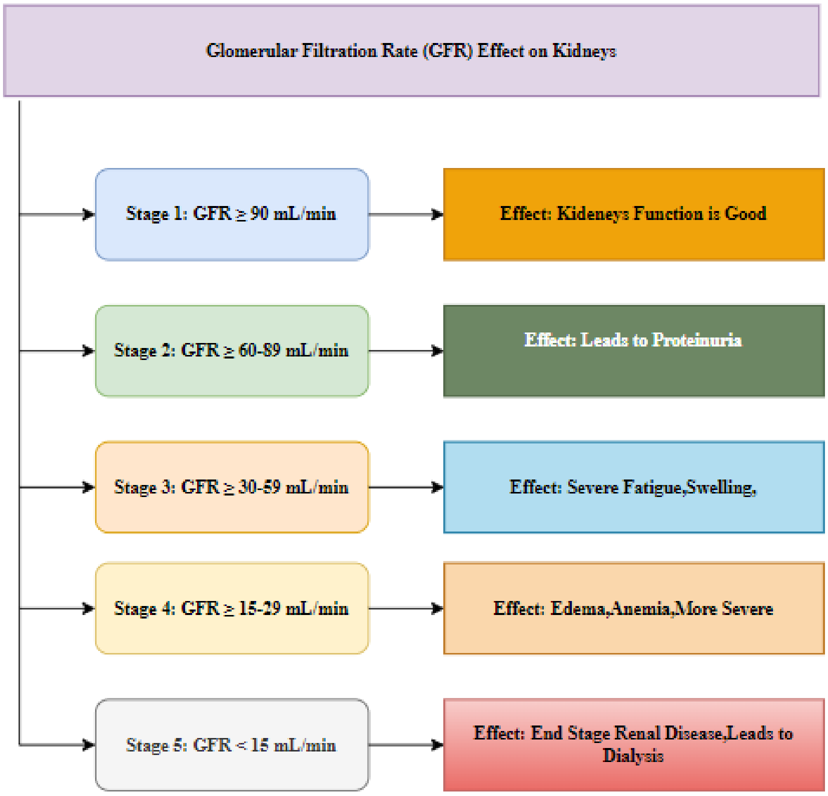

Fig.1. GFR Classification based on Severity

The below Fig.2. represents different types of chronic kidney diseases and possible symptoms which can be seen. It is identified that prolonged hypertension and diabetes of type-1 & type -2 leads to severe chronic kidney diseases.

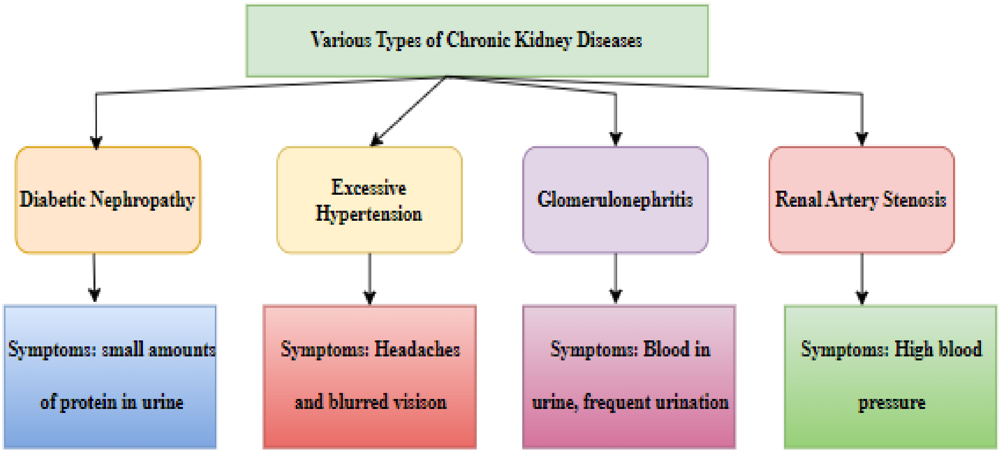

Fig.2. Different types of chronic kidney diseases

LITERATURE SURVEY

Singh et al. [1] proposed a DNN for early detection of CKD, Data cleaning is by considering parameters like blood pressure, glucose levels, creatinine levels then a deep layered neural network(DNN) was formed to capture non- linear relationship within data as it contain crucial information then Relu activation function added to add non linearity to the model in order to make the model diverse so that any change in the data it shouldn't affect the model. Training and validation were done on a 80-20- scale. By using Adam optimiser during backpropagation to ensure loos during training is done. Finally, dropout is made to prevent overfitting of the model and achieved an accuracy of 94.2%. Ma et al. [2] introduced a hybrid model which combined traditional neural networks with DNN to enhance feature extraction and model performance. Extensively focused of collecting good number of parameters so that it allows model to learn from diverse and relevant features related to CKD. Attributes include age, gender and blood pressure, blood glucose, creatinine levels, persons habits. Replacing missing values is done as of preprocessing By adding multiple hidden layers and for every hidden layer dropout was added to ensure certain percentage of layers get dropped such that model doesn't prone to overfit. Adam optimiser is involved which helps to adjust learning rates based on the frequency of updates. Finally, evaluation is done and achieved an accuracy of 92.8%.

Sabanayagam et al. [3] utilised the concept of deep learning and introduced a non-invasive technique by using retinal photographs which contains images of both CKD-positive and CKD-negative participants. Then a CNN model is build as it can extract retinal features that are relevant with underlying kidney disease so that it becomes easier to identify features that may indicate the presence of CKD, helping in early detection and diagnosis. Data augmentation done to ensure model learns diversified data without prone to errors. An accuracy of 90.5% is obtained.

Akter et al. [4] introduced a neural network based deep learning model that uses CNN and LSTM by utilising Chronic dataset from UCI repository multiple attributes were taken into consideration and data cleaning is done to handle missing values as it may affect the accuracy Data normalization is applied to ensure that all features contribute equally to model training. Since the attributes are age, Bp there is need to capture spatial hierarchies which tells how each feature which are not same are related to each other which in terms helps in capturing non linear relationships within the data. And LSTM's for capturing sequential data as it contains gated mechanism which helps to retain the necessary data and achieved an accuracy of 98.67%. Chittora et al. [5] made a comparative analysis by using multiple ML models like

SVM's and other ML classifiers the primary objective of this study is to identify the importance of feature selection and preprocessing in achieving good model performance. It is observed that Random Forests reported an high accuracy of 97.2% among all other ML classifiers this is because RF follows ensemble method that combines multiple DT to improve predictive performance. Moreover, it has every tree in RF helps the model to capture diverse data and RF is trained on each subset of data, Understanding Nonlinear relationships also added advantage together contributed towards higher accuracy.

Zhang et al. [6] utilized deep learning-based model and identified correlation between retinal health and systemic diseases this is because retina has small blood vessels that are located back of eye which supply nutrients and oxygen when the small blood vessels in the retina gets damaged, this can be seen in these retinal images. As a result, when doctors examine by retinal imaging which reflects the damage happening in the kidneys. And built a CNN model where dataset having both kidney disease and Type -2 diabetes were considered pre-trained model is utilised to improve performance accuracy and attained an accuracy of 85%. Alsuhibany et al. [7] proposed ensemble methods which are based dl to detect them early parameters like age, blood pressure, specific gravity, albumin, sugar was considered preprocessing is done to remove any missing values which affects the performance accuracy. As multiple dl models like CNN, RNN and LSTM's were combined by training individual models separately on the pre-processed dataset. And then Predictions from each model were combined using various ensemble techniques, such as majority voting and weighted averaging to achieve a accuracy of 92%.

Bai et al. [8] utilised ML techniques and proposed model for early-stage identification, as part of data cleaning noise is removed, important features contribute to better identification of disease was found by normalizing the data to similar scale. By using Multiple ML classifiers prediction was made it is identified that Gradient Boosting Machine (GBM) has reported good accuracy and better prediction rate this is because it is a ensemble of multiple decision trees which are placed in a n sequential manner due to this present trees learn mistakes made by previous trees and have ability to handle complex non-linear relationships and achieved an accuracy of 88%.

Islam et al. [9] developed a predictive model using ML and considered many parameters which are contributing to CKD to make the parameters much suitable for ML models one hot encoding is done. Among all ML classifiers Rf has shown good accuracy and outperformed many other metrics due to ensembling of decision trees which avoids the risk of overfitting that single decision trees often face, Every decision tree is trained on subset of data providing more generalised model. During training k-fold cross validation is used to avoid training time by dividing entire dataset into k-folds and achieved an accuracy of 91%.

Nishat et al. [10] conducted a survey on multiple ML models and identified most effective model by using features like age, gender, bp, sugar. And they are converted into feature encoders where categorical variables are converted into numerical format so that ML algorithms can understand Neural networks outperformed existing models due to feature

selection methods because they chose most important features and analyse how different features relate to each other and achieved an accuracy of 94%.

RESEARCH GAPS

Below are the identified existing challenges in the field of chronic kidney disease

Limited Data Availability and feature selection: In the field of Chronic diseases there is a lack of high-quality dataset which may limit the model's performance. Some datasets have more number of features in

such cases identifying most important features through feature selection will be a complex task for the models.
Overfitting nature: It is always a big challenge when training models on large datasets as there is a chance that the models may be overfit in such cases the prediction accuracy of models get affect.
Black box nature and Performance Evaluation: Due to black box nature DL models becomes difficult to interpret due to lack of transparency and Lack of standardized metrics for evaluating model performance
UCI CKD Dataset: This dataset is from UCI machine learning repository it consists of 400 instances of multiple patients having multiple features Each instance represents a different patient's information, including clinical and demographic features used for analysis and model training. It is extensively used for CKD detection.
Kaggle CKD Dataset: This dataset is best used for CKD detection as it contains more than 5000 instances of patients which have information like Demographics, Laboratory Results, Blood Pressure, BMI showing real world CKD cases.
MIMIC-III Clinical Database: It is large database which is publicly available it contains details of patients who were admitted to ICU and it is Longitudinal Data due to which it helps in analysing changes in health it consists of more than 40000 instances having vital signs.
Retinal Fundus Image dataset: This dataset consists high quality images of retina. This images represents damage happened to small blood vessels in retinal are as the directly reflect damage happened to kidneys. It consists of 10000 instances, and it plays a crucial role in identifying CKD through retina.

TABLE 1. A OVERVIEW OF METHODS USED AND RESULTS ACCHIEVD BY VARIOUS AUTHORS

S.NO	Author & Year	Methods Used	Databases	Results Achieved
1.	Singh, V. et al. (2022)	Deep Neural Network	UCI CKD Dataset	Accuracy: 94.2%
2.	Ma, F. et al. (2020)	Heterogeneous Modified Artificial Neural Network	Local Hospital Dataset	Accuracy: 92.8%
3.	Sabanayagam, C. et al. (2020)	Deep Learning Algorithm	Retinal Fundus Images Dataset	Accuracy: 90.5% retinal images successfully detected CKD
4.	Akter, S. et al. (2021)	Deep Learning Models	Multiple CKD Datasets	Accuracy: 98.67%
5.	Chittora, P. et al. (2021)	Machine Learning Algorithms	UCI CKD Dataset	Accuracy: 97.2%
6.	Zhang, K. et al. (2021)	Deep Learning Models	Retinal Fundus Images and Clinical Data	Accuracy: 85% of type-2 diabetes predicted
7.	Alsuhibany, S. A. et al. (2021)	Ensemble Deep Learning Models	Local Hospital and Public Datasets	Accuracy:92%

8.	Bai, Q. et al. (2022)	Multiple ML classiifers	NHANES	Accuracy: 88%
9.	Islam, M. A. et al. (2023)	ML Models	UCI CKD, Local Dataset	Accuracy: 91%
10.	Nishat, M. M. et al. (2021)	ML models, Neural network	UCI CKD and Local Hospital Dataset	Accuracy: 94% prediction
11.	Dritsas, E. & Trigka, M. (2022)	Machine Learning Techniques	Clinical Dataset	Accuracy:88%
12.	Debal, D. A. & Sitote, T. M. (2022)	ML models	Clinical Dataset	Accuracy: 90%
13.	Swain, D. et al. (2023)	ML classifier	UCI CKD Dataset	Accuracy: 91% CKD classified
14.	Wang, W. et al. (2020)	ML classifier	Clinical Dataset	Accuracy: 89%
15.	Emon, M. U. et al. (2021)	ML classifier	UCI CKD Dataset	Accuracy: 92%
16.	Ghosh, P. et al. (2020)	ML classifier	Clinical Dataset	Accuracy: 90%
17.	Venkatesan, V. K. et al. (2023)	ML based ensemble	Clinical Dataset	Accuracy: 93%
18.	Abdel-Fattah, M. A. et al. (2022)	Hybrid model	Clinical Dataset	Accuracy: 91%
19.	Elkholy, S. M. M. et al. (2021)	Deep Belief Network	UCI CKD Dataset	Accuracy: 92% effectively detected CKD
20.	Ekanayake, I. U. & Herath, D. (2020)	ML classifier	Clinical Dataset	Accuracy: 89%
21.	Qin, J. et al. (2019)	ML models	Clinical Dataset	Accuracy: 88%
22.	Mondol, C. et al. (2022)	Deep Learning Models	UCI CKD Dataset	Accuracy: 94%
23.	Aswathy, R. H. et al. (2022)	Optimized Tuned Deep Learning Model	Clinical Dataset	Accuracy: 92%
24.	Saif, D. et al. (2023)	DL models	Clinical Dataset	Accuracy: 93%

25.	Kriplani, H. et al. (2019)	Deep Artificial Neural Network	Clinical Dataset	Accuracy: 90%
26.	Chen, G. et al. (2020)	Adaptive Hybridized Deep Convolutional Neural Network	Internet of Medical Things Platform	Accuracy: 91%
27.	Al Imran, A. et al. (2018)	ML and DL models	Clinical Dataset	Accuracy: 89%
28.	Iliyas, I. I. et al. (2020)	Deep Neural Network	Clinical Dataset	Accuracy: 90%
29.	Almansour, N. A. et al. (2019)	Neural network and SVM	Clinical Dataset	Accuracy: 91%
30.	Navaneeth, B. & Suchetha, M. (2020)	Dynamic Pooling Based Convolutional Neural Network	Clinical Dataset	Accuracy: 92%
31.	Gaitonde, D. Y. et al. (2017)	ML classifiers	Clinical Dataset	Evaluation strategies are provided, no specific accuracy reported.
32.	Baumgarten, M. & Gehr, T. (2011)	ML classifiers	Clinical Dataset	Evaluation strategies are provided, no specific accuracy reported.
33.	Levey, A. S. et al. (2003)	Evaluation and Classification Guidelines	National Kidney Foundation	Evaluation strategies are provided, no specific accuracy reported.
34.	Radha, N. & Ramya, S. (2015)	ML classifiers	UCI CKD Dataset	Accuracy: 87%
35.	Gupta, R. et al. (2020)	ML classifiers	Clinical Dataset	Accuracy: 89%
36.	Sharma, S. et al. (2016)	ML classifiers	Clinical Dataset	Accuracy: 90%

37.	Berger, I. et al. (2016)	Systematic Review and Meta-Analysis	Clinical Dataset	Evaluation strategies are provided, no specific accuracy reported.
38.	Zhang, H. et al. (2018)	Artificial Neural Networks	Clinical Dataset	Accuracy: 91%
39.	Suresh, C. et al. (2020)	Neural Network Based Model	Clinical Dataset	Accuracy: 90%
40.	Borisagar, N. et al. (2017)	Back Propagation Neural Network Algorithm	Clinical Dataset	Accuracy: 91%
41.	Chotimah, S. N. et al. (2021)	Feature Selection and Artificial Neural Network	Clinical Dataset	Accuracy: 92%
42.	Ravindra, B. V. et al. (2018)	Neural Network Classifier	Clinical Dataset	Accuracy: 90%
43.	Ying, X. et al. (2020)	Neural Network Classifier	Clinical Dataset	Accuracy: 91%
44.	Biourge, V. et al. (2020)	Artificial Neural Network	Clinical Dataset	Accuracy: 89%
45.	Shankar, K. et al. (2018)	Deep Learning Classifier with optimised feature selection techniques	Clinical Dataset	Accuracy: 93%
46.	Gunarathne, W. H. S. D. et al. (2017)	ML classifier	Clinical Dataset	Accuracy: 88%
47.	Srivastava, S. et al. (2022)	Ensemble model	Clinical Dataset	Accuracy: 92%
48.	Sisodia, D. S. & Verma, A. (2017)	Ensemble model	Clinical Dataset	Accuracy: 89%
49.	Wibawa, M. S. et al. (2017)	Gradient boost	Clinical Dataset	Accuracy: 90%
50.	Kazemi, Y. & Mirroshandel, S. A. (2018)	Ensemble model	Clinical Dataset	Accuracy: 91%

DISCUSSIONS

As part of this study a extensive analysis is made by analysing many model both ML and DL basesd it is observed that Ensemble classifiers and DL have outperformed many other Models as ensemble model have Decision trees where mistakes at previous step are rectified.

A. Advantages and Disadvantages

The below Table 2. represents both advantages and disadvantages or limitations which have observed in the study.

S.NO	Author & Year	Advantages	Disadvantages
1.	Singh, V. et al. (2022)	Effective feature extraction neural network	Training dataset is limited, possibility of overfitting
2.	Ma, F. et al. (2020)	Generalised model to diversified data, detection accuracy improved	Model complexity and dataset is limited
3.	Sabanayagam, C. et al. (2020)	Non invasive imaging	Model complexity and dataset is limited
4.	Akter, S. et al. (2021)	high accuracy in early prediction, identifies risk factors effectively.	Model complexity and dataset is limited
5.	Chittora, P. et al. (2021)	Adaptive to diversified data	Model complexity and dataset is limited
6.	Zhang, K. et al. (2021)	Able to predict both CKD and Type-2 diabetes	Overfitting and training time is more
7.	Alsuhibany, S. A. et al. (2021)	Ensemble model try to overcome errors at previous step	Overfitting and training time is more
8.	Bai, Q. et al. (2022)	Predicts end-stage kidney disease using NHANES dataset	Difficult to make model generalise requires computation cost
9.	Islam, M. A. et al. (2023)	Hybrid model improved prediction accuracy	Overfitting and training time is more
10.	Nishat, M. M. et al. (2021)	Feature encoders helped to achieve better results	Model complexity and overfitting

B. Scope of Improvement

To enhance model performance, it is better to integrate multiple models to reduce complexity and feature selection methods have significant role in improving prediction accuracy, For ML based classifiers integrating ensemble techniques have shown promising results and for dl-based models it is suggestable to calculate loss by back propagating, avoiding overfitting may show good performance. The below Fig.3. represents Architecture of the proposed model

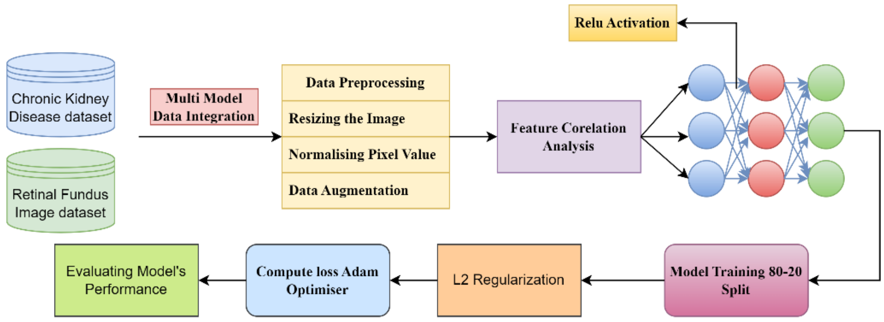

Fig.3. Architecture of the proposed model

CONCLUSION & FUTURESCOPE

Chronic kidney diseases are most common and can lead to end stage renal disease identifying them ata an early stage may reduce the chance of getting hospitalized. Both ensemble techniques and DL based models have shown promising results. It is because both these models extensively focused on feature enhancement and selection techniques which have improved prediction accuracy and have accuracy as better as 96%.

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