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Chronic Kidney Disease Prediction Using Deep Learning Classifiers

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ABSTRACT

Chronic Kidney Disease (CKD) or chronic renal disease has become a major issue with a steady growth rate. A person can only survive without kidneys for an average time of 18 days, which makes a huge demand for a kidney transplant and Dialysis. It is important to have effective methods for early prediction of CKD. Deep learning methods are effective in CKD prediction. Deep neural Network (DNN) is becoming a focal point in Machine Learning research. Its application is penetrating into different fields and solving intricate and complex problems. DNN is now been applied in health image processing to detect various ailment such as cancer and diabetes. In this project we can implement multi-layer perceptron algorithm to classify the chronic diseases with diagnosis information. Multilayer Perceptron is a Neural Network that learns the relationship between linear and non-linear data. The Multilayer Perceptron was developed to tackle this limitation. It is a neural network where the mapping between inputs and output is non-linear. A Multilayer Perceptron has input and output layers, and one or more hidden layers with many neurons stacked together. And while in the Perceptron the neuron must have an activation function that imposes a threshold, like ReLU or sigmoid, neurons in a Multilayer Perceptron can use any arbitrary activation function. Based on this function, we can identify the chronic kidney disease from the datasets which is downloaded from KAGGLE website. Experimental results shows that the proposed system provide improved accuracy in disease prediction.

Keywords : Chronic Kidney Disease, Machine Learning, Deep Learning, Multi-Layer Perceptron Algorithm, Disease Classification

I. INTRODUCTION

Chronic Kidney Disease (CKD) means the kidneys are damaged and not altering the blood the way it should. The primary role of kidneys is to filter extra water and waste from the blood to produce urine and if the person has suffered from CKD, it means that wastes are collected in the body. This disease is chronic because of the damage gradually over a long period. It is _attering a common disease worldwide. Due to CKD may have some health troubles. There are many causes of CKD like diabetes, high blood pressure, and heart disease. Along with these critical diseases, CKD also depends on age and gender. If the kidney is not working, then you may notice one or more symptoms like abdominal pain, back pain, diarrhea, fever, nosebleeds, rash, and vomiting. There are two main diseases of CKD: (i) diabetes and (ii) high blood pressure. So, controlling these two diseases is the prevention of CKD. Usually, CKD does not give any sign till the kidney is damaged badly. CKD is being increased rapidly as per the studies hospitalization cases increase by 6.23 percent per year but the global mortality rate remains fixed. Chronic kidney disease, also called chronic kidney failure, involves a gradual loss of kidney function. The kidneys filter wastes and excess fluids from the blood, which are then removed in the urine. Advanced chronic kidney disease can cause dangerous levels of fluid, electrolytes, and wastes to build up in the body. In the early stages of chronic kidney disease, you might have few signs or symptoms. You might not realize that you have kidney disease until the condition is advanced. Treatment for chronic kidney disease focuses on slowing the progression of kidney damage, usually by controlling the cause. But, even controlling the cause might not keep kidney damage from progressing. Chronic kidney disease can progress to end-stage kidney failure, which is fatal without artificial filtering (dialysis) or a kidney transplant. CKD has varying levels of seriousness. It usually gets worse over time though treatment has been shown to slow progression. If left untreated, CKD can progress to kidney failure and early cardiovascular disease. When the kidneys stop working, dialysis or kidney transplant is needed for survival. Kidney failure treated with dialysis or kidney transplant is called end-stage renal disease (ESRD). Learn more about ESRD. Not all patients with kidney disease progress to kidney failure. To help prevent CKD and lower the risk for kidney failure, control risk factors for CKD, get tested yearly, make lifestyle changes, take medicine as needed, and see the health care team regularly. Figure 1 shows the chronic kidney disease with side effects.

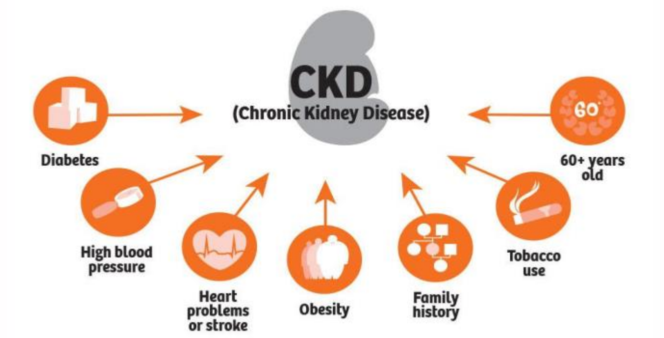

Fig 1: Chronic kidney disease attributes

II. RELATED WORK

Pankaj Chittora, et.al,…[1] implemented the system for handle chronic kidney disease and it is one of the most critical illnesses nowadays and proper diagnosis is required as soon as possible. The deep learning technique has become reliable for medical treatment. With the help of a deep learning classier algorithms, the doctor can detect the disease on time. For this perspective, Chronic Kidney Disease prediction has been discussed in this article. Chronic Kidney Disease dataset has been taken from the UCI repository. Seven classier algorithms have been applied in this research such as artificial neural network, C5.0, Chi-square Automatic interaction detector, logistic regression, linear support vector deep with penalty L1 & with penalty L2 and random tree. The important feature selection technique was also applied to the dataset.

Bilal Khan, et.al,…[2] employ experiential analysis of ML techniques for classifying the kidney patient dataset as CKD or NOTCKD. Seven ML techniques together with NBTree, J48, Support Vector Machine, Logistic Regression, Multi- layer Perceptron, Naïve Bayes, and Composite Hypercube on Iterated Random Projection (CHIRP) are utilized and assessed using distinctive evaluation measures such as mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), recall, precision, F-measure and accuracy.

Jiongming Qin, et.al,…[3] propose a deep learning methodology for diagnosing CKD. The CKD data set was obtained from the University of California Irvine (UCI) deep learning repository, which has a large number of missing values. KNN imputation was used to fill in the missing values, which selects several complete samples with the most similar measurements to process the missing data for each incomplete sample. Missing values are usually seen in real-life medical situations because patients may miss some measurements for various reasons. After effectively filling out the incomplete data set, six deep learning algorithms (logistic regression, random forest, support vector machine, k-nearest neighbor, naive Bayes classifier and feed forward neural network) were used to establish models. Among these deep learning models, random forest achieved the best performance with 99.75% diagnosis accuracy.

Anandanadarajah Nishanth, et.al,…[4] developed the system for analyzing chronic kidney disease and chronic kidney disease (CKD) are not aware that the medical tests they take for other purposes sometimes contain useful information about CKD disease. This information is sometimes not used effectively to tackle the identification of the disease. Therefore, attributes of different medical tests are investigated to identify what attributes contain useful information about CKD. Then, classification methods are also used to identify the dominant attributes. These analyses suggest that hemoglobin, albumin, specific gravity, hypertension and diabetes mellitus together with serum creatinine are the most important attributes.

Michele Bernardini, et.al,…[5] propose a novel Semi-Supervised Multi-Task Learning (SS-MTL) approach for predicting short-term KD evolution on multiple General Practitioners' EHR data. We demonstrated that the SS-MTL approach can (i) capture the eGFR temporal evolution by imposing a temporal relatedness between consecutive time windows and (ii) exploit useful information from unlabeled patients when labeled patients are less numerous with a gain of up to 4.1 % in terms of Recall. This situation reflects the real-case scenario, where available labeled samples are limited, but those unlabeled much more abundant. The SS-MTL approach, also given the high level of interpretability, might be the ideal candidate in general practice to get integrated within a decision support system for KD screening purposes.

MD.Rashed Al-Mahfuz, et.al,…[6] developed deep learning models using selective key pathological categories to identify clinical test attributes that will aid in the accurate early diagnosis of CKD. Such an approach will save time and costs for diagnostic screening. We have also evaluated the performance of several classifiers with k-fold cross-validation on optimized datasets derived using these selected clinical test attributes. Results: The results suggest that the optimized datasets with important attributes perform well in the diagnosis of CKD using the proposed deeplearning models.

Peter A, et.al,…[7] some of these approaches to a multi-racial Chronic Kidney Disease (CKD) dataset comprising of 20 continuous and 12 categorical variables with an over 30% missingness ratio, In addition, the results show that advanced imputation methods like multiple imputation, which take into consideration the uncertainty inherent in imputation, should be explored when clustering missing datasets. Three clusters were identified from the dataset which were significantly differentiated by age, sex, estimated Glomerular Filtration Rate (eGFR), creatinine, urea, and hemoglobin, but not by race or blood pressure.

Hui Zhang, et.al,…[8] provide precise information about the location and size of lesions in many medical applications. Manual and traditional medical testings are labor-consuming and time-costing. Nowadays, detecting lesions in CT automatically is an integral assignment to the paramount importance of clinical diagnosis. Computer-aided diagnosis (CAD) is needed to develop and improve medical testing efficiency. However, it is still a tremendous challenge to the extant low precision and incomplete detection algorithm. In this paper, we proposed a lesion detection tool using multi intersection over union (IOU) threshold based on morphological cascade convolutional neural networks (CNNs).

Hamada, et.al,…[9] study on the multimodal dataset from QBB revealed that physio-clinical and bioimpedance measurements have the most distinguishing power to classify these two groups irrespective of gender and age of the participants. Multiple feature subset selection techniques confirmed known CVD risk factors (blood pressure, lipid profile, smoking, sedentary life, and diabetes), and identified potential novel risk factors linked to CVD-related comorbidities such as renal disorder (e.g., creatinine, uric acid, homocysteine, albumin), atherosclerosis (intima media thickness), hypercoagulable state (fibrinogen), and liver function (e.g., alkaline phosphate, gamma-glutamyl transferase). Moreover, the inclusion of the proposed novel factors into the ML model provides better performance than the model with traditional known risk factors for CVD. The association of the proposed risk factors and comorbidities are required to be investigated in clinical setup to understand their role in CVD better

Frank G. Zollner, et.al,…[10] has achieved an increasingly important role in the clinical work-up of renal diseases such chronic kidney disease (CKD). A large panel of parameters have been proposed to diagnose CKD among them total kidney volume (TKV) which recently qualified as biomarker. Volume estimation in renal MRI is based on image segmentation of the kidney and/or its compartments. Beyond volume estimation renal segmentation supports also the quantification of other MR based parameters such as perfusion or filtration. The aim of the present article is to discuss the recent existing literature on renal image segmentation techniques and show today's limitations of the proposed techniques that might hinder clinical translation. We also provide pointers to open sthece software related to renal image segmentation.

III. EXISTING METHODOLOGIES

Chronic kidney disease (CKD) is a major public health concern around the world, with negative outcomes such as renal failure, cardiovascular disease, and early death. In machine learning, the quality and quantity of input data that is used for training the classifiers are very important. Most algorithms perform well when the prior probabilities of the target classes are similar. Data is said to be imbalanced if at least one of the target variable values has a significantly smaller number of instances when compared to the other values. Class imbalance is one of the vital issues in machine learning classification tasks. Machine learning algorithms trained on imbalanced data emphasize exploiting the total accuracy over the entire dataset leading to more attention being paid to the majority class samples. Due to this scenario, the minority class samples are poorly projected by the learning model. Both data mining and classification techniques are applied in chronic kidney disease prediction. Models like SVM, Decision tree, K-NN, Naive Bayes, neural networks are used for the prediction of the diseases. In random forest gave the best accuracy compared to decision tree and SVM. In Eleven techniques of decision trees like decision Stump, J48, CTC, LMT, NBTree, Random Forest, randomTree, REPTree, simple Cart, J48graft are applied to the dataset. Random forest outperforms other methods. Neural networks with three layers performed better compared with other models like SVM, DT, KNN, and Gradient Boost algorithm.

IV.PROPOSED METHODOLOGIES

The objective of developing a chronic kidney disease (CKD) classification model using an MLP algorithm is to create a reliable and accurate tool for identifying patients at risk of CKD based on their clinical and laboratory data. This model aims to assist healthcare professionals in making timely diagnoses, enabling early intervention and personalized treatment strategies. By leveraging advanced machine learning techniques, such as MLP algorithms, the objective is to improve the efficiency and accuracy of CKD diagnosis, ultimately leading to better patient outcomes, reduced healthcare costs, and improved quality of care. Fig 2 shows the proposed architecture diagram.

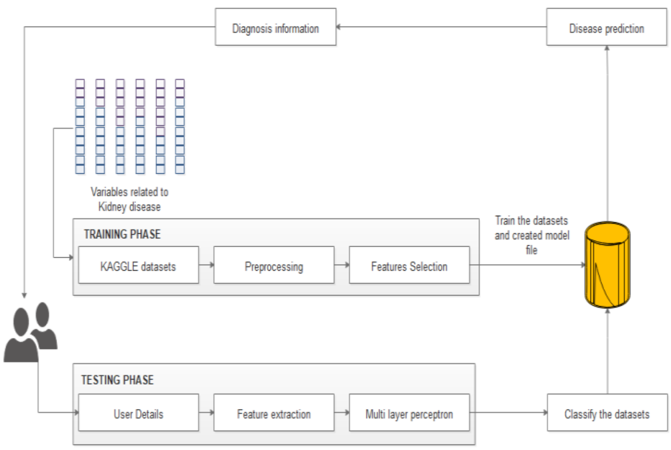

Fig 2 : Proposed System Architecture

DATASETS ACQUISITION

A data set (or dataset, although this spelling is not present in many contemporary dictionaries like Merriam-Webster) is a collection of data. Most commonly a data set corresponds to the contents of a single database table, or a single statistical data matrix, where every column of the table represents a particular variable, and each row corresponds to a given member of the data set in question. The data set lists values for each of the variables, such as height and weight of an object, for each member of the data set. Each value is known as a datum. The data set may comprise data for one or more members, corresponding to the number of rows. The term data set may also be used more loosely, to refer to the data in a collection of closely related tables, corresponding to a particular experiment or event. The module conducted using the CKD dataset. There are 400 rows and 24 columns in this dataset. The output column "class" has a value of either "1" or "0." The value "0" indicates that the patient is not a CKD patient, while the value "1" shows that the patient is a CKD patient.

PREPROCESSING

Data pre-processing is an important step in the [data mining] process. The phrase "garbage in, garbage out" is particularly applicable to data mining and machine learning projects. Data-gathering methods are often loosely controlled, resulting in out-of-range values, impossible data combinations, missing values, etc. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is first and foremost before running an analysis. If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take considerable amount of processing time. In this module, we can eliminate the irrelevant values and also estimate the missing values of data. Finally provide structured datasets.

FEATURES SELECTION

Feature selection refers to the process of reducing the inputs for processing and analysis, or of finding the most meaningful inputs. A related term, feature engineering (or feature extraction), refers to the process of extracting useful information or features from existing data. Filter feature selection methods apply a statistical measure to assign a scoring to each feature. The features are ranked by the score and either selected to be kept or removed from the dataset. The methods are often uni-variate and consider the feature independently, or with regard to the dependent variable. It can be used to construct the multiple heart diseases. In this module, select the multiple features from uploaded datasets. And train the datasets with CKD or NON-CKD and generate the model file for future classification

CLASSIFICATION

In this module implement classification algorithm to predict the heart diseases. And using deep learning algorithm such as Multi-layer perceptron algorithm to predict the diseases. A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. It (MLP) consists of multiple layers of nodes in a directed graph, and each layer is fully connected to the next one. Each node is a neuron with a nonlinear activation function except for the input nodes. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modified form of the standard linear perceptron and can distinguish data that are not linearly separable. If a multilayer perceptron (MLP) has a simple on-off mechanism i.e. linear activation function in all neurons to determine whether or not a neuron fires, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model. The gradient techniques are then applied to the optimization methods to adjust the weights to minimize the loss function in the network. Hence, the algorithm requires a known and a desired output for all inputs in order to compute the gradient of loss function. Usually, the generalization of MultiLayerd Feed Forward Networks is done using delta rule which possibly makes a chain of iterative rules to compute gradients for each layer. Back Propagation Algorithm necessitates the activation function to be different between the neurons. The ongoing researches on parallel, distributed computing and computational neuroscience are currently implemented with the concepts of MultiLayer Perceptron using a Back Propagation Algorithm. MLP Back Propagation Algorithm has also gained focus in pattern recognition domain. They are so convenient in research, because of their ability in solving complex problems, and also for their fitness approximation results even with critical predictions. MLP is one of the Neural Network models, has the same architecture of Feed-Forward back Propagation for Supervised training. The multilayer perceptron is the most known and most frequently used type of neural network. User can provide the features and automatically predict the diseases.

A back propagation is a feed forward artificial neural network structure that plots set of input data onto a set of appropriate outputs. It contains of numerous layers of nodes in a directed graph, and each layer is fully connected to the next one. Each node is a neuron with a nonlinear activation function excluding for the input nodes. Back propagation exploits a supervised learning technique called back propagation for training the network. If back propagation has a simple on-off mechanism i.e. linear activation function in all neurons, to regulate whether or not a neuron fires, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model. The gradient techniques are then practical to the optimization methods to regulate the weights to diminish the loss function in the network. Feed Forward Networks is done using delta rule which possibly makes a chain of iterative rules to compute gradients for each layer. Back Propagation Algorithm requires the activation function to be different between the neurons. The ongoing investigates on parallel, distributed computing and computational neuroscience are currently implemented with the concepts of Back Propagation They are so convenient in study, because of their ability in solving complex problems, and also for their fitness approximation results even with critical predictions. Back propagation is one of the Neural Network models, has the same architecture of Feed-Forward back Propagation for Supervised training. The back propagation is the most known and most frequently used type of neural network. User can provide the features and inevitably predict the diseases. The algorithm steps are follows

Step 1: Randomly set the weights and biases.

Step 2: Feed the training sample.

Step 3: Propagate the inputs forward; compute the net input and output of each unit in the hidden and output layers.

Step 4: Back propagate the error to the intermediate layer.

Step 5: Update weights and biases to replicate the propagated errors.

Training and learning functions are mathematical measures used to automatically regulate the network's weights and biases.

Step 6: Stop condition

DISEASE DIAGNOSIS

Medical decision support system is a decision-support program which is designed to assist physicians and other health professionals with decision making tasks, such as determining diagnosis of patients' data. In this module, provide the diagnosis information based on predicted diseases. Proposed system provides improved accuracy in disease prediction. Risk factors are conditions or habits that make a person more likely to develop a disease.

V. RESULTS AND DISCUSSION

In this study, we can develop the framework in Python language and build the model using Multi-layer perceptron algorithm. The performance the system analyzed in terms of accuracy parameter. In experimental results, from key features datasets, the sign facts are acquired which are employed to measure the usefulness of the suggested method. Using F-measure, Recall and Precision the performance of the system is being evaluated.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{F measure} = 2^* \frac{\text{Precision}*\text{Recall}}{\text{Precision+Recall}}$$

Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \text{ x } 100$$

ALGORITHM	ACCURACY
Random forest	87%
Support vector machine	83%
Multi layer perceptron algorithm	91%

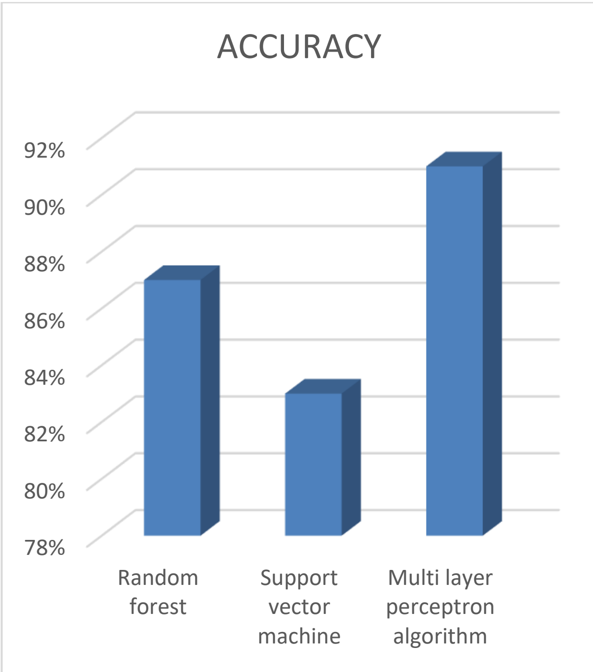

Fig 3: Performance evaluation

The prediction result is shown in following figures

VI. CONCLUSION

Chronic Kidney Disease, also known as chronic kidney failure, is a gradual loss of kidney function. The kidneys filter waste and fluids from our blood which are excreted through urine. The kidneys balance the salts and minerals such as calcium, phosphorus, sodium, and potassium that circulate in the blood. They also make hormones that help control blood pressure, make red blood cells and keeps the bones strong. When chronic kidney disease reaches an advanced stage, dangerous levels of fluid, electrolytes and wastes can build up in our body. The early stages of chronic kidney disease is characterised by few signs or symptoms, which makes it difficult to identify the disease. The symptoms may become apparent only when the kidney function is significantly impaired. If left untreated, chronic kidney disease can progress to end stage kidney failure, which is fatal without artificial filtering (dialysis) or a kidney transplant. In the work presented, neural networks are used for diagnosis of chronic kidney disease. With the above results we have achieved our objective to find the best model for CKD diagnosis. The multilayer perceptron with back propagation algorithm is a good model for diagnosis of CKD, its accuracy is 91%. The error rate is also considerably low. Thus, we have come to conclusion that multilayer perceptron trained with back propagation is one of the most suitable and efficient algorithms for kidney disease diagnosis. Limitation of the application is we do not have data of strength because of size of data set and missing attribute values

VII. REFERENCES

[1]. A. M. Cueto-Manzano, L. Cortés-Sanabria, H. R. Martínez-Ramírez, E. Rojas- Campos, B. Gómez-Navarro, and M. Castillero-Manzano, ``Prevalence of chronic kidney disease in an adult population,'' Arch. Med. Res., vol. 45, no. 6, pp. 507513, Aug. 2014.

[2]. A. Singh, G. Nadkarni, O. Gottesman, S. B. Ellis, E. P. Bottinger, and J. V. Guttag, ``Incorporating temporal EHR data in predictive models for risk stratication of renal function deterioration,'' J. Biomed. Informat., vol. 53, pp. 220228, Feb. 2015.

[3]. A. Subasi, E. Alickovic, and J. Kevric, ``Diagnosis of chronic kidney disease by using random forest,'' in Proc. Int. Conf. Med. Biol. Eng., Mar. 2017, pp. 589594.

[4]. A. U. Haq, J. P. Li, J. Khan, M. H. Memon, S. Nazir, S. Ahmad, G. A. Khan, and A. Aliss, "Intelligent deeplearning approach for effective recogni- tion of diabetes in E- healthcare using clinical data," Sensors, vol. 20, no. 9, p. 2649, May 2020.

[5]. A. Wosiak and D. Zakrzewska, "Integrating correlation-based feature selection and clustering for improved cardiovascular disease diagnosis," Complexity, vol. 2018, Oct. 2018, Art. no. 2520706

[6]. B. Deepika, "Early prediction of chronic kidney disease by using deeplearning techniques," Amer. J. Comput. Sci. Eng. Survey, vol. 8, no. 2, p. 7, 2020.

[7]. C. Barbieri, F. Mari, A. Stopper, E. Gatti, P. Escandell-Montero, J. M. Martínez- Martínez, and J. D. Martín-Guerrero, ``A new deeplearning approach for predicting the response to anemia treatment in a large cohort of end stage renal disease patients undergoing dialysis,'' Comput. Biol. Med., vol. 61, pp. 5661, Jun. 2015.

[8]. E. M. Karabulut, S. A. Ozel, and T. Ibrikci, "A comparative study on the effect of feature selection on classification accuracy," Procedia Technol., vol. 1, pp. 323–327, Jan. 2012.

[9]. F. Ma, T. Sun, L. Liu, and H. Jing, "Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artifi- cial neural network," Future Gener. Comput. Syst., vol. 111, pp. 17–26, Oct. 2020.

[10]. H. Polat, H. D. Mehr, and A. Cetin, ``Diagnosis of chronic kidney disease based on support vector deepby feature selection methods,'' J. Med. Syst., vol. 41, no. 4, p. 55, Apr. 2017.

[11]. J. M. Pereira, M. Basto, and A. F. D. Silva, "The logistic lasso and ridge regression in predicting corporate failure," Procedia Econ. Finance, vol. 39, pp. 634– 641, Jan. 2016.

[12]. L. Zhang, ``Prevalence of chronic kidney disease in China: A crosssectional survey,'' Lancet, vol. 379, pp. 815822, Mar. 2012.

[13]. M. S. Gharibdousti, K. Azimi, S. Hathikal, and D. H. Won, "Prediction of chronic kidney disease using data mining techniques," in Proc. Ind. Syst. Eng. Conf., K. Coperich, E. Cudney, H. Nembhard, Eds., 2017, pp. 2135–2140.

[14]. N. A. Nnamoko, F. N. Arshad, D. England, J. Vora, and J. Norman, "Eval- uation of filter and wrapper methods for feature selection in supervised deeplearning," in Proc. 15th Annu. Postgraduate Symp. Converg. Telecommun., Netw. Broadcast., Liverpool, U.K., 2014, pp. 2–33.

[15]. P. G. Scholar, "Chronic kidney disease prediction using deeplearn- ing," Int. J. Eng. Res. Technol., vol. 9, no. 7, pp. 137–140, 2020.

[16]. U. H. Amin, J. Li, Z. Ali, M. H. Memon, M. Abbas, and S. Nazir, "Recognition of the Parkinson's disease using a hybrid feature selection approach," J. Intell. Fuzzy Syst., vol. 39, no. 1, pp. 1–21, Jul. 2020.

[17]. Z. Chen, Z. Zhang, R. Zhu, Y. Xiang, and P. B. Harrington, ``Diagnosis of patients with chronic kidney disease by using two fuzzy classiers,''Chemometrics .W. Mula-Abed, K. A. Rasadi, and D. Al-Riyami, "Estimated glomerular filtration rate (eGFR): A serum creatinine-based test for the detection of chronic kidney disease and its impact on clinical practice," Oman Med. J., vol. 27, no. 4, pp. 339–340, 2012. [18]A. S. Levey, D. Cattran, A. Friedman, W. G. Miller, J. Sedor, K. Tuttle,

[18]. B. Kasiske, and T. Hostetter, "Proteinuria as a surrogate outcome in CKD: Report of a scientific workshop sponsored by the national kidney founda- tion and the US food and drug administration," Amer. J. Kidney Diseases, vol. 54, no. 2, pp. 205– 226, Aug. 2009.

[19]. S. Gerogianni, "Concerns of patients on dialysis: A research study," Health Sci. J., vol. 8, no. 4, pp. 423–437, 2014.

[20]. J. R. Chapman, "What are the key challenges we face in kidney transplan- tation today?" Transplantation Res., vol. 2, no. S1, pp. 1–7, Nov. 2013.