



ISSN: 2321-2152



IJMECE

*International Journal of modern
electronics and communication engineering*

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www.ijmece.com

CHRONIC KIDNEY STAGE IDENTIFICATION IN HIV INFECTED PATIENTS USING MACHINE LEARNING

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ABSTRACT

Chronic Kidney Disease (CKD) is one of worldwide medical challenges with high morbidity and death rate. Since there is no symptom during the early stages of CKD, patients often fail to diagnose the disease. Patients with HIV have more chances to be affected with CKD in critical condition. Early detection of CKD helps patients to obtain prompt care and delays the further progression of disease. With the availability of pathology data, the use of machine-learning techniques in healthcare for classification and prediction of disease has become more common. This paper presents the classification of CKD using machine learning models. Based on the glomerular filtration rate, the CKD stages are also calculated for patients diagnosed with CKD. DNN model outperforms with 99% of

accuracy in classifying CKD patients with HIV.

1. INTRODUCTION

CKD is an incurable condition of kidney associated with higher risk of many other diseases such as heart failure, anemia, and bone disease. Kidneys are very adaptable. However symptoms will reveal kidney damage slowly. In many cases, patients do not feel symptoms until disease is in last stage. Figure 1 shows the common symptoms that is overlapped with other disease. Some forms of kidney disease are treatable by avoiding symptoms. It helps patients to keep the disease from getting worse by restoring few kidney functions. Especially in case CKD, dialysis and kidney transplant are two major treatment options for end-stage kidney disease. Due to high treatment cost, only 10% of people receive dialysis or kidney transplant worldwide [2]. Each year, more

than one million individuals from 112 low earning countries suffer and die due to kidney failure [5]. Patients having Acquired Immunodeficiency Syndrome (AIDS) have more complication in kidney disease due to deficiency of glomeruli filters also known as nephrons. The medication used for Human Immunodeficiency Viruses (HIV) can also infect the cells in kidney. It is very important to detect, control, progression of CKD in early stage. Increasing interest in automated diagnosis and rapid development in machine learning methods has played an important role in healthcare. Although many researches have used machine learning techniques to classify CKD in multiple stages. However, a few researcher has identified relation of CKD with HIV. In this paper, we have explored ML techniques and done. Automated computer aided diagnose for CKD is a process of getting stage information using patient data such as age blood pressure, blood test reports. Yu et al. [2] has utilized the Support Vector Machine (SVM) algorithm to recognize and anticipate diabetic and pre-diabetic patients. The outcome show that SVM is able to distinguishes patients with common diseases. E. Perumal et al. [6] has used the decision tree algorithm to predict the occurrence of heart disease, Naïve Bayes

algorithm, and Probabilistic Neural Network (PNN) algorithm. It provides better results compared to other cardiovascular prediction algorithms. R. Shinde et al. [8] The Multilayered Perceptron (MLP) separator was used to predict HBV-induced hepatic cirrhosis, and the findings indicate that the MLP separator provides excellent predictive results for liver disease, particularly in HBV-related patients with liver failure.

2.LITERATURE SURVEY

Contemporary issues and new challenges in chronic kidney disease amongst people living with HIV Chronic kidney disease (CKD) is a comorbidity of major clinical significance amongst people living with HIV (PLWHIV) and is associated with significant morbidity and mortality. The prevalence of CKD is rising, despite the widespread use of antiretroviral therapy (ART) and is increasingly related to prevalent noninfectious comorbidities (NICMs) and antiretroviral toxicity. There are great disparities evident, with the highest prevalence of CKD among PLWHIV seen in the African continent. The aetiology of kidney disease amongst PLWHIV includes HIV-related diseases, such as classic HIV-associated nephropathy or immune complex

disease, CKD related to NICMs and CKD from antiretroviral toxicity. CKD, once established, is often relentlessly progressive and can lead to end-stage renal disease (ESRD). Identifying patients with risk factors for CKD, and appropriate screening for the early detection of CKD are vital to improve patient outcomes. Adherence to screening guidelines is variable, and often poor. The progression of CKD may be slowed with certain clinical interventions; however, data derived from studies involving PLWHIV with CKD are sparse and this represent an important area for future research. The control of blood pressure using angiotensin converting enzyme inhibitors and angiotensin receptor blockers, in particular, in the setting of proteinuria, likely slows the progression of CKD among PLWHIV. The cohort of PLWHIV is facing new challenges in regards to polypharmacy, drug–drug interactions and adverse drug reactions. The potential nephrotoxicity of ART is important, particularly as cumulative ART exposure increases as the cohort of PLWHIV ages. The number of PLWHIV with ESRD is increasing. PLWHIV should not be denied access to renal replacement therapy, either dialysis or kidney transplantation, based on their HIV status. Kidney transplantation

amongst PLWHIV is successful and associated with an improved prognosis compared to remaining on dialysis. As the cohort of PLWHIV ages, comorbidity increases and CKD becomes more prevalent; models of care need to evolve to meet the new and changing chronic healthcare needs of these patients. A Machine Learning Methodology for Diagnosing Chronic Kidney Disease Chronic kidney disease (CKD) is a global health problem with high morbidity and mortality rate, and it induces other diseases. Since there are no obvious symptoms during the early stages of CKD, patients often fail to notice the disease. Early detection of CKD enables patients to receive timely treatment to ameliorate the progression of this disease. Machine learning models can effectively aid clinicians achieve this goal due to their fast and accurate recognition performance. In this study, we propose a machine learning methodology for diagnosing CKD. The CKD data set was obtained from the University of California Irvine (UCI) machine 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 machine 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 machine learning models, random forest achieved the best performance with 99.75% diagnosis accuracy. By analyzing the misjudgments generated by the established models, we proposed an integrated model that combines logistic regression and random forest by using perceptron, which could achieve an average accuracy of 99.83% after ten times of simulation. Hence, we speculated that this methodology could be applicable to more complicated clinical data for disease diagnosis.

3. EXISTING SYSTEM

Corinne Isnard Bagnis, Jack Edward Heron, David M. Gracey et al. [1] conducted a report on Chronic Kidney Disease and its connection to more deplorable outcomes. It shows that controlling blood pressure with

angiotensin converting enzyme inhibitors and angiotensin receptor blockers slows the progression of CKD in HIV patients, particularly when proteinuria is present. Y. Liu, J. Qin, C. Feng, L. Chen, C. Liu, and B. Chen et al. [2] reveals that data imputation and sample diagnosis are possible with CKD. The integrated model presented in this paper can achieve sufficient accuracy using the KNN algorithm. Since the dataset contains two classes, Chronic Kidney Infection and Not Chronic Kidney Disease, the model cannot investigate the stages of chronic kidney disease. A. S. Anwar and E. H.

A. Rady et al. [3] uses lab dataset of 361 persistent kidney sickness patients. It uses PNN, SVM, and MLP algorithms to calculate period of chronic kidney sickness. This examination suggests that the probabilistic neural organization calculation is best performing calculation that can be utilized by doctors to kill demonstrative and treatment mistakes. M. N. Amin, A. Al Imran and F. T. Johora et al. [4] analyze model performance on real (imbalanced) data and model performance on oversampled (balanced) data using logistic regression and feed forward neural networks. Feed forward neural networks showed the best results for

both real and oversampled data, with 0.99 Recall, 0.97 Precision, 0.99 F1-Score and 0.99 AUC score. K. S. Vaisla, N. Chetty and S. D. Sudarsan et al. [5] recommended On the CKD dataset, attribute assessment and classification models were used. The attribute evaluator model performed better by decreasing the number of attributes from 25 to 6, 12, and 7. P. Arulanthu and E. Perumal et al. [6] utilizes JRip, SMO, Naive Bayes, algorithms and analyses that JRip generate best performance.

P. Manickam, K. Shankar, M. Ilayaraja and G. Devika et al. [7] uses Ant Lion Optimization (ALO) technique to choose ideal features for classification. This optimization results in better classification accuracy for deep neural network. R. Shinde, Maurya, R. Wable, S. John, R. Dakshayani and R. Jadhav, et al. [8] To slow the progression of CKD and to follow the recommended diet plans, use the potassium zone, which is computed using blood potassium levels. R. Yadav and S. C. Jat et al. [9] investigate the relation of various methods of selection and dimensionality reduction to the performance of chronic disease classification and prediction.

4. PROPOSED SYSTEM

There are several machine learning algorithms used in literature for CKD classification. In this paper, we have built 6 ML models using, KNN, SVM, random forest, decision tree, ada-boost and xg-boost algorithms, along with a simple deep neural network to classify whether a patient has CKD or not. The flow of the proposed experimental setup is depicted in Figure 2. For binary classification situations, A SVM (support vector machine) is a classification-based supervised machine learning model. K-nearest neighbors (KNN) algorithm utilizes feature comparing to predict a value according on how closely it is similar in the training dataset. A decision tree is used to visually represent decisions of classification. Often, a single decision tree is not sufficient for producing effective classification accuracy. Random Forest algorithm solves this problem by leveraging multiple decision trees.

AdaBoost algorithm, also called adaptive boosting, is a boosting technique used as an ensemble method in machine learning. It aims to convert a set of weak classifiers into a strong one by reassigning the weights to

each instance. XG Boost (eXtreme Gradient Boosting) is another boosting algorithm that uses a gradient boosting framework. Other than machine learning, many researcher have utilized feature based deep neural network (DNN) for better classification results. Deep neural networks are capable of detecting crucial disease since they use several layers of nodes to accomplish high-level functions from input data. Before applying classification algorithm, we have eliminated few features using feature selection method.

5.ARCHITECTURE

The system architecture of an optimal ambulance positioning project for road accidents using deep embedded clustering involves several components working together to collect, process, analyze, and act upon data to improve emergency response times.

The system architecture of an optimal ambulance positioning project for road accidents using deep embedded clustering is complex and multifaceted, involving the integration of various data sources, machine learning models, optimization algorithms, and decision-making systems. By leveraging these components effectively, the system aims to improve emergency response times,

reduce accident fatalities, and enhance overall public safety.

System Architecture mainly consists of 4 modules. Those are:

- a. Web Server
- b. Web Database
- c. Service Provide
- d. Remote User

1.Web Server

Acts as the central hub that handles requests from remote users and service providers, processes data, and serves the necessary response. Manages API calls between the remote users, service providers, and the web database. Implements the deep embedded clustering algorithm to analyze accident data, predict hotspots, and suggest optimal ambulance positions. Ensures the system can handle multiple requests efficiently without downtime

2.Web Database

Stores all the necessary data required for the system's operation, including real-time data, historical data, and user information.

3. Service Provider

Represents the backend services that provide and manage the core functionalities of the system, including the implementation of the deep embedded clustering algorithm. Collects and aggregates data from various sources such as traffic sensors, GPS, historical accident data, and weather reports. **Login:** Here we can login with Username and Password

1. Browse IOT Datasets and Train and Test Data Sets : Here, We browse the dataset and it will train the data set and test the data set

2. View Trained and Tested Accuracy in Bar chart: Here, after trained and tested the accuracy of the data the result will be displayed by bar charts.

3. View Trained and Tested Accuracy Results: Here, it will check the accuracy of the trained and tested data.

4. View Prediction of Threat Detection Status: It will view the prediction of the threat detection status Whether ambulance is in the position or not.

5. View Threat Detection Status

Ratio: It will view the threat detection status by the ratio analysis. It display the ratio of ambulance is in the position or not.

6. Download Predicted Data Sets: It will automatically download the Predicted datasets. It will perform after predicting the data.

7. View All Remote Users: Here, we can see the list of all the remote users who are registered and their status.

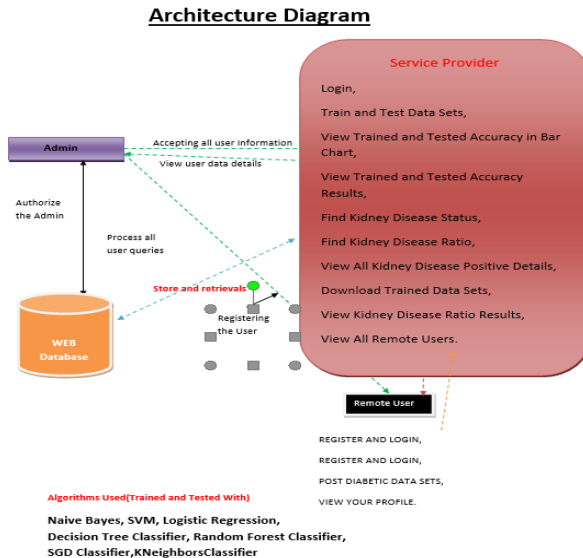
4. Remote User: Refers to users who access the system remotely, typically including ambulance drivers, emergency response coordinators, and potentially the general public. Provides a user-friendly interface (web or mobile app) for accessing real-time data on ambulance positioning and accident hotspots.

1. Register & Login: Once the User register successfully by providing all the required details and then he need to login with Username and Password. The user can perform the following operation

2. View user profile: The user can view their profile data.

3. Predict ambulance positioning

type: Here, the user will give the data and will predict the ambulance positioning type whether ambulance found or not found.



Trained Data Sets, View Kidney Disease Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like POST DIABETIC DATA SETS, VIEW YOUR PROFILE.

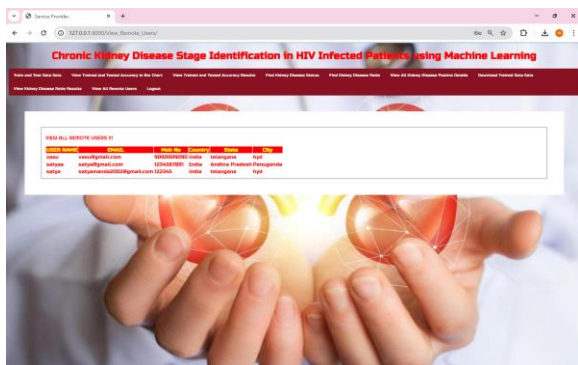
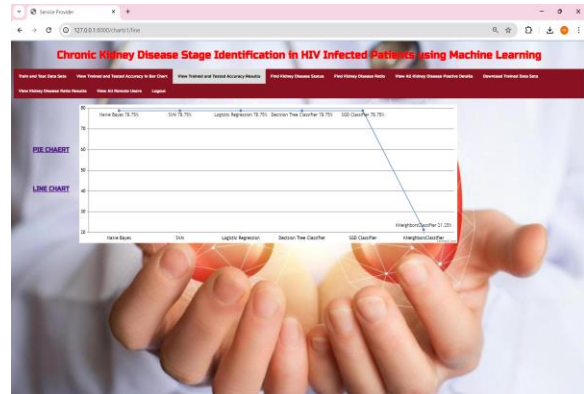
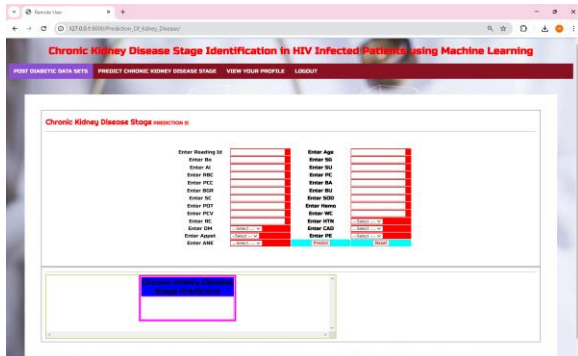
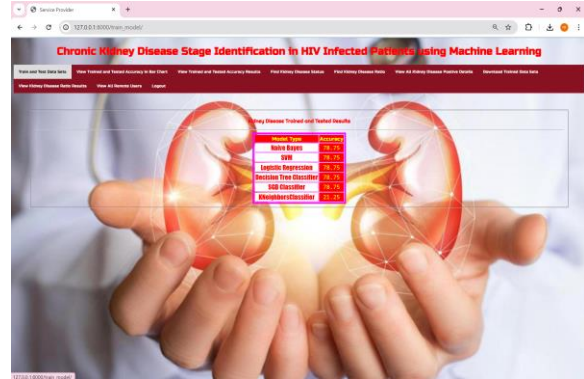
6. MODULES

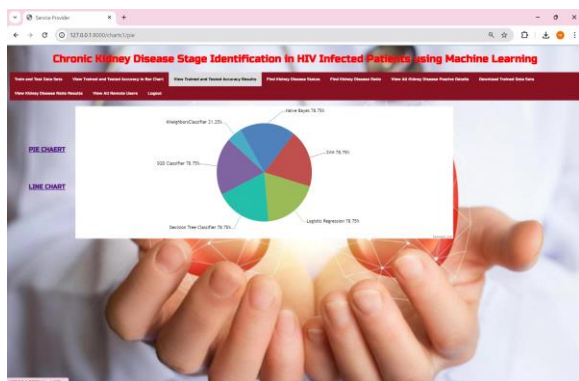
Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train and Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, Find Kidney Disease Status, Find Kidney Disease Ratio, View All Kidney Disease Positive Details, Download

7. OUTPUT SCREENS







8. CONCLUSION

Classification of Chronic Kidney diseases stage in HIV infected patient are extremely useful to patients as well as doctor for timely and accurate clinical decisions. In this paper we have compared the performance of state of art machine learning algorithms along with DNN for classification of CKD for patients having HIV. Our study indicates that DNN has outperformed in CKD classification. We have also shown the use of EGFR formula to identify stages of disease. In future, features based DNN can be combined with medical image analysis to support diagnosis based on different imaging modalities.

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