

“Chronic Kidney Disease Stage Identification in HIV Infected Patients using Machine Learning”

Tejaswini JB ¹, Vidya S ²

Dept. of MCA, Bangalore Institute of Technology, Bengaluru, India¹

Dept. of MCA, Asst. Professor Bangalore Institute of Technology, Bengaluru, India²

Abstract: Persevering Chronic Kidney Disease persistent Kidney Disease is quite possibly of the most widely recognized clinical issue, with a high harshness and deadness rate. Because there is no side effects in the first stages of chronic Kidney Disease, patient frequently give out to analyse the illness. Patient with HIV are more likely to develop CKD in their basic situation. First detection of CKD assists patients in obtaining brief consideration while also delaying the development of illness. With the obtainability of pathology information, the utilize of AI methods in medical care for order and sickness prediction has enhance more familiar. This paper discusses the categorization of CKD using AI representation. The CKD stages are also determined formed on the glomerular filtration rate in patients who have been diagnosed with CKD. In grouping CKD patients with HIV, the DNN model outperforms with the vast majority of precision.

Keywords: CKD stage identification; chronic kidney infection; support vector machine; machine learning, and KNN.

I. INTRODUCTION

CKD is a hopeless kidney situation associated with an increased threat of numerous infections such as cardiovascular breakdown, pallor, and cartilage disease. Kidneys are extremely adaptable. In any case, side effects will gradually reveal kidney damage. In general, long-suffering do not experience side effects till their illness has progressed to the end stage. Figure 1 depicts the typical side effects that are covered by another type of infection A few types of kidney infection can be treated by avoiding side effects. It prevents patients' illnesses from worsening by restoring a few kidney capabilities. Kidney and dialysis transplantation two are important options treatment for patients with end-stage kidney disease, particularly CKD. As a result of the high cost of treatment, only 10% of humans receive kidney or dialysis transplantation [2]. Every period, over 1,000,000 people from 112 low-income nation sustain and die as a result of kidney failure [5]. Because of a lack of channels glomeruli, also known as nephrons, patients with (AIDS) Acquired Immunodeficiency Syndrome have more confusion are kidney sickness. The medication used to treat (HIV) Human Immunodeficiency Viruses can also contaminate excretory organs. It is critical to distinguish, command, and move CKD in its primary stages. The growing interest in automated determination and the rapid advancement of AI strategies has had a significant impact on medical services. Despite the fact that many studies have used AI methods to classify CKD at various stages. Nonetheless, a couple of scientists have identified a link between CKD and HIV. For this paper, we investigated ML strategies and performed exploratory analysis to order CKD phases depending on glomerular filtration rate (GFR).

1. Reason of Chronic Kidney Disease

Mechanized PC-helped CKD assessment is a method for getting stage data by utilizing patient information like age, heartbeat, and blood test results. Yu et al. [2] closed SVM to see and anticipate diabetic's patients what's more pre diabetic patient .The results show that Support Vector Machine can see patients with average ailments. Perusal et al. [6] used the choice tree assessment, Nave Bayes calculation, and Probabilistic Neural Network (PNN) examination to anticipate the occasion of coronary difficulty. When stood isolated from other cardiovascular presumption evaluations, it makes besides made results. R. Shined and partners [8] The Multi layered Perceptron (MLP) separator is utilized to figure HBV persuade hepatic cirrhosis, and results show that the MLP separator has remarkable measure results for liver burden, particularly in HBV related liver with patients' disorder.

2. Model Selection

A couple of AI computations are use recorded as a hard copy for CKD portrayal. In this paper, we created six ML representations that utilization KNN, SVM, sporadic boondocks, decision tree, ada-help, and xg-support estimations, as well as an essential significant cerebrum association, to decide if patients has Chronic Kidney Disease or not. Figure 2 portrays the movement of the recommended preliminary plan. A (support vector machine) SVM is a gathering based

oversaw AI model for equal request circumstances. The K-closest neighbours (KNN) calculation using highlight separating to measure the worth considering how an eagerly it is comparable in the arranging datasets. A choice tree are used to address decision for social event clearly. A single choice tree is frequently insufficient for creating viable order precision. Arbitrary Forest calculation addresses this issue by utilising a variety of choice trees. Ada Boost calculation, also known as versatile helping, is a gathering strategy used in artificial intelligence. It intends to change a slew of asthenic classifiers into a strong one by realigning the loads to each occasion. Another assisting calculation that makes use of an inclination supporting system is XG Boost. (Extreme Gradient Boosting). Aside from AI, many specialists have used highlight-based profound brain. DNN organisation for improved characterization results because they use a few layers of hubs to achieve significant level capabilities from input data, deep brain networks are capable of distinguishing vital sickness. We eliminated a few elements using the highlight determination strategy prior to applying arrangement calculation.

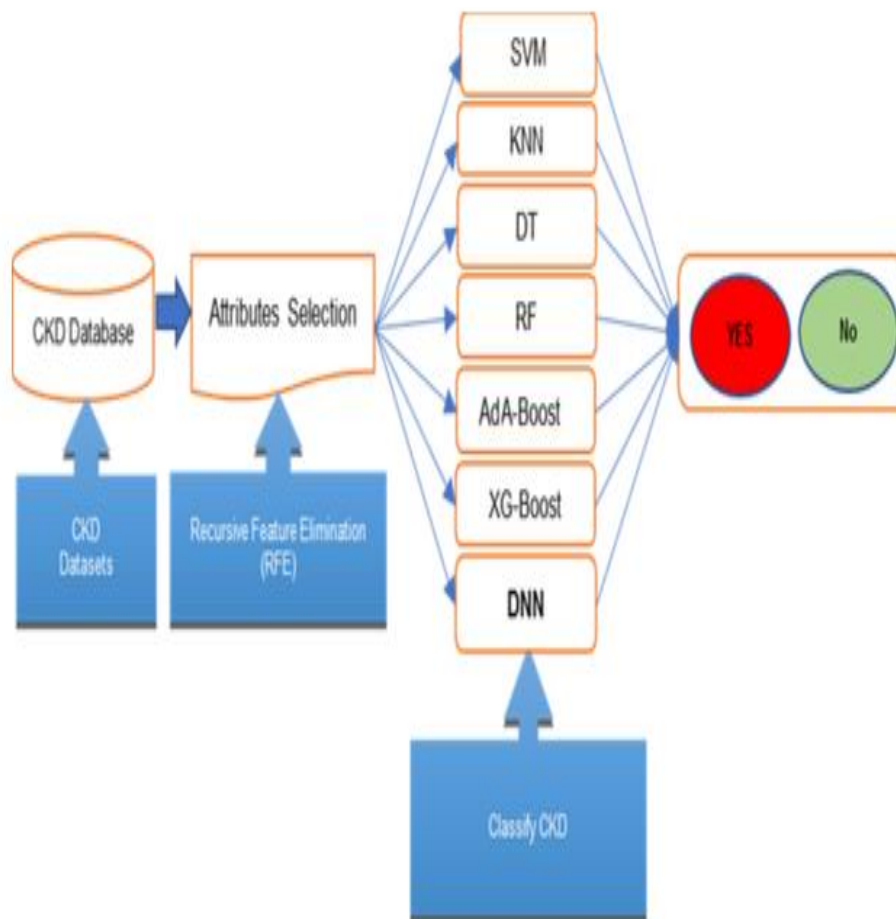


Fig 1: Proposed System

3. The Attributes of HIV (CKD) patient's datasets

A. Picking Attributes Recursive Feature Elimination, is a well-known quality determination calculation that (sections) picks highlights in the preparation datasets that are pretty much significant in gauging an objective factors. While utilizing Recursive Feature Elimination [RFE], there are 2 important arrangement option to consider: the numbers of component to choose from and algorithm used to select charter. Both of these flighty parameter can be inspect, though the methods exact is not dynamically based on them being customized. The features set is cut down to 14 attribute in our experiment. Chronic Kidney Disease grouping for categorization of HIV patient with Chronic Kidney Disease or not KNN, Support Vector Machine, xg-boost, decision tree random forest and ada-boost algorithm and as well (DNN) has been implemented.

Srno	Data	Type
1	Age	Numerical
2	Gender	Categorical
3	ethnicity	Numerical
4	Blood Pressure	Numerical
5	Specific Gravity	Numerical
6	Albumin	Numerical
7	Sugar	Numerical
8	Red Blood Cells	Numerical
9	Pus Cell	Numerical
10	Pus Cell clumps	Numerical
11	Bacteria	Numerical
12	Blood Glucose Random	Numerical
13	Blood Urea	Numerical
14	Serum Creatinine	Numerical
15	Sodium	Numerical
16	Potassium	Numerical
17	Haemoglobin	Numerical
18	Packed Cell Volume	Numerical
19	White Blood Cell Count	Numerical
20	Red Blood Cell Count	Numerical
21	Hypertension	Numerical
22	Diabetes Mellitus	Categorical
23	Coronary Artery Disease	Categorical
24	Appetite	Categorical
25	Pedal Edema	Categorical
26	Anaemia	Categorical
27	Class	Categorical

Fig 2: The Attributes of HIV (CKD) patient's datasets

4. Stages of chronic kidney disease (CKD)

Chronic Kidney Disease Stage ID After request of CKD patients into 2 class non-CKD and CKD, stage ID is done for patient having CKD. Considering eGFR there are 6 periods of Chronic Kidney Disease.

Stages	Explanation	GFR
One	Normal damage of kidney function	>90%
Two	Minor damage of kidney job	89-60%
Three (A)	Minor to Modest damage	59-45%
Three (B)	Modest to simple damage	44-30%
Four	Simple damage of kidney meaning	29-15%
Five	Kidney Stop Working	<15%

Fig 3: Stages of chronic kidney disease

II. ANALYSIS AND RESULTS

In this section, we announced the outcomes of each of model independently and demonstrated the similar examination in light of boundaries such as model exactness, accuracy, and review disarray framework.

Where genuine -ve (TN), genuine +ve (TP), misleading negative (FN), and bogus positive (BP) are used (FP). The Disarray Matrix is one of the instruments used to evaluate the performance of a twofold classifier. We used heat maps for each model to better represent the results.

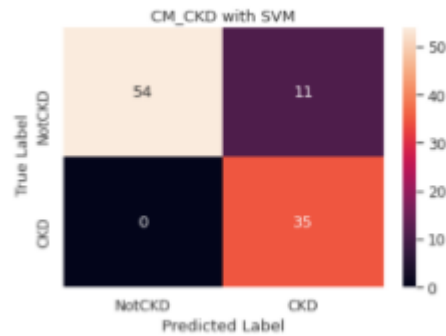


Fig 4: Classifier Results of SVM

As displayed in Fig 4, SVM is tried on 100 examples, with 54 examples delegated non-ckd, 35 examples named ckd, and 11 examples named bogus.

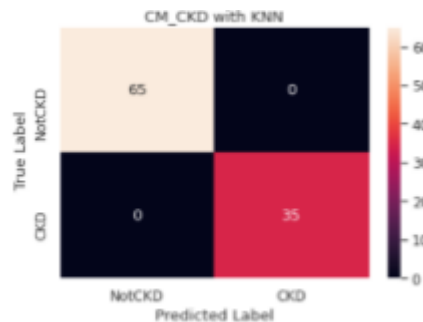


Fig 5: Classifier Results of KNN

As displayed in Fig 5, KNN is tried on 100 examples, 65 of which are ordered 35 as CKD.also, non-CKD.

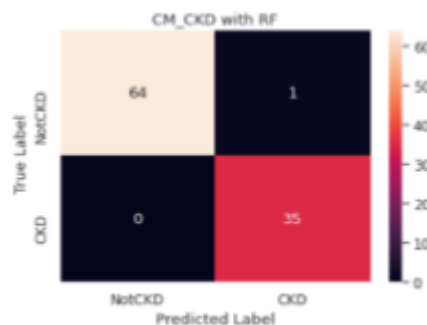


Fig 6: Classifier Results of Random Forest

As displayed in Fig 6, RF is tried on 100 examples, with 64 named non-ckd, 35 delegated ckd, and 1 named misleading.

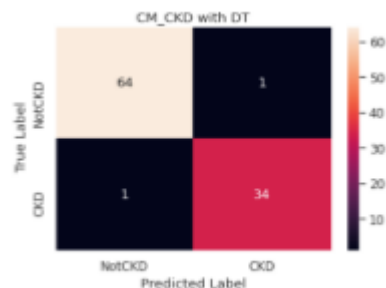


Fig 7: Classifier Results of Decision Tree

As displayed in Fig 7ss, DT is tried on 100 examples, with 64 delegated non-ckd, 34 named ckd, and the leftover two named bogus.

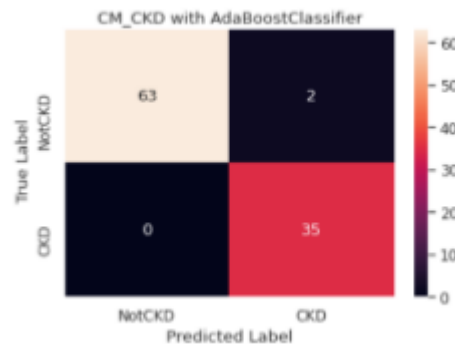


Fig 8: Classifier Results of Ada-boost.

As shown in Fig 8, 100 samples tested on Ada-Boost, with 63 non-ckd as classified, 35 classified as ckd, and the remaining two classified as false.



Fig 9: Classifier Result of XG-Boost

As displayed in Fig 8, XG-Boost was tried on 100 examples, with 64 named non-ckd, 35 delegated ckd, and 1delegatedbogus.

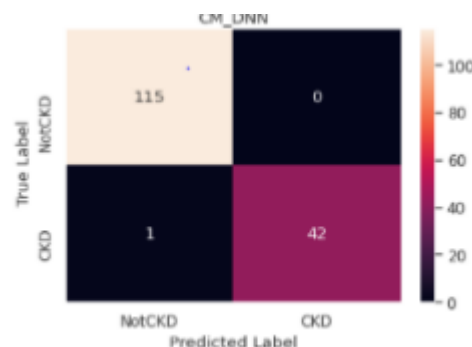


Fig 10: Result of Deep Neural Network (DNN)

We trained the DNN model using all 24 attributes. Figure 10 depicts a heat map are 158 instances of all classes. The outcomes show that DNN has executed high show notwithstanding involving 24 characteristic in contrasting with other strategy that main utilized 14 property. In adjusting to other AI calculations, SVM has performed ineffectively.

III. PRECISION, ACCURACY AND RECALL COMPARISION

The following table shows a comparison of different classifiers in terms of precision, accuracy, and recall as parameter. Fig 10 depicts the graph from the preceding comparison tables. DNN has a stage classification accuracy of nearly 99 percent.

Classifier	Attributes	Accuracy (%)	Precision (%)	Recall (%)
SVM	14	93	91	92
KNN	14	97	95	96
DT	14	97	96	96
RF	14	95	95	94
Ada Boost	14	97	96	97
XgBoost	14	97	95	96
DNN	24	99	99	98

Table 1: comparison of different classifiers in terms of precision, accuracy, and recall as parameter

1. Stages classification Using EGFR

Your kidneys channel your blood by eliminating waste and additional water to make pee. The glomerular filtration rate (GFR) shows how well the kidneys are separating. An expected 37 million grown-ups in the United States might have ongoing kidney sickness (CKD) and can make the strides expected to safeguard their kidney capability when it is seen as ahead of schedule.

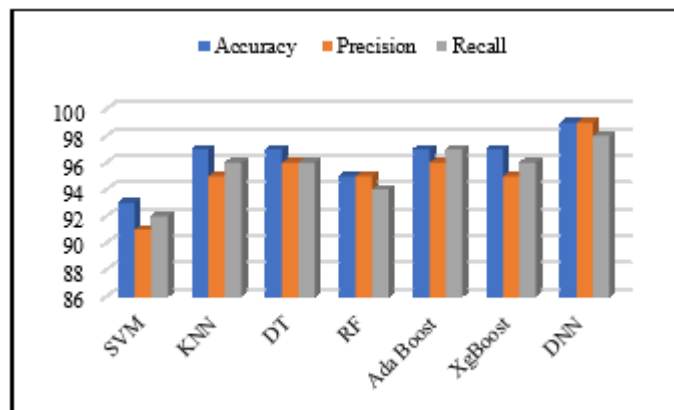


Fig 11: Stages classification Using EGFR

IV. CONCLUSION

The of CKD stages in HIV-infected patients is extremely doctors in making timely and accurate clinical decisions and useful for both patients. In this paper, we looked at the exhibition of state of the art AI calculations with profound unbiased organization for CKD grouping in HIV patients. As per our discoveries, DNN outflanks in Chronic Kidney Disease arrangement. We additionally showed how to utilize the eGFR recipe to distinguish sickness phases, everything being equal. Later on, highlights in light of profound unbiased organization can be joined with clinical picture examination to support analysis utilizing different imaged modalities.

REFERENCES

- [1] C. I. Bagnis, J. E. Heron, and D. M. Gracey, "Contemporary issues and new challenges in chronic kidney disease amongst people living with HIV," *AIDS Res. Ther.*, vol. 17, no. 1, pp. 1–13, 2020, doi: 10.1186/s12981-020-00266-3.
- [2] Y. Liu, C. Liu, J. Qin, L. Chen, C. Feng, and B. Chen, "A machine learning methodology for diagnosing chronic kidney disease," *IEEE Access*, vol. 8, pp. 20991–21002, 2020, doi: 10.1109/ACCESS.2019.2963053.
- [3] A. S. Anwar and E. H. A. Rady, "Prediction of kidney disease stages using data mining algorithms," *Informatics Med. Unlocked*, vol. 15, no. March, p. 100178, 2019, doi: 10.1016/j.imu.2019.100178.
- [4] M. N. Amin, A. Al Imran, and F. T. Johora, "Classification of Chronic Kidney Disease using Logistic Regression, Feedforward Neural Network and Wide Deep Learning," *2018 Int. Conf. Innov. Eng. Technol. ICIET 2018*, pp. 1–6, 2019, doi: 10.1109/CIET.2018.8660844.
- [5] S. D. Sudarsan, N. Chetty, K. S. Vaisla, "Role of attributes selection in classification of Chronic Kidney Disease patients," pp. 1–6, 2016, doi: 10.1109/cccs.2015.7374193.

- [6] E. Perumal , P. Arulanthu , “Predicting the Chronic Kidney Disease using Various Classifiers,” 4th Int. Conf. Electr. Electron. Commun. Comput. Technol. Optim. Tech. ICEECCOT 2019, pp. 70–75, 2019, doi: 10.1109/ICEECCOT46775.2019.9114653.
- [7] K. Shankar, G. Devika, P. Manickam, M. Ilayaraja, “Optimal Feature Selection for Chronic Kidney Disease Classification using Deep Learning Classifier,” 2018 IEEE Int. Conf. Comput. Intell. Comput. Res. ICCIC 2018, pp. 1–5, 2018, doi: 10.1109/ICCIC.2018.8782340.
- [8] R. Shinde, S. John, R. Jadhav, A. Maurya, R. Wable, and R. Dakshayani, “Chronic Kidney Disease Prediction and Recommendation of Suitable Diet Plan by using Machine Learning,” 2019 Int. Conf. Nascent Technol. Eng. ICNTE 2019 - Proc., no. Icнте, pp. 1–4, 2019, doi: 10.1109/ICNTE44896.2019.8946029.
- [9] S. C. Jat . R. Yadav, “Feature selection and dimensionality reduction methods for chronic disease prediction,” Int. J. Sci. Technol. Res., vol. 9, no. 4, pp. 2912–2918, 2020.
- [10] S. saraswat, S. Vashisth, I. dhal, CKD diagnosis using Multilayer Perceptron Classifier’ 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)” 2020.
- [11] K. Shankar, M. Elhoseny, J. Uthayakumar, “Intelligent Diagnostic Prediction and Classification System for Chronic Kidney Disease,” Sci. Rep., vol. 9, no. 1, pp. 1–14, 2019, doi: 10.1038/s41598-019-46074-2.
- [12] M. H. Abd Wahab, A. A. Johari, A. Mustapha, “Two-Class Classification: Comparative Experiments for Chronic Kidney Disease,” 2019 4th Int. Conf. Inf. Syst. Comput. Networks, ISCON 2019, pp. 789– 792, 2019, doi: 10.1109/ISCON47742.2019.9036306.
- [13] G. Saini, B. Pandey, A. Khamparia, S. Tiwari, D. Gupta, and A. Khanna, “KDSAE: Chronic kidney disease classification with multimedia data learning using deep stacked autoencoder network,” Multimed. Tools Appl., 2019, doi: 10.1007/s11042-019-07839-z.
- [14] S. Maheshwari, S. Singhal, and M. Meena, Recent Findings in Intelligent Computing Techniques, vol. 707. Springer Singapore, 2019.
- [15] V. Sharma, S. Sharma, A. Sharma, “Performance Based Evaluation of Various Machine Learning Classification Techniques for Chronic Kidney Disease Diagnosis,” 2016, [Online]. Available: <http://arxiv.org/abs/1606.09581>.
- [16] "Learn More About Kidney Disease: Types, Symptoms, and Causes, Siemens-healthineers.com, 2021. [Online]. Available: <https://www.siemens-healthineers.com/en-us/clinicalspecialities/kidney-disease/about-kidney-disease>. [Accessed: 04- Mar- 2021]
- [17] Estimated Glomerular Filtration Rate (eGFR), National Kidney Foundation, 2021. [Online]. Available: <https://www.kidney.org/atoz/content/gfr>. [Accessed: 04- Mar- 2021]
- [18] The dawn of a new era in chronic kidney disease, Astrazeneca.com, 2021. [Online]. Available: <https://www.astrazeneca.com/what-sciencecan-do/stories/the-dawn-of-a-new-era-in-chronic-kidney-disease.html>. [Accessed: 04- Mar- 2021]