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Machine Learning Algorithms to Predict Hiv-Related Chronic Kidney Disease

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Abstract. Chronic renal illness that persists Due to its extreme severity and high mortality rate, chronic renal disease may be the most well-known clinical condition. In the early phases of chronic renal disease, there are no adverse effects, therefore patients typically consent to having their health assessed. Over time, CKD is more likely to occur in HIV patients. Early CKD diagnosis allows patients to receive quick care while postponing the start of sickness. With the availability of pathology data, using AI techniques in medical care to predict illness and order is increasingly common. The classification of CKD using AI representation is covered in this work. In individuals with CKD, the glomerular filtration rate is used to categories the severity of their condition. When it comes to identifying HIV-positive patients with CKD, the DNN model excels.

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INTRODUCTION

The remarkable rise in the frequency of chronic kidney disease (CKD) over the past 20 years has led to the condition's ascent up the ranks to become the 18th biggest cause of mortality across the globe. The fact that this change was only second to that which was caused by HIV/AIDS highlights the relevance of the connection between HIV and CKD [1, 2]. This change was second only to the one brought about by HIV/AIDS in terms of the impact it had on chronic NCDs and communicable diseases [1,2].

As a result of breakthroughs in antiretroviral treatment, people who currently have HIV can anticipate living longer than their predecessors did (ART). As a consequence of renal impairment brought on by either chronic no communicable illnesses or HIV-associated nephropathy, chronic kidney disease, also known as CKD, has become increasingly prevalent among HIV patients. Chronic kidney disease (CKD) can be identified by its symptoms, which include proteinuria, electrolyte abnormalities, and kidney hypertrophy (HIVAN). Two medications used in antiretroviral therapy (ART) [4], including tenofovir and ritonavir, have been linked to kidney impairment in some patients. According to the findings of researchers, ESRD was related with HIV in between 0.4% and 0.7% of French patients and between 0.5% and 1.1% of Spanish patients. Cameroon and South Africa both have unemployment rates that are significantly lower than average, coming in at 6% and 28.5%, respectively. When conducting an analysis of the incidence of kidney disease in HIV patients, it is essential to point out that after only 3.7 years of follow-up, 3.3% of HIV-positive people who had normal baseline estimated glomerular filtration rates (eGFR) developed chronic kidney disease. This was the case despite the fact that these individuals had been monitored for the entire study period (CKD) [2, 5]. Estimates of the percentage of the HIV-positive population that has chronic kidney disease (CKD) range from 2% to 38%, depending on the reporting methods and CKD criteria that are utilized. In spite of the growing body of published research, no exhaustive study of the data that characterizes the prevalence of CKD in HIV-positive individuals has been out [5,6].

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When compiling and analyzing the data on the prevalence of CKD among HIV patients, we drew from a wide variety of national and international sources. The primary purpose of this research was to lay the groundwork for the development of efficient and contextually appropriate prevention and control measures with the intention of reducing the incidence of chronic renal illness in this community [7,8].

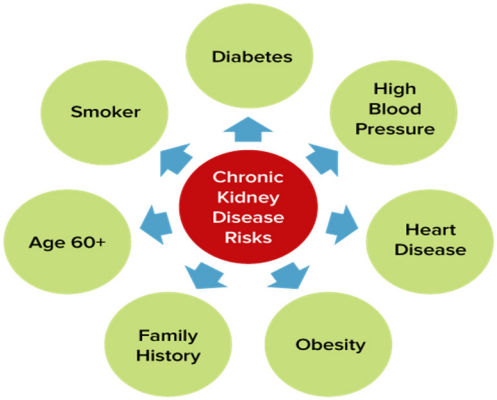

FIGURE 1. Causes of Chronic Kidney Disease

BACKGROUND DATA

Antiretroviral treatment has resulted in a significant extension of life expectancy for HIV patients (ART). Because chronic kidney disease (CKD) is so common among HIV-positive people, it has developed into a significant problem for the general public's health [7]. HIV, the sort of antiretroviral therapy (ART) that is being utilized, and the ever-expanding list of recognized risk factors for CKD are all things to take into mind [9,10].

Albuminuria (albumin excretion rate of 30 mg/day or albumin creatinine ratio (ACR) of 30 mg/g) or an estimated glomerular filtration rate (eGFR) of 60 mL/min/1.73 m2 are both diagnostic criteria for chronic kidney disease [6]. Albuminuria is the more specific of the two criteria. The diagnosis of chronic renal disease can be made based on the presence of any of these two criteria (CKD).

Those individuals who are ineligible to participate in the study include those who have had a kidney transplant in the past, those who have tubular difficulties (as shown by abnormal urine sediment), those who have electrolyte and other abnormalities, those who have structural abnormalities detected by histology and imaging, and those who have other reasons for being excluded from the study [11,12].

Between eight and sixteen percent of the world's population is affected by chronic renal disease (CKD). There is a wide range of variation in the percentage of HIV-positive individuals who also have a chronic renal ailment, ranging from 2% to 38% [7, 9]. The Northwest region of Mexico has a greater incidence of the disease (11.7%) than any of the other regions (9.0%), including the rest of Mexico, North America, and Europe combined. On the other hand, the prevalence of chronic renal disease varies greatly both within and between different ethnic groups [13,14].

Patients who are receiving antiretroviral medication (ART) have the opportunity to improve their immune systems and arrest the progression of HIV in their bodies. On the other hand, they may have to deal with chronic inflammation and accelerated ageing, both of which are factors that lead to the development of metabolic disorders and no communicable diseases that are associated with CKD. In addition to this, they might have to deal with the challenges that come along with CKD (such as hyperlipidemia, diabetes, hypertension, and aberrant body fat composition).

- Immune-complex kidney disease,
- Lupus-like glomerulonephritis,
- Iga nephropathy,
- Thrombotic microangiopathy,
- Membranous glomerulonephritis,
- Focal segmental glomerulosclerosis,
- Classical hiv-associated nephritis, and lupus-like glomerulonephritis.

The antiretroviral medication (ART) that people with HIV take can produce a range of side effects, one of which is damage to the kidneys. In this category are conditions such as tubulointerstitial nephritis, crystal nephropathy,

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tenofovir disoproxil fumarate nephrotoxicity (Franconia syndrome), infiltrative lymphoma or Kaposi's sarcoma kidney lesions, hepatitis C coinfection, and hepatitis B [15,16].

It has been determined whether or not the equations that are used to compute eGFR are accurate when they are applied to people who are HIV-infected. Patients living with HIV who are currently receiving antiretroviral treatment (ART) typically have the most accurate estimations when utilizing the Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) equation. When doing this computation, both the blood creatinine level and the demographic information are taken into consideration. Patients who are taking medications that are commonly recommended should have their blood creatinine levels and estimated glomerular filtration rate (eGFR) measured regularly. This is necessary because many medications can interfere with the production of creatinine in the proximal renal tubules. In the event that this is not done, the levels of creatinine in the blood may rise, as well as the results of the eGFR test [17].

HIV-ASSOCIATED KIDNEY DISEASE

Causes of Impairment of the Kidneys HIV-associated nephropathy (HIVAN), which was first found in the HIV-positive population, is a condition that is very uncommon in regions where antiretroviral medication is easily accessible. Acute kidney injury (AKI) and chronic kidney disease (CKD) are both possible outcomes of HIV infection. Acute kidney injury (AKI) and chronic kidney disease (CKD) are observed more frequently in individuals who have recently been diagnosed with advanced HIV infection or who have discontinued antiretroviral treatment. HIV-related kidney disease can manifest in a wide variety of ways, including the HIV nephrotic syndrome (HIVANS), which is more prevalent, and thrombotic microangiopathy, which is not as prevalent.

African Americans are overrepresented at a rate that is disproportionately high in ESRD patients that are caused by HIVAN. In patients whose HIV illness has progressed to an advanced stage, HIVAN has been related to an increased risk of ESRD. A collapsing form of focal segmental glomerulosclerosis is a distinguishing feature of HIV-associated nephropathy, which contributes to the peculiar histology of this form of nephropathy (FSGS). It is essential for the progression of HIV/AIDS for tubular and glomerular epithelial cells of the kidney to become infected. Systemic HIV infection, immunological dysfunction, and local kidney infection are all possible factors that could be contributing to the course of the disease. There is a considerable racial disparity in HIVAN and related ESRD, which may be explained by the fact that apolipoprotein 1 (APOL1) gene variants are connected with trypanosomiasis susceptibility. Corticosteroids, angiotensin-converting enzyme inhibitors (ACEIs), and angiotensin receptor blockers (ARBs) are a few examples of alternative treatments for HIV-associated neurocognitive impairment (HIVAN) that have showed promise in lowering the severity of patients' symptoms. Patients on antiretroviral treatment who are showing signs of deterioration are, in the opinion of some medical authorities, candidates for receiving corticosteroids.

The research into one specific kind of glomerular disease has been slowed down as a result of the frequent use of the term "HIVICK." The case for a causal link between infection and HIVAN is supported by the data more strongly than the case for HIVICK. There is a need for additional research to determine whether or not HIVICK can be slowed or prevented by the use of antiretroviral therapy.

COMORBID KIDNEY DISEASE

HIV-positive people who already have chronic kidney disease should be more vigilant of HIV-associated nephropathy, despite the fact that it occurs less frequently (HIVAN). It is challenging to differentiate the impact of HIV infection in this population due to the high prevalence of established risk factors for CKD, such as diabetes, hypertension, and HCV coinfections. Research conducted by medically and colleagues indicates that those who have both diabetes and HIV have an increased risk of developing chronic kidney disease (CKD). Data obtained from experiments conducted on animals suggest that this may be the outcome of an uncontrolled relationship between diabetes and HIV infection.

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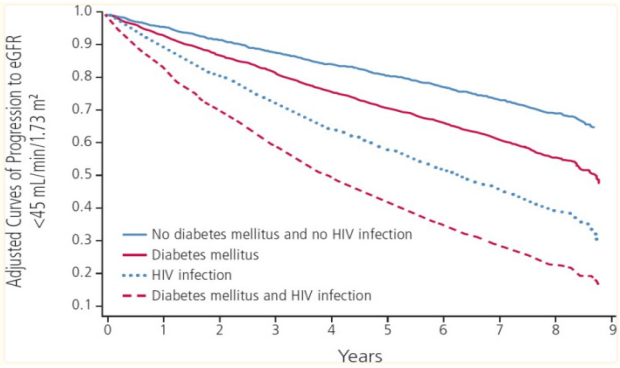

FIGURE 2. The progression of diabetes and HIV-related chronic kidney disease.

Those who are HIV positive and who have HCV infection have a greater chance of having renal impairment. It is not known if the higher risk of renal disease is solely owing to injecting drugs or whether it is also attributable to other risk factors for HIV and HCV infections. Neither of these answers can be determined with certainty. Although some research have found that persons with HCV viremia had a higher risk of renal injury, other studies have not found this to be the case. This finding is dependent on the methodology used in the investigation. However, data from the North American AIDS Cohort Collaboration for Research and Design demonstrated an increased risk of CKD associated with HCV infection regardless of HCV RNA level. Both primary and secondary analyses of HIV treatment trials discovered a significant correlation between HCV viremia and an increased risk for CKD (NA-ACCORD) [4, 5]. Although there have been reports of improvements in kidney function in particular people with HIV/HCV coinfections after HCV treatment, the effect of widespread HCV treatment on the risk of chronic kidney disease (CKD) in HIV-positive individuals remains unknown. It will be shown that there is a potential for adverse drug interactions between antiretroviral therapy and direct-acting antiviral medications; medical professionals who are treating HIV/AIDS patients should be aware of the likelihood that these interactions may occur.

ANALYSIS AND RESULTS

Here, we detail the results from each model and provide comparisons based on criteria like the level of detail in the models and the clarity of the evaluation process [6]. In cases when false positives (FP) are utilized with false negatives (FN) and true negatives (TN), and vice versa (FP). One way to evaluate the efficacy of a binary classifier is with the use of the Disarray Matrix. The findings of each model were visualized using heat maps for clarity.

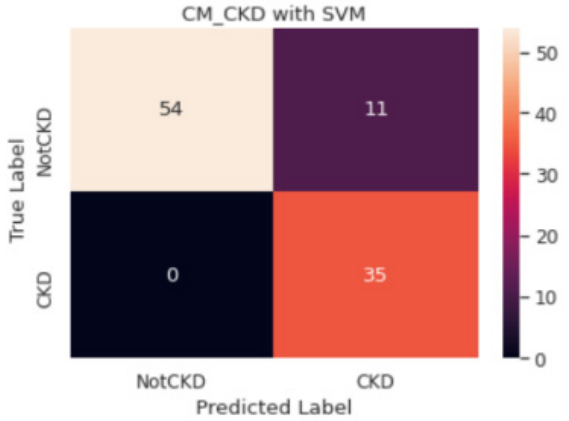

FIGURE 3. Predicted Label for SVM

Example Outcomes from a Support Vector Machine Classifier SVM analysis of 100 samples yielded the following results (Figure): 54% of the samples were classified as not ckd, 35% as ckd, and 11% as fraudulent.

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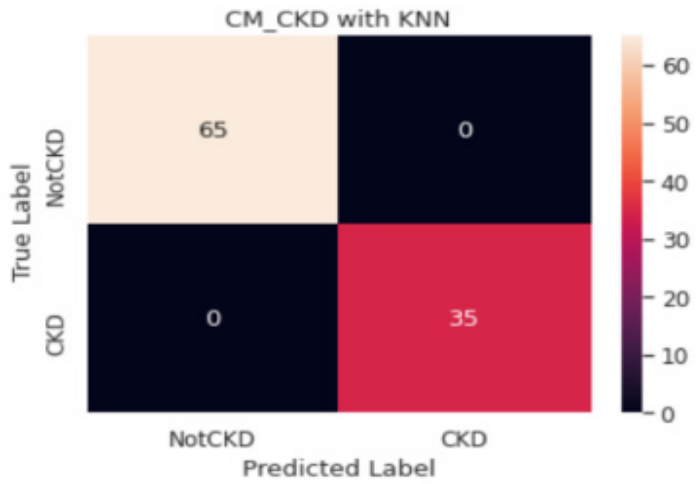

FIGURE 4. Predicted Label for KNN

Summarized Outcomes from a K-Nearest Neighbor Classifier As can be seen in Fig., 65 of the 100 samples are classified as having CKD, whereas the remaining 35 are classified as not having CKD.

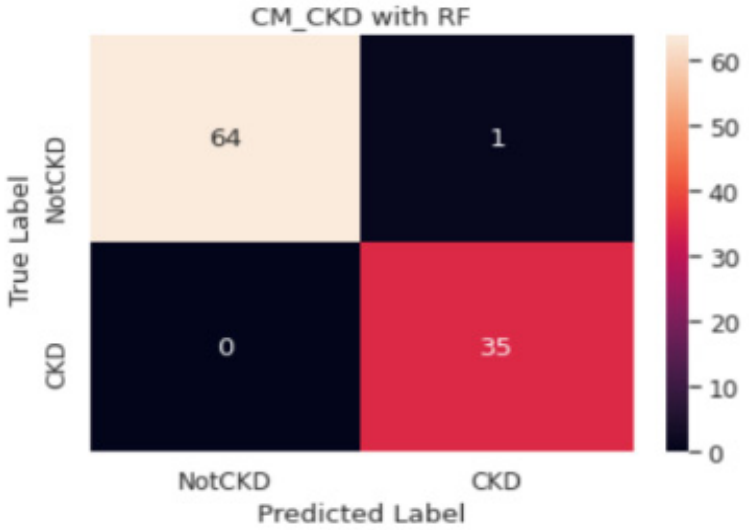

FIGURE 5. Predicted Label for RF

Outcomes of a Random Forest Classifier As can be shown in Fig. 1, when RF is applied to a dataset of 100 cases, 64 are classified as non-ckd, 35 as delegated ckd, and 1 as deceptive.

Decision Trees Classification Outcomes As can be shown in Fig, out of a total of 100 samples tested for DT [3, 7], 64 were determined to be non-ckd, 34 were determined to be ckd, and 2 were determined to be fake.

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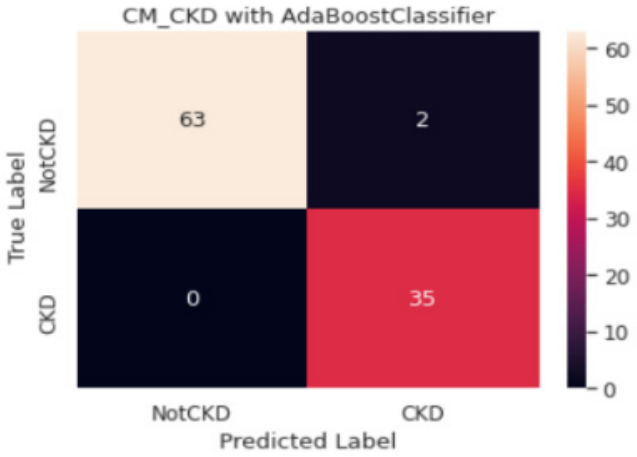

FIGURE 6. Predicted Label for AdaBoostClassifier

Outcomes of the AdaBoost Classifier as shown in a graphical format. Of the 100 samples analysed using Ada-Boost, 63 were correctly labelled as being outside the ckd range, 35 were correctly labelled as being within the ckd range, and the remaining two were wrongly labelled as being outside the ckd range (as shown in Fig).

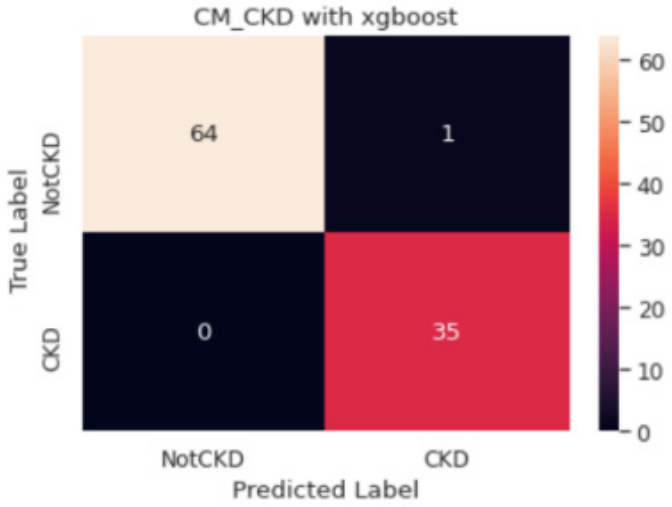

FIGURE 7. Predicted Label for xgboost

Figure Depicting the Results Obtained from Utilizing the XG-Boost Classifier One hundred different samples were given an XG boost, as seen in Figure 1. Only one of the delegations was found to be invalid, while the other 34 were judged to be correct.

A deep neural network's output (DNN) The DNN training approach included each of the twenty-four features in its overall process [3, 8]. A cluster diagram of all 158 classes can be found depicted in Figure 10. DNN performed better than other algorithms, the majority of which only employed 14, despite the fact that it utilized all 24 criteria. The SVM algorithm has not performed as well as some of the other AI algorithms.

CONCLUSION

It is possible that medical professionals and their HIV-positive patients can better prepare for the advancement of CKD if they have a better understanding of its origins and mechanisms. We took a close look at the most recent artificial intelligence-based estimations for CKD classifications in HIV patients, paying particular attention to the

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degree of objectivity with which the data was presented. We demonstrate that DNN is superior to other approaches that have been taken to prepare for renal failure. We also showed that the eGFR calculation can be utilized to differentiate between stages of illness even when all other factors were kept the same. Soon, clinical image analysis will be able to provide highlights based on comprehensive impartial organization, which will facilitate the streamlining of research into a wide variety of picture modalities.

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