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CHRONIC KIDNEY DISEASE STAGE IDENTIFICATION 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

Chronic kidney disease (CKD) is a chronic illness that cannot be cured and increases the risk of several other illnesses, including anemia, bone disease, heart failure, and kidney failure. The kidneys are very versatile. Kidney injury, however, will not be immediately apparent. A lot of the time, people don't notice anything is wrong until the sickness is too advanced. The symptoms that are prevalent and might be confused with other diseases are shown in Figure 1. Avoiding symptoms may be a treatment for certain types of renal disease. It aids patients in preventing the progression of their illness by restoring a subset of kidney functions. Dialysis and kidney transplantation are two main methods for treating advanced kidney

disease, particularly in cases of chronic kidney disease. Only 10% of the global population gets dialysis or a kidney transplant because of how expensive the treatments are [2]. Over a million people in 112 low-income nations have renal failure and lose their lives every year as a result [5]. A lack of glomeruli filters, sometimes called nephrons, makes kidney disease more complicated in patients with Acquired Immunodeficiency Syndrome (AIDS). Kidney cells are susceptible to infection by the Human Immunodeficiency Virus (HIV) treatment. Identifying and managing chronic kidney disease (CKD) at an early stage is crucial. The fast advancement of machine learning techniques and the growing fascination with automated diagnosis have both had significant impacts on the healthcare industry. Regardless, a large body of literature has employed machine learning to categorize CKD into its many phases. Nevertheless, a small number of researchers have shown a link between CKD and HIV. We have investigated ML methods and performed in this study Using patient data like age, blood pressure, and blood test results, automated computer-aided diagnosis for CKD may provide stage information. To identify and foresee individuals who may develop diabetes or pre-

diabetes, Yu et al. [2] used the Support Vector Machine (SVM) method. According to the results, SVM can differentiate between individuals who have similar illnesses. The decision tree, Naïve Bayes, and Probabilistic Neural Network (PNN) algorithms were used by E. Perumal et al. [6] to forecast the development of cardiac disease. It outperforms competing cardiovascular prediction systems in terms of accuracy. The authors of the study are R. Shinde and colleagues In order to forecast HBV-induced hepatic cirrhosis, researchers used the Multilayered Perceptron (MLP) separator. The results show that the MLP separator is quite good in predicting liver disease, especially in patients with liver failure associated to HBV.

2.LITERATURE SURVEY

SURVEY-1:-

St. Paulo's Hospital is where we got all our data. Among the many people admitted to Ethiopia's second-largest public hospital, many suffer from long-term health conditions. Dialysis and a kidney transplant clinic exist on the premises of the hospital. Table 2 shows that the dataset used for this investigation consists of chronic kidney

disease patient records who were admitted to the renal ward between 2018 and 2019. There are a few that came from the same set of patient records but collected at various points in time. The dataset was prepared and characteristics were understood via conversations with domain experts. In all, there are 1718 occurrences in the dataset, and of them, 12 have numerical characteristics and 7 have nominal ones. Table 3 shows the features included in the dataset, which include age, gender, blood pressure, specific gravity, chloride, sodium, potassium, blood urine nitrogen, serum creatinine, hemoglobin, red blood cell count, white blood cell count, mean cell volume, platelet count, hypertension, diabetic mellitus, anemia, and heart disease. According to the multi-class distribution, 441 cases (or 25.67%) are in the end-stage renal disease stage or stage five, 399 cases are in the severe stage or stage four, 354 cases are in the moderate stage or stage three, 248 cases are in the mild stage or stage two, and 276 cases are normal, meaning they do not have chronic kidney disease. From stages 1–5, 1442 students (or 83.93%) were classified as ckd, whereas 276 students (16.07%) were classified as not ckd. An uneven distribution exists in the binary-class set. To make sure

that the minority group's worth is equal to that of the majority group, researchers have turned to oversampling data resampling. All things considered, the binary class dataset's overall size after resampling

SURVEY-2:-

It is unclear what has caused a number of instances of chronic kidney disease (CKD) reported in various parts of India and Sri Lanka. Young men who work as farmers are disproportionately hit. The histology reveals interstitial fibrosis, interstitial mononuclear cell infiltration, and tubular atrophy, while the clinical presentation is similar to interstitial nephritis. The government of Sri Lanka decided a few years ago to stop CKD in its tracks by making sure heavy metals, industrial chemicals, fertilizers, pesticides, and other pollutants don't get up in the country's water supply or food supply. The fact that no elevated levels of heavy metals were detected in the water during a research supported by the International Society of Nephrology's Research and Prevention Committee in the Udhanam area of Srikakulam district (Andhra Pradesh, India) is puzzling [19]. In autosomal dominant polycystic kidney disease (ADPKD), the advancement of chronic kidney disease

(CKD) is linked to the total kidney volume and the pace of kidney growth. An very dangerous genetic disorder, ADPKD mostly strikes adults and may be fatal if left untreated. Mutations in the PKD1 and PKD2 genes are the most common causes, with 80% and 15% of cases, respectively, of this condition. Kidney cyst development in ADPKD most likely starts before birth and continues at an exponential rate throughout a person's life. As time goes on, cysts gradually compress and harm nearby tissues including tubules and vasculature, leading to inflammation and interstitial fibrosis [7]. Below, you will find a list of risk factors for chronic kidney disease (CKD) organized by stage [17].

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, Chronicle 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.

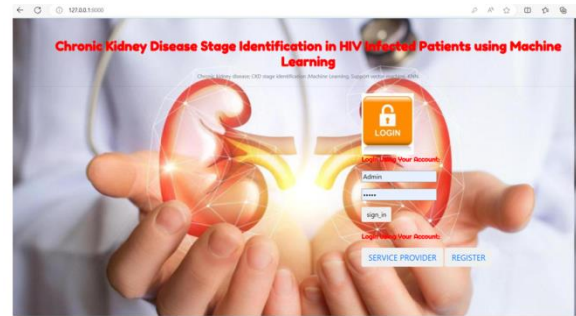
Johora et al. [4] analyze model performance on real (imbalanced) data and model performance on oversampled (balanced) data using logistic regression and feed forward neural networks. Feed forward neural networks showed the best results for both real and oversampled data, with 0.99 Recall, 0.97 Precision, 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. OUTPUT SCREENS

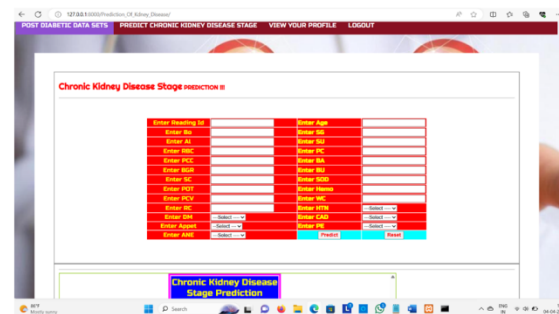
Remote User Login:



Kidney Data Set Details:

| Patient ID | Age | Sex | BMI | Blood Pressure | Hemoglobin | Hematocrit | Hemoglobin A1c | ... | | | | | | | | | | | |
|-----------------|-----|-----|-------|----------------|------------|------------|----------------|------------|------------|-----|-----|-----|-----|-----|------|-----|-------|-----|-----|
| ECORCR195667244 | 48 | 80 | 1.02 | 1 | 0 | normal | normal | notpresent | notpresent | 101 | 35 | 1.2 | 108 | 3.1 | 10.4 | 104 | 7800 | 5.2 | yes |
| ECORCR195667666 | 7 | 50 | 1.02 | 4 | 0 | normal | normal | notpresent | notpresent | 230 | 18 | 0.8 | 131 | 3.7 | 10.3 | 108 | 8000 | 4.4 | no |
| ECORCR195667666 | 52 | 80 | 1.01 | 2 | 1 | normal | normal | notpresent | notpresent | 422 | 53 | 1.8 | 108 | 4.3 | 9.8 | 101 | 7500 | 4.4 | no |
| ECORCR195667789 | 48 | 70 | 1.035 | 4 | 0 | normal | abnormal | present | notpresent | 117 | 58 | 3.8 | 101 | 2.5 | 11.2 | 102 | 8700 | 3.9 | yes |
| ECORCR195667846 | 51 | 80 | 1.01 | 2 | 0 | abnormal | normal | notpresent | notpresent | 106 | 28 | 1.4 | 108 | 3.7 | 10.6 | 105 | 7300 | 4.6 | no |
| ECORCR195667877 | 80 | 100 | 1.015 | 3 | 0 | abnormal | abnormal | notpresent | notpresent | 76 | 25 | 1.1 | 142 | 3.4 | 10.2 | 108 | 7800 | 4.4 | yes |
| ECORCR195667884 | 68 | 70 | 1.01 | 0 | 0 | normal | normal | notpresent | notpresent | 100 | 54 | 24 | 104 | 4 | 10.4 | 106 | 7300 | 4.4 | no |
| ECORCR195667884 | 24 | 80 | 1.015 | 2 | 1 | normal | abnormal | notpresent | notpresent | 140 | 31 | 1.1 | 108 | 3.1 | 10.4 | 104 | 8600 | 5 | no |
| ECORCR195667935 | 52 | 100 | 1.015 | 3 | 0 | normal | abnormal | present | notpresent | 108 | 60 | 1.9 | 108 | 3.9 | 10.8 | 103 | 8600 | 4 | yes |
| ECORCR195667972 | 53 | 80 | 1.02 | 2 | 0 | abnormal | abnormal | present | notpresent | 70 | 107 | 3.2 | 116 | 3.7 | 9.5 | 109 | 12100 | 3.7 | yes |
| ECORCR195667978 | 50 | 140 | 1.01 | 2 | 4 | abnormal | abnormal | present | notpresent | 140 | 50 | 4 | 108 | 4.5 | 9.4 | 108 | 7300 | 4.4 | yes |
| ECORCR195667931 | 63 | 70 | 1.01 | 3 | 0 | abnormal | abnormal | present | notpresent | 180 | 60 | 2.7 | 131 | 4.2 | 10.8 | 102 | 4500 | 3.8 | yes |
| ECORCR195667947 | 68 | 70 | 1.015 | 3 | 1 | abnormal | normal | present | notpresent | 200 | 72 | 2.1 | 108 | 5.8 | 9.7 | 108 | 10200 | 3.4 | yes |
| ECORCR195667924 | 68 | 70 | 1.02 | 2 | 1 | abnormal | abnormal | notpresent | notpresent | 98 | 68 | 4.9 | 130 | 3.4 | 9.8 | 104 | 7300 | 4.4 | yes |
| ECORCR195667980 | 68 | 80 | 1.01 | 3 | 2 | normal | abnormal | present | present | 197 | 90 | 4.1 | 130 | 3.4 | 9.8 | 106 | 10000 | 2.8 | yes |

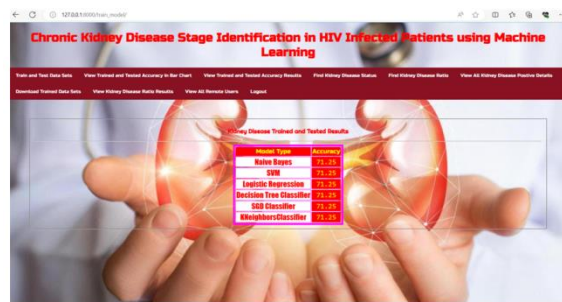
Search and Predict Health:



Service Provider Login:



Train Test Details:



5. CONCLUSION

Having a system in place to categorize the stages of chronic kidney disease in HIV-infected individuals allows both the patient and the clinician to make more informed clinical choices in a timely manner. In this study, we evaluated DNN and other cutting-edge machine learning methods for HIV patient CKD categorization. When it comes to CKD categorization, our research shows that DNN is the way to go. We have also shown that the EGFR formula may be used to determine illness stages. Eventually, medical

image analysis and features-based DNN may work together to bolster diagnostics using a variety of imaging modalities.

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