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Role of Machine Learning in Disease Prediction

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Abstract: *Chronic kidney disease (CKD) and cardiovascular diseases are important public health problems in today's world. The diseases cause a loss in productive labor hours for the patient and their family members. In such a situation, the use of artificial intelligence, especially, machine learning becomes more important for timely diagnosis of the diseases and taking curative measures before the situation becomes worse. The current systems are lacking in finding anaccurate solution for the different people affected by the same disease. Thus, successful functioning in the healthcare sector would involve better predictive modelling techniques. The study in this research paper is conducted with the main aim of determining the role of machine learning tools for early detection of chronic kidney and heart disease.*
Keyword: *Chronic kidney disease (CKD), CardiovascularDisease (CVD),Machine Learning, Artificial Intelligence(AI)*

I. Introduction

Chronic kidney disease (CKD) is described as the "existence of a kidney structure or functional abnormality that has a negative effect on health for more than three months"[1]. There's no doubt that inflammation is a part of chronic kidney disease progression[2], but it is also being debated the association between disease initiation and injury. Like many chronic diseases, CKD is followed by subtle systemic inflammation as described in the following section, and the renals are present in many ways. Notably, remote causes of inflammation, such as gut microbiota dysregulation [3] or intestinal barrier alteration [4], may have a detrimental effect on CKD development and symptoms associated with uremia. The connection between diet, intestinal flora and CKD is further established in this section of the research. The association between CKD, systemic inflammation, and malignancy is one specific concern to be discussed in this study. In addition, systemic inflammation is linked to renal cancers as well as encouraging cell-transformation and metastases [15], it is normal in some medical disorders (colon and rectum [5], pancreas [6], respiratory [7], prostate violent [8], lungs [9], ovary [10], or brain [11]). This analysis would explore in more depth whether CDK development towards malignancy is a risk that should be regarded by a clinician in the light of systemic inflammation. Eventually, the study end with information on biomarker proteomic research for diagnosis, correct stratification, or progression from one point to the next.This is being tested as part of a worldwide search for outstanding biomarkers.

Vulnerability of Kidneys Facing Inflammation

Since the late 1990s, people have seen the role of inflammation in the pathogenesis of CKD. At that time, the first controversial view was proposed, namely, monocytes through interleukin 1 (IL-1), a major inflammatory cytokine Release that causes inflammation. Point of origin and mortality of major complications in patients with chronic dialysis [16]. This further shows the effect of polymorphism in various inflammatory measures on the frequency of IL-1 gene products in IL-1's gene community. Up to then, the interest in active use, as a separate forecast for cardiac dysfunction and death in CKD patients, of inflammatory cytokines produced in the uremic area of CKD increased substantially. Though the production of pro-inflammatory cytokines may have beneficial effects, persistent inflammation is known to have serious consequences.There are several contributing factors to CKD including decreased cytokine development, oxidative stress and acidosis, recurrent and resulting infections, fatty tissue disease and intestinal atrophy.Genetic and epigenetic factors are often seen to affect the inflammatory activity of CKD. Consequently, many strategies were suggested to combat inflammation in CKD, including improvements in diet, medications, and enhancement of dialysis [17].Research to date has shown to indicate that inflammation and inflammation from a common source can modify or interact with intracranial micro vascular regulation and fat distribution and may trigger kidney harm, thus encouraging chronic kidney disease growth. The role of the microcirculation network is well known in the kidney and maintaining the pressure of the cortical glomerular osmotic gradient is extremely important for the absorption and maintenance of fluid. The distribution of vasculature in the kidney is irregular under oxidative strain and the medulla is in a hypoxic state. Metabolites comprising hormones and active molecules in the blood vessels (prostaglandins, endothelium, kin, myelin, nitric oxide, and other molecules) are the main source of mass in this unit [18].Notwithstanding the highly controlled microcirculatory equilibrium that makes the kidneys functional, it should be noted that any minor difference in the relationship between such molecules may modify the operation of the kidneys Make the kidneys understand microscopic surroundings.Inflammation in the system or kidney can cause the microvasculature to react uncontrollably to its regulator and support excessive toxicity of the tube (including oxygen species (ROS), which can lead to bladder injury, kidney failure and chronic kidney disorder. Circulating cytokines activate intracellular micro vessels, especially endothelial cells and leukocytes, leading to the proliferation of local inflammatory factors and ROS. Such processes impact molecules that bind to the cell surface and damage the glycocalyx membrane. Activity of the endothelial membrane, coagulation system stimulation, and vasoreactivity induced by receptors are often impaired. Such alterations in inflammation can cause irreversible tube damage and kidney failure [19].

There is inseparable oxidative strain and damage, an essential feature of CKD and the CKD regulator. Increased oxidative stress associated with CKD is the presence and severity of systemically injuries, result of which ROS production exceeds antioxidant systems [20]. The inflammatory environment under the mediation of cytokines leads to a significant reduction in reactive oxygen / nitrogen products, functional fat and adhesion molecules. Cytokines are responsible for promoting abnormal matrix assembly in the kidney, proliferation of endothelial cells and promoting endothelial function. Cytokines regulate the inflammatory response and fight for their downstream effects by supporting cell surface proteins (including C-reactive proteins, fibrinogen and albumin). The relationship between a group of non-inflammatory biomarkers and the development of CKD in setting chronic cohort renal insufficiency is investigated in a recent review. Reduced albumin is associated with a progressive deterioration of kidney function and normal function in patients with CKD, these markers are independent CKD progression predictors [21].

End-stage renal dysfunction is a well-known source of elevated mortality which is blamed for many early-paralytic complications, such as muscle fatigue, muscular count and certain types of muscular disease, exhaustion, osteoporosis and fatigue. The aging process frequently requires uremic inflammation such as short telomeres, mitochondrial disruption and nutritional disruption sensations, which may directly influence the activity of the tissue and cell [22]. In vitro experiments have shown that circulating inflammation monocytes may be separated into osteoclasts and play a major role in mineral diseases in elderly patients with CKD or hemodialysis. Patients with impaired renal function and elevated inflammation and bone damage [23] are impacted by CKD. The signs of CKD frequently intensify progressively as the condition progresses and the on-spring of hemodialysis tends to improve. Systemic illness is related to weight and body fat, which are correlated with a number of diseases, including the most popular triggers for cardiac failure, in the population. Research in people and other chronic patients shows that increased daily use can reduce systemic inflammation over a longer period of time. In addition, there seems to be a significant improvement in the population with a high rate of systemic inflammation at baseline during exercise [24].

Besides the loss of reso activity, the body's resistance to internal and external forces may even be weakened by systemic inflame by can functional and tissue structure and destroying normal organs, which greatly raises the likelihood of national fracture. There was a summary [25]. In fact the signs of systemic inflammation are avoided by people with CKD. Although inflammation, malnutrition and protein loss are significant mortality triggers for patients with CKD, any intervention that may have a beneficial effect on the disorder should be taken into consideration [25]. The incidence and morbidity of patients is still strong, following recent developments in managing renal disease (CKD) and late kidney disease (ESRD). Persistent low-grade inflammation has been described as an essential component of CKD that leads to fibrosis and kidney failure, which plays a major role in disease progression which pathophysiology that leads much to its problems [19].

In today's world chronic kidney disorder (CKD) is now one of the major issues in public health. CKD is the destructive kidney disease and may grow worse with time. If the kidneys are seriously damaged than they are unable to function. It is known as Renal Depression (ESRD), or Disney End Syndrome. According to the study from [26], 6000 renal transplants are conducted annually in India. CKD among citizens is also stated to be growing increasingly across the world. The most common causes of kidney disease include diabetes, heart disease, hereditary and high blood pressure. Nevertheless, it was found that with adequate medical attention, if CKD is detected at an early point, only then can it prevent a kidney failure.Health professionals or doctors detect CKD through signs, physical assessment, urine check, and blood checks. Therefore, if a professional program can foresee kidney failure in patients, it would be really convenient for the medical professionals or doctors to provide the patients adequate care in time. In today's world a lot of work is being conducted in the area of medicine. Today, machine learning algorithms are widely used for effective prediction of various diseases in our society as stated in [27].

According to a recent study[28] approximately 8 to 10 percent of people worldwide experience some form of kidney injury and, due to complications of chronic kidney failure, mortality among affected persons rises steadily per year. A disorder marked by impaired kidney function [29], known as chronic kidney dysfunction (CKD). The renal system's two kidney organs serve many important roles, including extracting waste products from the blood, maintaining fluid levels regulated and producing hormones to generate red blood cells. Many health problems such as diabetes, high blood pressure, high cholesterol, kidney disease, urine output, etc. can be associated with chronic kidney disorders [30]. There are usually no signs of an early stage kidney disorder. However, signs such as diarrhea, loss of appetite, exhaustion, tiredness, hypertension, sleep disruptions, edema, blood in the urine and reduced mental alertness can occur at the advanced stage [28]. Since chronic kidney disease is not controlled, routine monitoring is important to identify means of growing and avoiding symptoms.

Chronic renal disease (CDK) is more likely to occur in patients with elevated potential for systemic heart failure. The prevalence of CKD has improved according to [29], and the writers say that such changes are susceptible to problems such as diabetes, obesity, hypertension and dyslipidemia. Since the actual mortality statistics for CKDs are large and causes like this, health care practitioners and the general population need an appropriate method to forecast CKD outcomes based on established risk factors. CKD is a condition that has a four-month mean effect on kidney development and activity, with damaged kidneys or a reduced function [30]. The deadliest result of the condition is kidney failure, among the multiple symptoms of CKD, which is often known as a re-stadium kidney disorder. CKDs are very high death rates and big factors are the volume of dials and implantations. While the consequences of these signs are severe, they can be anticipated and utilized with sufficient documentation, and appropriate steps initiated before problems are incurred. Machine training is one of the most important methods of predicting products which focus on confidential practices, which are accurate and efficient. In the area of data science, it has been common and influential and makes sense. Computer learning is part of the fast-expanding knowledge industry. Machine learning. Machine learning algorithms are extremely efficient and reliable methods for transmitting information to 'smart' structures. A logical hospital network, for example, connected to electronic medical or general electronic data, could, for approved patients, providing timely diagnostic advice based on information entered in a laboratory or consultation desk. It is a mixture of scientific, machine and infatic approaches. The knowledge and AI concept of the CKD prognosis system can benefit healthcare professionals as it ensures a more accurate diagnosis of medical conditions. The selected algorithm learns and discusses the essence of experimental learning and uses it to classify experimental data as conceptual groups dependent on the criteria and goals of the analysis. Health practitioners may use GLR evidence and their signs or indications in order to diagnose CKD. Considering these risk factors, work on GFR and its risk factors may be expected to be useful in the prediction and provenance of failure and the issue is that the cause of death can deteriorate.

Chronic kidney disease (CKD) arises as a more prevalent condition, meaning that an early warning program is required such that no error can be created in the necessary care. Chronic kidney failure that may induce different degrees of dysfunction and kidney impairment in patients. If a person has discovered CKD, he / she may suffer from the disease that can impair both his / her working ability and quality of life. CKD frequently plays a significant part in triggering many serious conditions such as elevated blood pressure, anemia (low blood count). The glomerular filtration rate (GFR) is perhaps the most important measurement element based on determining chronic kidney disease. GFR is the most commonly used indicator for chronic kidney disease in health care institutions. "The health institution's physician may measure GFR from the patient's blood creatinine, age , ethnicity, class, and other variables based on the type of formally-recognized measurement method employed" [31-32]. GFR shows the safety of the patient's kidney, which is often used to assess the seriousness level of a condition with or without CKD. The key purpose of this paper is to provide an advanced method for the diagnosis of kidney disease and can often be utilized by common citizens to provide an effective means for physicians to diagnose kidney disease. This smart machine achieves strong consistency in the inclusion or absence of kidney failure into the human body. UCI machine learning repository stores the input data for device preparation, validation, and checking.

One of the most influential challenges in decision-making in the real world setting is the classification question. Classification plays a significant role in a number of problems involving machine learning (ML). The overall aim of solving pharmaceutical problems is to find the solution to the concept of the art in the predefined categories centered on the amount of physical artifacts identified with a particular category and to have several measures to decide whether or not a given sector is a real culture. Classification roles are used in several decision-making processes in diverse areas such as health, research, business etc. Many methods are proposed in the literature on how to address classification problems. A traditional method based on Bayesian decision theory, with a central and indirect method [33]. There is one return, however, that merits attention: potential alternatives only announce great success if the maximum limit for these methods is correct. And, for all their benefits, there is a significant shortcoming in Probabilistic strategies. Users should have an appropriate understanding of all material characteristics and application requirements in order to achieve outstanding results.

Therefore certain forms of classification addressed in separate data set that perform better than probabilistic approaches. Another approach would be to exploit various ML techniques in solving the classification problems. Different ML algorithms were proposed for this purpose. Such a classification algorithm will produce improved outcomes that are important for more knowledge about how artifacts are allocated to certain classes (classes) and how model output can be enhanced. The neural network (ANN) and its advanced models, SVM, K Nearest Neighbor (k-NN), were widely used in tree segmentation methods and are now the subject of standard research in current research studies.The decision tree approach has been commonly used for the classification issues. In the case of classification tasks [34-36], the Random Forest (RF) has the best results. It is important to note that some research into fragmentation issues have found that spontaneous forest fragmentation is a more viable solution than the various approaches available. In the other hand, standard solutions to ML ANN, KNN, and SVM have been used in many computational experiments for various classification activities. The general aim of ML is to create automatic models which can easily be condensed into a priori examples (categorized) and to generate ML by modeling or learning the functional dependency between the input (feature) and the output (category). Thus, treating CKD is essentially ML, with the intention of translating data from diseases (symptoms) into categories of operation (stable community, CDK communities or other diseases). The therapy often centers on the management of CRD. The CKD is a radical condition of health that makes up approximately 10 % of the world's population [37, 38]. In actual life, CKD tends to be correlated in certain instances with elevated likelihood of hospital entry, morbidity and death related to coronary disease and gradual deterioration of function(s) in the kidney. People with severe kidney failure have an elevated chance of having atherosulinosis and certain forms of syndromes that impact them. The impact of these syndromes on quality of life is significant. CKD treatment entails primarily disruption to the kidneys [39].

The progress of CKD is also associated with several symptoms or risk factors, so these variables could have a strong influence on CKD recognition. The effects of these syndromes on quality of life are severe. CKD treatment primarily includes losses to the kidneys [39]. The progression of CKD is related to several signs or risk factors, which may affect CKD identification significantly. New research into the pragmatic essence of CKD provides a great opportunity to advance CKD treatment by studying modern predictive diagnostics models focused on ML paradigms [40]. Models focused on Fuzz's CKD diagnosis have been proposed in multiple studies [40-41]. The purpose of this analysis is to identify an appropriate classification that enhances the consistency of the ranking. We also established popular solutions to machine learning, the artificial neural network, the vector support system (SVM), K nearest neighbor (k-NN), decision tree C4.5 and random forest (RF) as a means of building a strongly promising paradigm for the diagnosis of CKD. We tested the proposed real-time data model (CKD data set), presented for machine learning by the University of Irvine in California (UCI) [42], using an experimental model to demonstrate the power and proximity of such methods to machine learning. The heart is a substantial part of the human body. Blood is injected into all body sections. If it does not function, the brain and other organs may cease to operate and die within minutes. Lifestyle changes, work-related stress, and poor diets have led to an increased incidence of several heart-related diseases. Heart disease is one of the world leading causes of death. It is important to predict and accurately predict heart related diseases. Worldwide, medical centers gather information about various health problems. To use this data for useful information, they may use a variety of soft learning techniques. The data collected is however very large and the data can be very noisy in many cases. These complex specifics are overwhelming, and can be discussed quickly using various soft learning techniques. Hence, such algorithms have recently become very useful in determining correctly the occurrence or absence of heart-related diseases.

II. Research background

Long et al. (2015) in this paper, they propose a cardiac diagnostic program based on a reduction in group behavior estimates and a more sensitive classification scheme for type 2 (IT2FLS). Groups that reduce major IT2FLS attributes and integrate are designed to address the challenges and uncertainties of high quality data sets. IT2FLS applied an automated learning method requiring modification of parameters using a basic integration algorithm called Firefly, Disorder, and Hybrid Algorithm. In math this learning phase is expensive, particularly when applied to a very large collection of data. Consider raising the attribute utilizing dirty fire algorithms to determine the equilibrium based on an approximate range. That reduces complexity and enhances the efficiency of IT2FLS. Study findings show that the program has more important advantages for the Naïve Bayers than other machine learning methods, and embraces vector machines and artificial neural networks. The proposed model can therefore be used as a diagnostic support system for cardiovascular disease.

Santhanam &Ephzibah (2015) Medical errors are generally expensive and harmful. They cause many deaths every year around the world. Clinical decision support systems offer the opportunity to reduce medical errors and improve patient safety. One of the most important aspects of applying this system is the diagnosis and treatment of heart disease. Implement data mining classification techniques to analyze different heart-based problems. This paper aims to develop a heart disease prediction system using data mining clustering method. A health care system is a system that is rich in data however knowledge. This health care data to extract knowledge to further predict disease. Currently, data mining technology is widely used in clinical expert systems to predict different diseases. These technologies have discovered relationships and patterns hidden in medical data. Therefore, trying to support the diagnostic process with the knowledge and experience of multiple experts and the clinical screening data of patients in the database is considered a major challenge. Unfortunately, the healthcare industry collects large amounts of heart disease data that cannot be effectively diagnosed to identify hidden information.

Alaoui et al. (2018),this study attempted to utilize two key forms of data analysis, longitudinal and quantitative studies to analyze evidence on kidney disease. The findings collected will be a guide to extracting information from the study, predicting the new patients' CKD status and implementing effective approaches.

Alloghani et al. (2020),in this article, a historical online scientific data on chronic kidney disease was examined using 12 controlled machine learning algorithms. The decision tree was the decision tree of the tested algorithms, and the CN2 basis inference was the least successful one. The most efficient and accurate algorithm was the vector polynomial support. Studies also shown that among the most prominent ones were the 253 double mutant strains with muscle and smoking status.The study addressed 544 outpatients, while 48 did not fulfill the requirements for inclusion and some 21 other groups had missed principles and were omitted from the research.

Alloghani et al. (2020),when the kidneys begin to work, chronic kidney disease (CKD) may be observed. This paper established an advisory committee that could forecast CKD in patients. The data collection can be located on the website of the Kaggle Learning System. For CKDPS, the Algorithm of the Random Forest is chosen because it gives 100 per cent recovery aid, exactness and precision. This document also compares the exact results in many past work with the use of the same or different CKD datasets for various machine learning algorithms.

Key Extraction

- CKDPS software datasets are taken from the servers for Kaggle Machine Learning.
- Many machine learning algorithms were used until the adoption of CKDPS, for example K-Nearest Neighbor (KNN), Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Naive Bays and System Vector Service (SVM).
- The findings of many algorithms from historically identical tasks utilizing the same or different CKD datasets can also be used in this paper.

A framework for estimating chronic kidney disease using a random forest algorithm was developed in this paper. Random forest is an algorithm of machine learning, which incorporates decision trees in order to allow predictions more accurate and reliable. Different machine learning algorithms delivers different results in terms of accuracy, precision, and recall. This paper established the Chronic Kidneys Disease Prediction Method (CkDPS) and was established by the researchers at the University of California, San Francisco.

Mihai et al. (2018), low-grade inflammation is a well-known complication of chronic kidney disease (CKD). CKD is a significant public health problem that affects 10-15 per cent of the population. It is not available in the original groups, and when it is created its development will not go back to. The authors suggest that recent developments in the omeic area will offer fresh insights into the disease's pathophysiology. We conclude that development of blush biomarker panels utilizing state-of-the-art protein technologies will enhance early identification, tracking and treatment of CKD.

Kleiman et al. (2018),Calciphylaxis is a disorder with a high mortality rate which results in necrotic cutaneous lesions. Risk factors and function of illness are not well known. Such research reflects on the usage of computer education to forecast the hazards and leading factors for diseases. This will offer an outstanding opportunity to turn the statistical models described in this paper into clinical. Late-stage CKD and ESRD patients are at a much higher risk for calciphylaxis. This is a neurological disease with a death rate of more than 50 per cent over one year. By identifying at-risk patients, they offer these patients an opportunity to take action to mitigate their risk factors and avoid a potentially deadly illness. They intend to explore the potential for translating these models into a clinical setting where they could be used to identify high-risk patients for disease development.

Abdelaziz et al. (2019),to archive it in the cloud, IOT tools (digital sensors and so on) may be used to submit broad data on chronic kidney disease (CKD). Big data is used to maximize the performance of CKD in cloud forecasting. The accuracy of the hybrid smart model is 97.8 percent which is 64 percent better than any of the models listed in the works concerned. In smart cities, cloud computing is funded by patients to anticipate kidney failure everywhere and anywhere. Predicting dangerous diseases like CKD-based cloud-IOT is deemed a major challenge confronting health care stakeholders.

- In health care, cloud and IOT play a major role, particularly in the prediction of disease in intelligent cities.
- In chronic kidney disorder (CKD), IOTs (digit sensors, etc.) can be used to send large data into the cloud.
- Such broad data also improves the precision of ERC cloud forecasts.
- Severe disease simulation, including the IOT cloud focused on CKD, is used in intelligent communities as a big health issue.
- This paper focuses on modeling as an illustration of cloud infrastructure for clinical care with chronic kidney disease.
- Cloud infrastructure allows patients to predict CKD in smart communities everywhere and anywhere.
- To that end, this paper recommends using two innovative approaches, Linear Regression (LR) and Network (NN) as a hybrid model for IoT Cloud Analytics based on CKD.
- LR is used for the identification of essential variables affecting CKD.
- CKD is predicted using NN.
- Results indicate the hybrid smart model accuracy in CKD estimation is 97.8 percent. In fact, an adaptive hybrid model is extended to azure windows as an illustration of a cloud infrastructure system to forecast CKD for patient care in smart cities.
- The template suggested is 64 per cent higher than the other examples in the accompanying article.

Borisagar et al. (2017),Here, Chronic Kidney Disease (CKD) detection system is successfully implemented using neural network. A program of forecasts has achieved high accuracy and can be an effective tool for physicians. Normal people can also use it to find probability of having CKD. Future research will concentrate on improving the strategies for identifying certain diseases. Their main objective is to improve the system for the detection of diseases especially for chronic and severe diseases. This will measure the efficiency of the neural network on the disease utilizing specific learning algorithms.

Charleonnan et al. (2016),this article discusses the machine learning methods that clinical evidence uses to predict chronic kidney disease. Including the closest neighbors K (KNN), support vector machine (SVM), logistic regression (LR), and decision tree classifiers, four methods of machine learning have been explored. From experimental results, it can be shown that the SVM Classifier provides the highest accuracy. Upon preparation and research by the suggested approach SVM has the greatest responsiveness.

Polat et al. (2017),In terms of medical diagnoses, machine learning techniques are important because they can be classified at high accuracy rates. The Support Vector Machine algorithm for the diagnosis of chronic kidney disorder has been used in this study. The accuracy of the classification algorithms depends on utilizing appropriate feature selection algorithms in order to reduce the data set scale. The findings revealed that, when the filtered subset evaluator with the optimum function is used for the first search engine, the classificatory is more reliable (98, 5%). Chronic Kidney Disorders (CKD) is a major public health issue affecting about 10 percent of the world's population,

Subase et al. (2017). There's no clear details about the likelihood that recurrent kidney failure will be handled consistently and reliably. ML algorithms have become a major force in identifying imbalances in different physiological outcomes and involve themselves in many successful classification tasks. The workbook of the Random Forest Workshop (RF) has almost complete revision of the topic of the CKD. This analysis shows that during classification activities, the RF classifier results in very large outputs. This system is capable of classifying two separate groups with a maximum rating score, 100%. RF measures are therefore good for accuracy and F. We also implemented methods for the decision tree ANN, k-NN, SVM and C4.5 and achieved good output tests.

Yildirim (2017),neural networks, including data mining and judgment structures, are popular in a variety of applications. Reverse diffusion networks are a popular type of the neural network to identify specific patterns. Unbalanced data group distribution will seriously affect traditional classifications. This study demonstrates that sampling algorithms can improve classification algorithm efficiency and the learning rate is a critical parameter that can influence the multi-layered viewpoint significantly.

III. Machine Learning Techniques Used by Researchers in Medical Domain

Model	Year	Techniques	Disease	Tool	Accuracy
Otoom et al.	2015	Bayes Net SVM Functional Trees	Heart	Weka	84.5% (All)
Vembandasamy et al.	2015	Naive Bayes	Heart	Weka	86.4 %
Parthiban et al.	2012	Naive Bayes	Heart	Weka	74.1 %
Latha and Jeeva	2019	Majority vote with NB, BN, RF and MP	Heart Disease	Python	85.48%
Tarawneh&Embarak	2019	Naïve Bayes, SVM, KNN, NN, J4.8, RF, and GA	Heart Disease	Python	89.2%,
Sajeev et al.	2019	DL - Multi-Layer Perceptron	Heart Disease	Python	83.4%
Amin et al.	2018	Vote with Naïve Bayes and Logistic Regression	Heart Disease	Python	87.41%
Burse et al.	2019	Multi-Layer Pi-Sigma Neuron Model (MLPSNM)	Heart Disease	Python	94.53%
Chauhan et al.	2018	Decision Tree	Heart Disease	Rapid Miner	75.10%
Desai et al.	2019	BPNN	Heart Disease	Python	85.07%
Dwivedi	2016	k-NN	Heart Disease	Python	0.80%
Gokulnath&Shantharajah	2018	SVM	Heart Disease	MATLAB	88.34%
Maji & Arora	2019	Hybrid-DT	Heart Disease	Weka	78.14%
Dalia M. Atallah et.al	2019	Data mining techniques	Kidney	Python	80.77%
Hoill Jung et.al	2013	decision supporting method	Chronic disease	Python	NA
Pavleen Kaur et.al	2019	Machine learning	Healthcare	Python	80.1%.

IV. Conclusion & Future Scope

This article explores the work done by researchers in machine learning to predict the heart disease and Kidney Disease (CKD) and it has been found that machine learning techniques have been used as an effective tool for predicting the patients with a Chronic kidney disease or a Cardiovascular disease.Machine learning can be an astonishingly valuable tool to reveal unknown insights and predict CKD and Heart diseases. Data mining as older and the machine learning as recent techniques has put a bench mark analysis in fulfilling the need of disease prediction.In the future, availability of doctors to a large number of people will be a very difficult task for huge population of world. In this situation, an automated system can prove to be a boon to the doctors. The above table also opens up the door of delving into new machine learning techniques which can be used to predict patients with a kidney or heart disease. A more robust model with better accuracy is the need of an hour in this domain.

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