



# A comprehensive evaluation and meta-analysis of machine learning techniques for identifying and classifying chronic renal disease

**Shibi Mathai**

Ph.D., Scholar (Part-Time)

Department of Computer Science,

Vels Institute of Science, Technology and Advanced Studies, Pallavaram, Chennai, India.

**Dr. K.S. Thirunavukkarasu**

Assistant Professor and Research Supervisor

Department of Computer Science,

Vels Institute of Science, Technology and Advanced Studies, Pallavaram, Chennai, India.

**Abstract**— Heart failure (HF), atherosclerotic cardiovascular disease, and end-stage kidney disease are all signs of chronic kidney disease brought on by type 2 diabetes (CKD). However, because it has no symptoms, CKD is frequently overlooked or misdiagnosed. A person can only survive for around 18 days without kidneys, necessitating dialysis and a kidney transplant. It is crucial to have trustworthy techniques for early detection of CKD. Additionally, patients frequently forego the common urine protein-based CKD detection test. It describes a medical condition that damages the kidneys and has an impact on the body as a whole. Inadequate diagnosis and care can lead to end-stage renal disease, which eventually kills the patient. In response to the shortcomings of conventional biomarkers and the requirement for early therapeutic intervention in cats with CKD to improve outcomes, new renal biomarkers for the detection of glomerular or tubular dysfunction have been discovered and validated. Changes in the concentrations of these biomarkers in the blood or urine may reveal early kidney damage or forecast the development of kidney disease before changes in conventional biomarkers can be seen. CKD forecasting is effortless with machine learning (ML) approaches. The current study's strategy for predicting CKD status using clinical data involves data preparation, a mechanism for managing missing values, data aggregation, and feature extraction. We examine some recent works on ML-based CKD detection and classification in this systematic review. Data source, data preprocessing, feature extraction, feature selection, detection, and classification are the various tasks that make up the process of CKD detection and classification. To be more precise, we group this systematic review into two main categories: supervised learning, and unsupervised learning-based CKD detection and classification. Peer-reviewed papers were gathered using reputable search engines like Elsevier, IEEE Xplore, PubMed, Scopus, Web of Science, and others. Finally, we briefly discuss current problems and the requirements for linking academic research on CKD detection and classification to industry-based solutions that will improve standard clinical care.

**Keywords**— machine learning, chronic kidney disease, CKD, detection, classification

## I. INTRODUCTION

Kidney diseases are conditions that impair the kidney's ability to function. In the later stages of the disease, kidney failure can result. Haemodialysis is provided to 10,203 patients with kidney disease, according to data recently released by the Saudi Centre for Organ Transplant Registry [1]. Chronic kidney disease (CKD) is among the biggest drivers of long-term kidney damage worldwide. The glomerular filtration rate (GFR) is a well-known CKD screening test that evaluates kidney function in relation to the glomerulus, which is the nephron's blood-filtering component [2]. Chronic kidney disease (CKD) is a disorder in which the kidneys are impaired and unable to filter blood and eliminate metabolic waste. CKD tend to get worse slowly over time. It is estimated that about 800 million people globally are affected by renal disease, including CKD. In order to produce urine, the kidneys' main job is to remove extra water and waste from the blood. Waste has accumulated in the body of a person with chronic kidney disease (CKD) [3]. As a result of the harm occurring gradually over a long period of time, sickness persists. A few of the many factors that cause CKD include heart disease, diabetes, and high blood pressure. Similar to these serious illnesses, chronic kidney disease (CKD) affects your kidneys and may also result in back pain, diarrhoea, fever, nosebleeds, a rash, and nausea. Diabetes and hypertension are two examples of the two primary infections that contribute to CKD. Therefore, managing these two conditions also means avoiding CKD. Typically, kidney damage is severe before CKD manifests [4].

The estimated glomerular filtration rate (eGFR), urine specimen, and blood pressure are the only available modalities of diagnosis for CKD. [5]. Your kidneys' ability to purge the blood is shown by the EGFR score. A value of 90 or higher indicates a healthy kidney. You've got chronic kidney disease if it's less than 60. Due to the fact that kidneys produce urine, a kidney function test is also recommended by the doctor. If your urine encompasses blood and protein, your kidney is not operating properly. The doctor can gauge your heart's pumping ability by taking your blood pressure. A patient with end-stage kidney disease is affected. If the eGFR score is below 15. Dialysis and kidney transplantation are the only available treatments at this time. Age, orientation, recurrence, and length of dialysis all have an impact on the patient's quality of life after dialysis, as well as the physical and emotional development of their bodies. If dialysis is not an option, the doctor's only choice is kidney transplantation. But the cost is astronomically high.

As a result, it is essential for the early detection, management, and monitoring of the disease. Anticipating the development of CKD with suitable accuracy is crucial because of the early hidden and dynamic nature of CKD, as well as the patience anomaly. [6]. Early CKD detection through the use of machine learning techniques can aid in CKD prevention. When it comes to applying classification and regression methods to extrapolate future outcomes from existing data, machine learning techniques play a crucial role within the field of artificial intelligence. Machine learning techniques come in supervised and unsupervised varieties [7]. Supervised algorithms need machine learning capabilities to provide some input, the desired output, and feedback on prediction accuracy during algorithm training [8]. Data scientists select the variables that will be analysed and used by a model to make predictions. Thus, data mining plays a crucial role in medicine by computing hidden information from the large patient medical and treatment dataset that clinicians routinely get from patients in order to implement exact treatment regimens and obtain snippets of symptomatic data. [9].

It has been pondered if chronic kidney disease (CKD) could be predicted using machine learning methods that incorporate many data sets. The dataset from the UCI store is one of them and is known as a benchmark dataset. To speed up the process of creating accurate models, many businesses are turning to machine learning. This theory rests on the premise that a system is capable of learning from data and identifying significant patterns for better decision-making with little involvement from humans [10, 11]. The phrase "machine learning" is used to describe a computer algorithm that can analyse a pattern and deduce its properties. This technology makes it possible to accurately and affordably diagnose diseases, making it a potentially useful tool for CKD diagnosis [12]. As information technology has advanced, electronic health records have quickly developed into a new class of medical tool. Finding previously undiscovered information within sizable datasets is referred to as "data mining" in this context. Data mining techniques are frequently incorporated into and applied in a variety of contexts and industries. To forecast, categorise, filter, and cluster data, we can use data mining techniques. The aim defines how the algorithm should process a given data set consisting of training attributes and goals. [13]. Data mining works well when the dataset is large, but we can also use machine learning to mine a small dataset using data mining. Data analysis and pattern recognition are two further components of machine learning. Machine learning algorithms are ideal for improving the accuracy of diagnosis and forecasting [14]. We make use of numerous health datasets. Due to the rapidly expanding number of electronic databases used in healthcare, machine learning methods are seeing increased application.

## II. PROPOSED METHODOLOGY

The method of carrying out research in a methodical manner is known as research methodology. It entails conducting a theoretical analysis of all theories pertaining to a specific field. The primary procedures and research techniques used to collect data. The next section goes into depth on how to spot and categorise chronic renal disease. To do this, we initially foster a pursuit crystal system that features watchword choice, search procedures, search sources, and sifting. The systematic survey is expected to distinguish, classify and look at existing methods examination on chronic kidney disease (CKD) detection and classification. There have been numerous studies on CKD detection and classification over the past ten years. However, none of these studies have been geared toward conducting a systematic literature review on detailed analysis of machine learning techniques. This article provides comprehensive review to systematically classify and compare existing CKD detection and classification techniques. The accompanying examination questions were formed to direct the systematic survey of the writing.

RQ1: What are the various data types and benchmark datasets are mostly used for the CKD detection and classification?

RQ2: What is the need of pre-processing in CKD detection and classification? What is the drawback of without pre-processing techniques?

RQ3: What is the role of feature extraction and feature selection in CKD detection and classification, how it improves the overall system performance.

RQ4: What machine learning methods are primarily employed for CKD classification and detection?

RQ5: What is the most commonly used performance metric for validation and compute over rated detection and classification techniques?

## III. LITERATURE SURVEY

### A. CKD detection using supervised learning techniques

We discuss the review of CKD detection and classification methods using supervised learning techniques in this subsection. Supervised learning is the machine learning paradigm that is most frequently used. It is the easiest to understand and put into practise. As a result, task-oriented is a term that is frequently used to describe supervised learning. It is intensely focused on one particular task, handling an increasing number of calculation aids until it can complete that task with accuracy.

According to Polat et al., chronic kidney disease was diagnosed using a support vector machine (SVM) classification system. [15]. To minimise the size of the dataset, two crucial feature selection techniques—wrapper and filter approaches—were selected for the diagnosis of chronic kidney disease. The greedy stepwise search engine of Best First and the classifier subset evaluator were used. The correlation feature selection subset evaluator, the Best First search, and the greedy stepwise search engine were used. 98.5 percent of the time, the SVM classifier with filtered subset evaluator and the Best First search engine feature selection method correctly identified chronic kidney disease. In order to determine the various diet plans, Wickremasinghe et al. [16] suggested predicting the potassium zone of CKD patients based on their blood potassium level. The multiclass decision tree, with a 99.17 percent accuracy, is the more precise method for predicting the potassium zone. Several different algorithms, including multiclass logistic regression, multiclass neural networks, multiclass decision trees, and multiclass decision forests, are used in the experiment. The experiment's findings show that the Multiclass Decision Forest algorithm outperforms the competition and has a 99.17 percent accuracy rate. A diagnosis for CKD based on machine learning has been proposed by Qin et al. [17]. Many values are missing in the CKD data set that was received from the machine learning repository at the University of California, Irvine. Using KNN imputation, we select a set of complete samples whose measurements are most similar to the missing data in each incomplete sample. Data gaps were filled by six machine learning techniques (logistic regression, random forest, support vector machine, and k-nearest neighbour). Narrow Bayes and feed-forward neural networks were used to build the models. With a diagnosis accuracy rating of 99.75 percent, Random Forest surpassed the other machine learning models. Xiao et al. [18] created and analysed nine models to predict the likely progression of CKD during outpatient monitoring based on easily accessible clinical characteristics. According to the findings, Elastic Net, Lasso, Ridge, and LR were the four linear models with the highest overall predictive power. During follow-up operations, the developed online tool can aid in predicting proteinuria progression. A prediction model of eGFR has been proposed and verified using data from a regional health system by Zhao et al. (19). Data from primary care clinics, including patient demographics, medical histories, and test results. Random Forest regression was utilised throughout the construction of the model, with goodness-of-fit and discrimination measures employed for assessment. After

cleaning the data, a total of 61,740 patients were included in the cohort used for model training and verification. With eGFR, age, gender, BMI, obesity, diabetes, high blood pressure, and hypertension included, the average coefficient of determination of the final model was 0.95. Patients with high macro- and micro-averaged eGFRs were given higher CKD stages based on the estimated eGFRs. The future function of the kidney can be precisely predicted by a model that uses information from actual electronic medical records (EMRs). This model supports clinical decisions.

The results of a study of prospective cohorts using simple clinical predictors to forecast the risk of cardiovascular diseases (CVDs) with those of logistic regression and machine learning (ML) algorithms have been proposed for comparison by Nusinovici et al. [20]. Diabetes, hypertension (HTN), and chronic kidney disease (CKD). Using some of the most popular ML models in an epidemiological study with a constrained number of events, a constrained set of straightforward clinical predictors, and When it comes to predicting the risk of common chronic diseases over a constrained time frame—less than six years—logistic regression performs as well as ML models. We believed that conventional regression models should still be effective at predicting the likelihood of developing a disease. Additional studies that account for different study settings and characteristics are needed to confirm this result. An internal glucose and urea monitoring system suggested by Parab et al.[21] will be helpful to diabetics with CKD. Inverse propagation In a comparison study, the partial least square regression (PLSR) model and the artificial neural network (BP-ANN) were both used to predict blood urea and glucose. The NVIDIA Jetson Nano board, which has a steady discharge force of 1.2 m, controls the 57 Drove frequency spectra, which span 2.0 m to 2.5 m. Examples adjusting with significant blood test constituents were set up in the research facility and recorded. 53 of these samples were used to train and calibrate the BP-ANN/PLSR model, and the model was validated using the remaining 4 samples. A fruit fly optimization algorithm (FFOA) and a powerful multi-kernel support vector machine (MKSVM) for disease classification have been presented by Rubini et al. [22]. The best features are initially chosen from the set of available features using FFOA. The MKSVM receives the selected and processed features from the medical dataset for the purpose of classifying medical data. The proposed CKD classification method was simulated using MATLAB. Accuracy, sensitivity, specificity, positive predictive value, negative predictive value, false positive rate, and false negative rate are used to evaluate the efficacy of a CKD classification system. Using ML methods for introspective analysis, Khan et al.[23] propose classifying the renal patient dataset as CKD or NOTCKD. NBTree, as well as mean absolute error (MAE), J48, Support Vector Machine, Logistic Regression, Multi-layer Perception, and seven additional machine learning techniques recall, precision, F-measure, accuracy, root mean squared error (RMSE), relative absolute error (RAE), and root relative error (RRSE) (CHIRP) are used to evaluate the effectiveness of naive Bayes and composite hypercube on iterated random projection. As a whole, the results show that CHIRP is successful in its goal of improving accuracy while simultaneously decreasing mistake rates. Ventrella et al. proposed the use of eGFR as the primary metric for assessing CKD development in the present day. [24]. The encouraging results show that computational models can be developed using machine learning techniques. Personalised patient care and hospital resource allocation benefit greatly from these models when combined with clinical expertise and knowledge.

Table 1 describes the summary of research gaps which gathered from existing works with respect to Supervised learning based CK detection and classification [15]-[24].

Ref	Methodology	Dataset	Preprocessing	Feature extraction	Feature selection	Classifier	Binary/Multi class
[15]	Diagnosis of CKD	UCI data repository	Artifact removal	Numerical attributes	Wrapper and filter	SVM	Binary class
[16]	CKD detection using Blood Potassium	UCI data repository	Data doubling	Semantic features	NA	Random forest	Multi-class
[17]	Diagnosis of CKD	UCI data repository	KNN for missing data imputation	Optimal subset regression	NA	Logistic regression, random forest, SVM, KNN	Multi-class
[18]	Prediction of CKD	Huadong Hospital	Missing data imputation	Outpatient blood biochemistry, demographic features	Cuckoo search	XGBoost	Binary class
[19]	Prediction of CKD from EMR data	Sanford EMR	Remove non-numeric data	Statistics and discrimination metrics	NA	Random forest	Multi-class
[20]	Predicting major CKD	Real-time data	Missing data imputation	Semantic features	NA	Logistic regression	Binary class
[21]	Prediction of Blood Urea and Glucose in CKD Patients	Sigma Aldrich Ltd	Missing data imputation	Glucose, ascorbate, urea, lactate, and alanine	NA	BP-ANN	Binary class
[22]	Classification of CKD	UCI data repository	De-noising, solve absent values	Glucose, ascorbate, urea, lactate, and alanine	Fruit fly optimization algorithm (FFOA)	Multi-kernel SVM (MKSVMD)	Multi-class
[23]	Empirical evaluation of CKD	UCI data repository	Missing data imputation	Semantic features	NA	NBTree, J48, SVM, Logistic regression	Multi-class
[24]	Prediction of CKD	Vimercate Hospital EMR	Missing data imputation	Creatinine level, urea, red blood cells count, eGFR trend	Recursive feature selection	Extremely randomized trees	Multi-class

### B. CKD detection using unsupervised learning techniques

Using a sizable EHR data set, Luo et al[25] 's novel method has been proposed for estimating disease stage transition rates. It is challenging to use EHR data for this purpose due to the size of the data and the wide range of observation times. We examined the impact of different levels of discretization on the transformation of a continuous-time HMM into a discrete-time HMM in a simulation study. For CKD detection and classification, a discretization technique is employed. The unique approach developed by Anraeni et al.[26] utilises a Singular Value Decomposition (SVD) feature and a one-dimensional discrete Hidden Markov Model (HMM) classifier to identify kidney abnormalities in iris pictures. We hope to speed up methods, reduce complexity, and minimise memory consumption in hardware implementations by using a 7-state HMM and a few tiny SVD coefficients for the model configuration picture. Two hundred iris photographs were used to test the system. Both the normal kidney condition and the abnormal kidney condition each had 100 images. The work of Chimwayi et al. [27] can be incorporated into healthcare and utilised to inform recommendations by making it easier for doctors and nurses to identify and treat patients and to find correlations between diseases that patients have. Future work should put the main emphasis on implementing more big data-focused tools and techniques that speed up and enhance the process. The biggest barrier in the healthcare industry is the lack of adequate and appropriate data, but there are many applications that can be used to advance the industry. A correct and appropriate diagnostic procedure is necessary for chronic kidney disease in order to give relevant and appropriate treatment that is consistent with the diagnosis, according to Pujianto et al. [28]. The diagnosis process can be completed easily with the technology that is currently being developed. Utilizing data mining techniques like clustering and classification, the diagnosis can be made. The K-Means algorithm for clustering and the SVM algorithm for classification are both examined in this study. The SVM algorithm is used to classify data using the polynomial, RBF, and sigmoid nonlinear kernels. The fuzzy clustering algorithm, which uses z-numbers extensively in the development of uncertain information and has greater authority to describe human knowledge, has been suggested by Jamal et al. [29]. To propose a dependable fluffy bunching calculation utilizing z-numbers and using the defined membership functions, to group patients with CKD according to the chosen indicators and determine which cluster they belong to multiple classes are Cluster 0, Cluster 1, Cluster 2, or Cluster 3. To demonstrate that z-numbers can manage human knowledge and unclear information, we will employ the idea of developing a dependable fuzzy clustering algorithm to analyse data from a case study of CKD patients using the selected indicators. Grover et al. [30] looked into the evaluation of the progress rate, mean stay times, chances proportions for misclassification probabilities, and probabilities of misclassifying stages. The study comes to the conclusion that CKD stages can be misclassified

whether or not prognostic factors are present. The mean sojourn time increases when stage misclassification is taken into consideration. Nithya et al. [31] have proposed design and development of a clustering and classification approach in combination for kidney disease segmentation and detection. Stone detection and segmentation is a crucial step in modern surgical and therapeutic planning using ultrasound images. The majority of kidney stone segmentation in ultrasound pictures, however, is still performed manually in clinical practise. This is why an artificial neural network and the multi-kernel k-means clustering technique are employed to divide up kidney stones. The system typically consists of four modules: feature extraction, classification, segmentation, and preprocessing. The median filter is primarily used to remove noise from the input image. According to Khamparia et al. [32], the alarming increase in chronic kidney disease has become a significant national issue. Despite the fact that risk factors for kidney disease include obesity, cardiovascular disease, and diabetes, none of these conditions specifically target the kidneys. However, there is limited information about the health effects of kidney disease and kidney failure. Consequently, high-tech diagnostic methods that improve patients' health are essential. It seeks to combine the data reduction method principal component analysis (PCA) with the supervised classification method support vector machine (SVM) to analyse kidney illness in patients who have already experienced it. According to Lee et al. [33], pathologists should analyse kidney biopsy samples from patients using visual classification to ascertain the underlying cause of kidney disease. However, reproducibility is challenging and the evaluation is only qualitative or, at most, semi-quantitative. An unsupervised bag of words model is used to identify previously unidentified characteristics that predict patient outcomes and account for significant server variability. To demonstrate that this method has an accuracy of 0.93 AUC in predicting both the glomerular filtration rate at the time of the biopsy and the loss of function at one year..

**Table 2 describes the summary of research gaps which gathered from existing works with respect to Unsupervised learning based CK detection and classification [33]-[41].**

**Table 2 Summary of research gaps with respect to unsupervised machine learning technique based CKD detection [33]-[41]**

Ref	Methodology	Dataset	Preprocessing	Feature extraction	Feature selection	Classifier	Binary/Multi class
[33]	Detection of CKD	UCI data repository	Missing data imputation		NA	Hidden Markov model (HMM)	Binary class
[34]	Detection of CKD	Real-time image	De-noising	Singular value decomposition (SVD)	NA	Hidden Markov model (HMM)	Multi-class
[35]	Risk level prediction of CKD	UCI data repository	Data cleaning, Under sampling	Glucose, ascorbate, urea, lactate, alanine	NA	Hierarchical Clustering	Multi-class
[36]	Prediction of CKD	UCI data repository	Missing data imputation	Numerical attributes	NA	K-means clustering	Multi-class
[37]	Wellness of CKD	UCI data repository	Missing data imputation	Numerical attributes	NA	Fuzzy c-Means (FCM)	Binary class
[38]	Prediction of CKD	UCI data repository	Missing data imputation	Numerical attributes	NA	Hidden Markov model (HMM)	Multi-class
[39]	Prediction of CKD using US	Real-time image	De-noising	Texture, GLCM features	CSA	ANN-PCA	Multi-class
[40]	Detection of CKD	UCI data repository	Missing data imputation	Numerical attributes	Linear discriminant analysis (LDA)	PCA-SVM	Multi-class
[41]	Prediction of CKD	George O'Brien Kidney Center at the University of Michigan	Patch removal	K-means clustering	Bag-of-words approach	K-means clustering	Binary class

#### IV. CONCLUSION AND DISCUSSION

The entire body of research on the detection and classification of chronic kidney disease (CKD) was examined in this paper. The paper examined each characteristic shed light on various aspects of the medical informatics literature from a computer-aided system perspective. With the end goal of our examination, we gave two particular extensive systems: The first is the most categorical. frequently used supervised machine learning methods for CKD detection and classification, while the second suggests a framework for unsupervised machine learning methods. The training dataset, the methods for selecting features, the data preparation phase, and the input data are all found to have a significant impact on an implemented ML for CKD's efficacy and accuracy. After looking at a number of routines and literature-based ensemble ML techniques, this was found. In general, ensemble methods that were

successfully implemented outperformed routine MLs in terms of performance. In addition, we came to the conclusion that it is possible to achieve maximum efficiency by combining multiple ML methods. Additionally, gaps in the existing body of knowledge were discovered, and the directions for future research are discussed; There aren't many more complex DL methods in the literature to investigate various aspects of CKD using computer vision techniques.

Our systematic review is possible to answer for above formulated research questions.

1. We provide a response for RQ1 based on a brief systematic review. Accepted clinical approaches for the diagnosis of clinically relevant CKD detection techniques typically combine methods from various sources. The numerical files or clinical images of patients with CKD serve as the data sources. UCI machine learning data repository is the dataset most frequently utilized for this CKD detection.

2. In order to keep the model from departing from the proper training set, the response to RQ2 necessitates data pre-processing to eliminate outliers and unwanted noise from the dataset. Anything that is hindering the model's effectiveness is addressed at this stage. It is necessary to clean and prepare the data for model construction after it has been collected. This statement demonstrates the significance of the miss leading of data pre-processing techniques, which has the greatest impact on overall detection accuracy.

3. Response for RQ3, accurate CKD detection and classification are largely dependent on feature extraction. The majority of machine learning techniques are based on well-designed features; however, feature extraction typically requires prior work. An end-to-end learning system will result from the simultaneous execution of feature extraction and classifier learning in this era. Dimensionality reduction is a useful machine learning pre-processing step that removes irrelevant and redundant data, improves learning accuracy, and makes results easier to understand. However, the recent increase in data dimensionality poses a significant challenge to many of the existing methods for feature selection and extraction in terms of their efficiency and effectiveness.

4. In response to RQ4, machine learning techniques are currently having a significant impact on disease prediction within the medical industry. Utilizing a procedure that utilizes AI, we want to foster viable instruments for predicting the occurrence of CKD. According to our comprehensive survey, supervised machine learning techniques are the most commonly used method for predicting CKD.

5. Response for RQ5, we examine precision, accuracy, recall, the F-measure, and specificity of qualitative measures. Reproduction results and relative investigation show that gathering and SVM classifiers perform really against the CKD identification and characterization. Later on, we further broaden our exploration approach with the crossover AI based CKD location and arrangement to guarantee the early discovery and finding.

## REFERENCES

1. Hussain,M.A., Hamarneh,G. and Garbi,R., 2021. Protruded retrogression neural nets for order localization and segmentation-free volume estimation. *IEEE Deals on Medical Imaging*, 40( 6),pp.1555- 1567.
2. Bukhari,H.A., Palmieri,F., Ramirez,J., Laguna,P., Ruiz,J.E., Ferreira,D., Potse,M., Sanchez,C. and Pueyo,E., 2020. Characterization of T surge breadth, duration and morphology changes during hemodialysis Relationship with serum electrolyte situations and heart rate. *IEEE Deals on Biomedical Engineering*, 68( 8),pp.2467- 2478.
3. Hodneland,E., Keilegavlen,E., Hanson,E.A., Andersen,E., Monssen,J.A., Rørvik,J., Leh,S., Marti,H.P., Lundervold,A., Svarstad,E. and Nordbotten,J.M., 2018. In vivo discovery of habitual order complaint using towel distortion fields from dynamic MR imaging. *IEEE Deals on Biomedical Engineering*, 66( 6),pp.1779- 1790.
4. McAllister,J., Li,Z., Liu,J. and Simonsmeier,U., 2018. Erythropoietin cure optimization for anemia in habitual order complaint using recursive zone model prophetic control. *IEEE Deals on Control Systems Technology*, 27( 3),pp.1181- 1193.
5. Nishanth,A. and Thiruvaran,T., 2017. relating important attributes for early discovery of habitual order complaint. *IEEE reviews in biomedical engineering*, 11,pp.208- 216.
6. Estudillo- Valderrama,M.A., Talaminos- Barroso,A., Roa,L.M., Naranjo- Hernandez,D., Reina- Tosina,J., Aresté- Fosalba,N. and Milan- Martin,J.A., 2014. A distributed approach to alarm operation in habitual order complaint. *IEEE journal of biomedical and health informatics*, 18( 6),pp.1796- 1803.
7. Celik,B. and Vanschoren,J., 2021. adaption strategies for automated machine literacy on evolving data. *IEEE Deals on Pattern Analysis and Machine Intelligence*, 43( 9),pp.3067- 3078.

8. Bucak,S.S., Jin,R. and Jain,A.K., 2013. Multiple kernel literacy for visual object recognition A review. IEEE Deals on Pattern Analysis and Machine Intelligence, 36( 7),pp.1354- 1369.
9. Ahmed,C.F., Tanbeer,S.K., Jeong,B.S. and Lee,Y.K., 2009. Effective tree structures for high mileage pattern mining in incremental databases. IEEE Deals on Knowledge and Data Engineering, 21( 12),pp.1708- 1721.
10. Kuno,T., Mikami,T., Sahashi,Y., Numasawa,Y., Suzuki,M., Noma,S., Fukuda,K. and Kohsaka,S., 2022. Machine literacy vaticination model of acute order injury after percutaneous coronary intervention. Scientific reports, 12( 1),pp.1- 12.
11. Bai,Q., Su,C., Tang,W. and Li,Y., 2022. Machine literacy to prognosticate end stage order complaint in habitual order complaint. Scientific reports, 12( 1),pp.1- 8.
12. Hirakawa,Y., Yoshioka,K., Kojima,K., Yamashita,Y., Shibahara,T., Wada,T., Nangaku,M. and Inagi,R., 2022. Implicit progression biomarkers of diabetic order complaint determined using comprehensive machine literacy analysis of non-targeted metabolomics. Scientific Reports, 12( 1),pp.1- 13.
13. Kanda,E., Suzuki,A., Makino,M., Tsubota,H., Kanemata,S., Shirakawa,K. and Yajima,T., 2022. Machine literacy models for vaticination of HF and CKD development in early- stage type 2 diabetes cases. Scientific reports, 12( 1),pp.1- 13.
14. Kokkinos,Y., Morrison,J., Bradley,R., Panagiotakos,T., Ogeer,J., Chew,D., O'Flynn,C., De Meyer,G., Watson,P. and Tagkopoulos,I., 2022. An early vaticination model for canine habitual order complaint grounded on routine clinical laboratory tests. Scientific reports, 12( 1),pp.1- 10.
15. Polat,H., DanaeiMehr,H. and Cetin,A., 2017. opinion of habitual order complaint grounded on support vector machine by point selection styles. Journal of medical systems, 41( 4),pp.1- 11.
16. Wickramasinghe,M.P.N.M., Perera,D.M. and Kahandawaarachchi,K.A.D.C.P., 2017, December. Salutory vaticination for cases with habitual order complaint( CKD) by considering blood potassium position using machine literacy algorithms. In 2017 IEEE Life lores Conference( LSC)(pp. 300- 303). IEEE.
17. Qin,J., Chen,L., Liu,Y., Liu,C., Feng,C. and Chen,B., 2019. A machine learning methodology for diagnosing habitual order complaint. IEEE Access, 8,pp.20991- 21002.
18. Xiao,J., Ding,R., Xu,X., Guan,H., Feng,X., Sun,T., Zhu,S. and Ye,Z., 2019. Comparison and development of machine literacy tools in the vaticination of habitual order complaint progression. Journal of translational drug, 17( 1),pp.1- 13.
19. Zhao,J., Gu,S. and McDermaid,A., 2019. Predicting issues of habitual order complaint from EMR data grounded on Random Forest Regression. Mathematical biosciences, 310,pp.24- 30.
20. Nusinovici,S., Tham,Y.C., Yan,M.Y.C., Ting,D.S.W., Li,J., Sabanayagam,C., Wong,T.Y. and Cheng,C.Y., 2020. Logistic retrogression was as good as machine literacy for prognosticating major habitual conditions. Journal of clinical epidemiology, 122,pp.56- 69.
21. Parab,J., Sequeira,M., Lanjewar,M., Pinto,C. and Naik,G., 2021. Backpropagation neural network- grounded machine literacy model for vaticination of blood urea and glucose in CKD cases. IEEE journal of translational engineering in health and drug, 9,pp.1- 8.
22. JerlinRubini,L. and Perumal,E., 2020. Effective bracket of habitual order complaint by using multi - kernel support vector machine and fruit cover optimization algorithm. International Journal of Imaging Systems and Technology, 30( 3),pp.660- 673.
23. Khan,B., Naseem,R., Muhammad,F., Abbas,G. and Kim,S., 2020. An empirical evaluation of machine literacy ways for habitual order complaint vaticination. IEEE Access, 8,pp.55012- 55022.
24. Ventrella,P., Delgrossi,G., Ferrario,G., Righetti,M. and Masseroli,M., 2021. Supervised machine literacy for the assessment of habitual order complaint advancement. Computer styles and Programs in Biomedicine, 209,p. 106329.
25. Luo,L., Small,D., Stewart,W.F. and Roy,J.A., 2013. styles for estimating order complaint stage transition chances using electronic medical records. eGEMs,
26. Anraeni,S., Nurtanio,I. and Indrabayu,I., 2015. Discovery of order Organ Condition Using retired Markov Models. TELKOMNIKA Indonesian Journal of Electrical Engineering, 15( 2),pp.294- 300.

27. Chimwayi,K.B., Haris,N., Caytiles,R.D. and Iyengar,N.C.S., 2017. threat position vaticination of habitual order complaint using neuro-fuzzy and hierarchical clustering algorithm( s).
28. Pujiyanto,U., Ramadhani,N.A.Y. and Wibawa,A.P., 2018, November. Support Vector Machine with Purified K- Means Clusters for habitual order complaint Discovery. In 2018 2nd East Indonesia Conference on Computer and Information Technology( EIconCIT)(pp. 56- 60). IEEE.
29. Jamal,N.M., Khalif,K.K. and Mohamad,M.S., 2019, November. The perpetration of z- figures in fuzzy clustering algorithm for heartiness of habitual order complaint cases. In Journal of Physics Conference Series(Vol. 1366,No. 1,p. 012058). IOP Publishing.
30. Grover,G., Sabharwal,A., Kumar,S. and Thakur,A.K., 2018. On the estimation of misclassification chances of habitual order complaint using continuous time hidden Markov models. Journal of Nephro pharmacology, 8( 1),pp.e07- e07.
31. Nithya,A., Appathurai,A., Venkatadri,N., Ramji,D.R. and Palagan,C.A., 2020. order complaint discovery and segmentation using artificial neural network andmulti- kernel k- means clustering for ultrasound images. dimension, 149,p. 106952.
32. Khamparia,A. and Pandey,B., 2020. A new integrated top element analysis and support vector machines predicated individual system for discovery of habitual order complaint. International Journal of Data Analysis ways and Strategies, 12( 2),pp. 99- 113.
33. Lee,J., Warner,E., Shaikhouni,S., Bitzer,M., Kretzler,M., Gipson,D., Pennathur,S., Bellovich,K., Bhat,Z., Gadegbeku,C. and Massengill,S., 2022. Unsupervised machine knowledge for relating important visual features through bag- of- words using histopathology data from habitual order complaint. Scientific reports, 12( 1),pp. 1- 13.M. Young, The Technical Writer's textbook. Mill Valley, CA University Science, 1989.