ACO-KNN Predictive Model for Diagnosis of Chronic Kidney Disease

Olukiran Oyenike Adunni[1], Omidiora Elijah Olusayo[2], Olabiyisi Stephen Olatunde[3], Shoyemi Olufemi Segun[4], Segun Aina[5]

[1]*Department of Mathematical and Computing Sciences, Faculty of Applied Sciences, Kola Daisi University, Ibadan, Oyo State, Nigeria*
[2, 3] *Department of Computer Science and Engineering, Faculty of Technology and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria*
[4]*University of Plymouth, School of Nursing and Midwifery, Plymouth, United Kingdom*
[5] *Department of Computer Science and Engineering Obafemi Awolowo University, Nigeria*

Abstract: **Chronic Kidney Disease (CKD) remains a worldwide health challenge that is increasing steadily. It is a chronic situation accompanied by an increase in morbidity, mortality, and also a risk of other several diseases like cardiovascular diseases and high healthcare costs. More than two million individuals over the globe receive dialysis or transplanting kidney treatment to stay alive, yet this figure shows only 10% represent people who need treatment to live. Early detection and management of CKD are necessary. It is important to predict the progression of CKD with reasonable accuracy due to its dynamic and covert nature in the early stages and patient heterogeneity. This paper presents a CKD predictive model by the introduction of a nature-inspired computation algorithm known as Ant Colony Optimization for the selection of discriminant attributes from the CKD indigenous dataset and employing some selected machine learning algorithms for classification. The CKD predicted model was evaluated using an indigenous dataset collected from Ladoke Akintola University of Technology (LAUTECH) teaching hospital, Ogbomoso and Osogbo, University College Hospital (UCH), Ibadan, Oyo State and Obafemi Awolowo University Teaching Hospital (OAUTH), Ile-Ife, Osun State, Nigeria. Experimental results showed that binary classification for CKD predictive model produced the best accuracy of 99.13%, the best specificity of 0.9839, the best sensitivity of 0.9929 in ACO-KNN and also for the multistage CKD predictive model, the best outputs for accuracy, specificity, sensitivity are given respectively with 99.65%, 0.9956 and 1.000 in CKD patients with stage 2 disease Severity using ACO-KNN.**

Keywords**: Ant Colony Optimisation, Chronic Kidney Disease, Predictive Model, Morbidity**

I. INTRODUCTION

Chronic kidney disease (CKD) is a continuous change in kidney structure, a function that leads to structural irregularities like cysts, tumours, malformations and atrophy that are obvious observations on imaging (Tabassum, Mamatha & Majumdar, 2017). Chronic Kidney Disease (CKD) has become a transnational fitness problem, it is a situation where kidneys are damaged and that can no longer filter toxic wastes within the frame. A person diagnosed with CKD may suffer from reduced performance as well as the quality of living. CKD leads to other chronic diseases such as diabetes, high blood pressure and other disorders [2]. High-risk groups are classified as a person with diabetes, hypertension, and hereditary [3]. Chronic kidney disease can be stopped through early diagnosis and proper treatment once the progress of the disease is observed it may greatly lead to kidney failure. Risk factors for the development and progression of CKD include low nephron number at birth, nephron loss due to increasing age and acute or chronic kidney injuries caused by toxic exposures or diseases like obesity and type II diabetes mellitus [4] The majority of patients with CKD are at a possibility of faster cardiovascular disease and death [5]. For those who progress to end-stage renal disease (ESRD), the limited accessibility to renal replacement therapy is a problem in many parts of the world. CKD patients can be managed by prompt diagnosis or prevention, treatment of the underlying cause to reduce the progression and attention to secondary processes that contribute to ongoing nephron loss [6].

Blood pressure control and renin-angiotensin system inhibition are the predominant aspects of therapy. The common pathological manifestation of CKD, irrespective of the initiating insult or disease, is some form of renal fibrosis. The Kidney Disease Improving Global Outcomes (KDIGO) initiative categorises a person as having CKD if defects of kidney structure or function persist for twelve weeks. KDIGO describes a severity classification, defining many CKD stages based on glomerular filtration rate (GFR; either estimatedGFR (eGFR) or measuredGFR(mGFR) and the extent of albuminuria. GFR and albuminuria are used to classify CKD because GFR is a well-established marker of renal excretory function and albuminuria is an indicator of renal barrier dysfunction (glomerular injury). To reduce the number of deaths from CKD, there is a need for a quick and efficient detection model. Several techniques have been developed to build an effective predictive model for CKD diagnosis such as a combination of machine learning techniques or models [7][8]. One of the significant stages in data mining techniques is feature/attribute selection which is needed to incorporate a systematized structure into the information set before it is sent to learning algorithms (classifiers) [9]. Feature selection is identified to be an active research area in the development of

predictive, diagnostic models and data mining communities [10]. The selection of features is used to get a subset of input variables by removing irrelevant features with little or no information for prediction [11]. This technique considerably enhances the comprehensibility of the resulting models and often constructs a model that generalizes better to unseen points [12]. In a predictive model, the selection of features is a significant pre-processing phase that is employed to effectively minimize high data dimensions [10], remove an inappropriate attribute, increase learning accuracy and improve output [13].

There are several techniques in feature selection; filter, wrapper, hybrid method and swarm intelligence algorithms [14]. The filter approach chooses the subset of a feature based on essential characteristics of the data and independent of the mining algorithm [15]. The wrapper method requires a scheduled algorithm to know the best subset of features and the predictive accuracy of an algorithm [16]. The hybrid method combines filter and wrapper to achieve the advantages of both methods [17] but shows better outputs with expensive computation when used on a large dataset [18]. Swarm intelligence algorithm consists of several naturally inspired techniques such as Genetic Algorithm (GA), Tabu Search (TS), and Bat Optimization Algorithm.

II. RELATED WORK

Identification of the stages involved in CKD diagnostic model through the application of data mining technique was proposed by [19]. The study developed the diagnostic model using Naïve Bayes, and C4.5 decision tree algorithms for classification purposes, because classification is considered to be an important phase in data mining tasks and the importance of classification is to propose a classification function or classification model (classifier). Historical patient data was applied to evaluate the model.

[20] classified the risk of kidney stones in Nigerians applying learning algorithms using the historical information obtained from the risk of kidney stones among Nigerians. Three supervised learning algorithms; Decision Tree, Multi-layer perception and Genetic Algorithm were engaged in classification. Waikato Environment for Knowledge Analysis (WEKA) was used to simulate the model. The evaluation of the model was done through a historical dataset of kidney stone risk based on evaluation metrics: accuracy, sensitivity, precision and specificity. Results showed that the multi-layer perceptron had the best performance overall using the 33 initially identified variables by the endocrinologists with an accuracy of 100%.

[21] applied Artificial Intelligence (AI) technique to overcome the occurrence of local minima and local maxima in diagnosing the progression of kidney disease. The AI technique involved a mixture of Ant Lion Optimiser (ALO) and Adaptive Neuro-fuzzy Inference Systems (ANFIS) to develop Enhanced Adaptive Neuro-fuzzy Inference Systems (E-ANFIS) were introduced. The normal backpropagation was used in ANFIS but the proposed employed a new optimizer ALO. The performance of ANFIS was improved by utilizing the Ant Lion Optimizer. The enhanced ANFIS was used to diagnose the progression stage of the CKD. The proposed model was simulated in a MATLAB environment and compared with the existing techniques ANFIS, fuzzy, and ANN. The performance evaluation in terms of accuracy, recall, precision, F-measure and specificity showed that the results of E-ANFIS outperformed the existing algorithms.

[22] predicted CKD with reduced individual classifiers. The study applied different classifiers: Naïve Bayes, HoeffdingTree, Random Tree, Reptree, Random Subspaces, Adaboost and IBk were applied for the diagnosis of chronic kidney disease. The model performance was evaluated with five evaluation parameters: accuracy, kappa, mean absolute error (MAE), root mean square error (RMSE), and F-measure. The classification performance of the six reduced features provided better and more rapid classification performance. Seven individual classifiers were applied to classify six features and the best results were obtained using individual random tree and Instance Based Learning (IBk) classifiers[23].

A new algorithm known as an Improved Hybrid Fuzzy C-Means (IHFCM) which is an improvisation of FCM with Euclidean distances was developed to predict kidney diseases in patients' datasets [24], the model recorded accuracy of 96%. sensitivity of 95.744% and specificity of 27.027%.

III. METHODOLOGY

The development of an ACO-KNN predictive model for the prediction and management of indigenous Chronic Kidney Disease (CKD) was made up of four distinct step-wise phases. The steps are discussed as follows: CKD data acquisition, CKD data cleaning/pre-processing, CKD diagnostic/treatment and CKD Clinical Decision Support (CDS) application development. The detailed framework is shown in Figure 1.

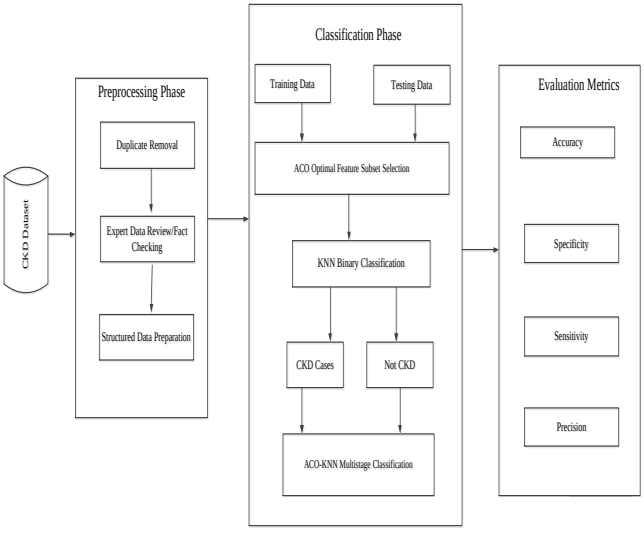

Figure 1: Framework of ACO-KNN CKD Predictive Model

3.1 CKD Dataset Acquisition

The CKD dataset used to evaluate the performance of CKD predictive model was collected from Ladoke Akintola University of Technology (LAUTECH) teaching hospital, Osogbo, University College Hospital (UCH), Ibadan, Oyo State and Obafemi Awolowo University Teaching Hospital (OAUTH), Ile-Ife, Osun. The two hospitals (nephrological centres) are located in Oyo and Osun states within the South western of Nigeria.

3.2 CKD Dataset Description

The CKD dataset was taken over three months between March 2019 and June 2019 from case notes of patients from these dedicated kidney patients' treatment centers. This is also accompanied by prior expert treatment records for each of the captured CKD cases, leading to domain knowledge-based development on cause-and-effect relationships among symptoms, stages of CKD and possible treatment options. The dataset collected consists of sixty-seven (67) attributes as illustrated in Table 1 respectively.

Table 1: Description of CKD Determinant Features in the Dataset used for Analysis

Serial	Variables (Features)	Class	Type
1	Age	Predictor	Numerical
2	Gender	Predictor	Categorical
3	BPS	Predictor	Numerical
4	BPD	Predictor	Numerical
5	Weight	Predictor	Numerical
6	Urea	Predictor	Numerical
7	CRT	Predictor	Numerical
8	Leg Swelling	Predictor	Categorical
9	Facial Swelling	Predictor	Categorical
10	Insomnia	Predictor	Categorical
11	Watery stool	Predictor	Categorical
12	Irrational Talk	Predictor	Categorical
13	Hypertension	Predictor	Categorical
14	Fever	Predictor	Categorical
15	Diabetes	Predictor	Categorical
16	Body Swelling	Predictor	Categorical
17	Cough	Predictor	Categorical
18	Painful urination	Predictor	Categorical
19	Abdominal pain	Predictor	Categorical
20	Body itching	Predictor	Categorical
21	High BP	Predictor	Categorical
22	Hiccups	Predictor	Categorical
23	Dizziness	Predictor	Categorical
24	Headache	Predictor	Categorical
25	Malaria	Predictor	Categorical
26	Breathlessness	Predictor	Categorical
27	Loss of vision	Predictor	Categorical
28	Abdominal swelling and pain	Predictor	Categorical
29	Body weakness	Predictor	Categorical
30	Weight loss	Predictor	Categorical
31	Reduction in urine	Predictor	Categorical
32	Coloured Urination	Predictor	Categorical
33	Vomiting	Predictor	Categorical
34	Poor sleep	Predictor	Categorical
35	Loss of memory	Predictor	Categorical
36	Heart disease	Predictor	Categorical
37	Kidney disease	Predictor	Categorical
38	Side pain	Predictor	Categorical
39	Passage of blood in stool	Predictor	Categorical
40	Renal Failure	Predictor	Categorical
41	Body ache	Predictor	Categorical
42	Restlessness	Predictor	Categorical
43	Elevated Creatinine	Predictor	Categorical
44	Joint Pain	Predictor	Categorical
45	Persistent Proteinuria	Predictor	Categorical
46	Eye Pain	Predictor	Categorical
47	Painful Menstruation	Predictor	Categorical
48	Yellowness of the Eye	Predictor	Categorical
49	Easily fatigued	Predictor	Categorical
50	Bilateral Pedal Swelling	Predictor	Categorical
51	BOO Secondary to BPH	Predictor	Categorical
52	Painful Micturition	Predictor	Categorical
53	Flank pain	Predictor	Categorical
54	Pedial swelling	Predictor	Categorical
55	Altered Consciousness	Predictor	Categorical
56	Jaundice	Predictor	Categorical
57	Obstructive Uropathy	Predictor	Categorical
58	Chest Pain	Predictor	Categorical
59	Bone Pain	Predictor	Categorical
60	Back Pain	Predictor	Categorical
61	Urinary Dribbling	Predictor	Categorical
62	Chronic Glomerulonephritis	Predictor	Categorical
63	GFR	Target	Categorical
64	ESRD	Predictor	Categorical
65	CRF	Predictor	Numerical
66	AKI	Predictor	Categorical
67	CCF	Predictor	Categorical

3.3 CKD Data Cleaning /Preprocessing

At this phase, the duplicate records captured and those with missing or incomplete values of significant attributes were removed from the CKD dataset. The expert nephrologists conducted a review of the resulting data for reliability and fact cross-checking purposes. A feature subset selection using ACO was conducted to identify CKD optimal discriminating features so that the dimension of the entire features could be reduced before final classification. After cleaning and preprocessing, the resulting CKD dataset contains 283 records of patients with CKD and 62 records of persons without CKD.

3.4 Performance Evaluation Metrics

The evaluation metrics used in this paper are as follows:

(i) Sensitivity: This is a measure that helps to determine the level to which a classifier can correctly determine that a test case suffers from CKD.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (1)$$

(ii) Specificity: It helps to determinethe level to which a classifier can correctly determine that a test case is CKD-free

$$\text{Specificity} = \frac{TN}{TP+FP} \quad (2)$$

(iii) Accuracy: Determines how correctly a classifier can determine the total number of people with or without CKD.

$$\text{Accuracy} = \frac{TN+TP}{TP+FP+TN+FN} \times 100 \quad (3)$$

Where TP, FP, TN, and FN are defined as follows.

True Positive (TP): The diagnostic system yields positive test results for CKD and thepatient has the disease

False-Positive (FP): The diagnostic system yields positive test results for CKD but thepatient does not have the disease

True Negative (TN): The diagnostic system yields negative test results for CKD andthe patient does not have the disease;

False-Negative (FN): The diagnostic system yields negative test results for CKD andthe patient has the disease.

IV. RESULTS AND DISCUSSION

4.1 Result of Binary Classification of CKD Dataset

The result of binary classification for CKD dataset is represented in Table 2

Table 2: Result for Binary Classification of the CKDdataset (10-fold cross validation)

Algorithms	TP	TN	FP	FN	Accuracy(%)	Specificity	Sensitivity
ANN	279	61	1	4	98.55	0.9839	0.9859
K-NN	277	60	2	6	97.68	0.9677	0.9788
Naïve Bayes	275	57	5	8	96.23	0.9194	0.9717
Decision Tree	278	59	3	5	97.68	0.9516	0.9823
SVM	270	55	7	13	94.20	0.8871	0.9641
ACO-kNN	281	61	1	2	99.13	0.9839	0.9929

From Table 2, different results were obtained for accuracy, specificity and sensitivity. The lowest accuracy of 94.20% was recorded in SVM classifier while the best accuracy of 99.13% was recorded in ACO-kNN. The lowest specificity result of 0.8871 was obtained in SVM and the best specificity of 0.9839 was obtained in both ANN and ACO-KNN. The lowest sensitivity of 0.9641 was obtained in SVM, while the best sensitivity of 0.9929 in ACO-kNN. The ACO-kNN model shows significant improvement over other selected learning algorithms due to the introduction of an ACO-based feature selection into the development of ACO-kNN for CKD model. This indicates that ACO-kNN is the best-fit algorithm for the binary classification of indigenous CKD datasets.

4.2 Results of Multi-Stage CKD Classification

With a homogenous CKD dataset containing 283 records of patients with CKD (50 cases of Stage 1 CKD, 55 cases of Stage 2 CKD, 42 cases of Stage 3 CKD, 37 cases of Stage 4 CKD and 99 cases of Stage 5 CKD), the results of the Stage 1 CKD disease severity classification determined using SVM, Naïve Bayes, *K*-NN, Decision Tree, ANN, and the developed ACO-kNNalgorithms are presented in Table 3.

Table 3: Result of the CKD patient stage 1 Disease Severity (10-fold cross-validation)

Algorithms	TP	TN	FP	FN	Accuracy (%)	Specificity	Sensitivity
ANN	48	230	3	2	98.94	0.9871	0.9600
K-NN	47	228	5	3	97.17	0.9785	0.9400
Naïve Bayes	47	221	12	3	94.70	0.9485	0.9400
Decision Tree	46	229	4	4	97.17	0.9828	0.9200
SVM	46	218	15	4	93.29	0.9356	0.9200
ACO-kNN	49	231	2	1	98.94	0.9914	0.9800

In Table 3, the lowest accuracy of 93.29 % was recorded in SVM and the best accuracy of 98.94% was recorded in ANN and ACO-kNN. The lowest specificity value of 0.9356 was obtained in SVM and the best specificity value of 0.9914 was recorded in ACO-KNN. The lowest sensitivity value of 0.9200 was obtained in Decision Tree and SVM and the best sensitivity value of 0.9800 was recorded in ACO-KNN.

Table 4: Result of the CKD Patientswith stage 2 Disease Severity **(**10-fold cross validation**)**

Algorithms	TP	TN	FP	FN	Accuracy (%)	Specificity	Sensitivity
ANN	53	225	3	2	98.23	0.9868	0.9636
K-NN	54	223	5	1	97.88	0.9781	0.9818
Naïve Bayes	54	221	7	1	97.17	0.9693	0.9818
Decision Tree	53	220	8	2	97.17	0.9649	0.9636
SVM	52	217	11	3	95.05	0.9518	0.9455
ACO-kNN	55	227	1	0	99.65	0.9956	1.0000

In Table 4, the lowest accuracy of 95.05% was recorded in SVM and best accuracy of 99.65% was recorded in ACO-kNN. The lowest specificity value of 0.9518 was obtained in SVM and the best specificity value of 0.9956 was recorded in ACO-KNN. The lowest sensitivity value of 0.9455 was obtained in SVM and the best sensitivity value of 1.0000 was recorded in ACO-KNN.

Table 5: Result of the CKD Patientswith stage 3 Disease Severity **(**10-fold cross validation**)**

Algorithms	TP	TN	FP	FN	Accuracy (%)	Specificity (%)	Sensitivity(%)
ANN	41	238	3	1	98.59	0.9876	0.9762
K-NN	41	236	5	1	97.88	0.9793	0.9762
Naïve Bayes	41	232	9	1	96.47	0.9627	0.9762
Decision Tree	38	233	8	4	95.76	0.9668	0.9048
SVM	36	229	12	6	93.64	0.9502	0.8571
ACO-kNN	41	239	2	1	98.94	0.9917	0.9762

In Table 5, the lowest accuracy of 93.64% was recorded in SVM and best accuracy of 98.94% was recorded in ACO-kNN. The lowest specificity value of 0.9502 was obtained in SVM and the best specificity value of 0.9917 was recorded in ACO-KNN. The lowest sensitivity value of 0.8571 was obtained in SVM and the best sensitivity value of 0.9762 was recorded in ANN, K-NN, Naïve Bayes and ACO-KNN.

Table 6: Result of the CKD Patientswith stage 4 Disease Severity **(**10-fold cross validation**)**

Algorithms	TP	TN	FP	FN	Accuracy (%)	Specificity	Sensitivity
ANN	36	239	7	1	97.17	0.9715	0.9730
K-NN	36	241	5	1	97.88	0.9797	0.9730
Naïve Bayes	36	238	8	1	96.82	0.9675	0.9730
Decision Tree	35	236	10	2	95.76	0.9594	0.9460
SVM	34	232	14	3	93.99	0.9431	0.9189
ACO-kNN	37	244	2	0	99.29	0.9919	1.0000

In Table 6, the lowest accuracy of 93.99% was recorded in SVM and best accuracy of 99.29% was recorded in ACO-kNN. The lowest specificity value of 0.9431 was obtained in SVM and the best specificity value of 0.9919 was recorded in ACO-KNN. The lowest sensitivity value of 0.9189 was obtained in SVM and the best sensitivity value of 1.0000 was recorded in ACO-KNN.

Table 7: Result of the CKD Patientswith stage 5 Disease Severity **(**10-fold cross-validation**)**

Algorithms	TP	TN	FP	FN	Accuracy (%)	Specificity	Sensitivity
ANN	98	181	3	1	98.59	0.9837	0.9899
K-NN	96	177	7	3	96.47	0.9620	0.9697
Naïve Bayes	95	179	5	4	96.82	0.9728	0.9596
Decision Tree	94	178	6	5	96.11	0.9674	0.9495
SVM	92	174	10	7	93.99	0.9457	0.9293
ACO-kNN	98	182	2	1	98.94	0.9891	0.9899

In Table 7, the lowest accuracy of 93.99% was recorded in SVM and best accuracy of 98.94% was recorded in ACO-kNN. The lowest specificity value of 0.9457 was obtained in SVM and the best specificity value of 0.9891 was recorded in ACO-KNN. The lowest sensitivity value of 0.9293 was obtained in SVM and the best sensitivity value of 0.9899 was recorded in ACO-KNN.

V. CONCLUSION

Chronic Kidney Diseases have been responsible for over 41.5% of the mortality rate globally due to the very limited number of qualified medical doctors who specialize in kidney care. The lack of qualified nephrologists and existing models not having enough relevant attributes to develop a predictive diagnostic system for CKD has necessitated automated intervention to support nephrologists towards more improved and efficient service delivery, especially in the prediction of CKD. This paper presents an improved CKD model by application of ACO algorithm and learning algorithms. The results showed that ACO-kNN predictive model gave significant improvement over K-NN and other selected machine learning algorithms in terms of accuracy, specificity and sensitivity due to the introduction of an ACO-based feature selection into the development process of ACO-kNN classification model.

REFERENCES

[1] J. Tabassum, S., Mamatha B.& Majumdar, "Analysis and Prediction of Chronic Kidney Disease using Data Mining Techniques," Int. J. Eng. Res. Comput. Sci. Eng., vol. 4, no. 9, pp. 25–32, 2017.

[2] R. Arasu, S.D., & Thirumalaiselvi, "Review of Chronic Kidney Disease based on Data Mining Techniques," Int. J. Appl. Eng. Res., vol. 12, no. 23, pp. 13498–13505, 2017.

[3] M. Gopika, S. & Vanitha, "Survey on Prediction of Kidney Disease by using Data Mining Techniques," Int. J. Adv. Res. Comput. Commun. Eng., vol. 6, no. 1, pp. 198–201, 2019.

[4] R. . Pasadana, I. A., Hartama, D. zarlis, Sianipar, A.S, Munandar,

S.B, & Alam, “Chronic Kidney Disease Prediction by Using Different Decision Tree Techniques,” Int. Conf. Comput. Sci. Appl. Math., vol. 1255, pp. 1–6, 2019.
[5] P. M. Patil, “Review on Prediction of Chronic Kidney Disease Using Data Mining Techniques,” Int. J. Comput. Sci. Mob. Comput., vol. 5, no. 5, pp. 135–141, 2016.
[6] M. K. Ameta, M. A., & Jain, “Data Mining Techniques for the Prediction of Kidney Diseases and Treatment : A Review,” Int. J. Eng. Comput. Sci., vol. 6, no. 2, pp. 20376–20378, 2017.
[7] S. Vijayarani and S. M. Sylviaa, “Comparative Analysis of Dimensionality Reduction Techniques,” Int. J. Innov. Res. Comput. Commun. Eng., vol. 4, no. 1, pp. 23–29, 2016.
[8] L. Duan, C. Aggarwal, M. Shuai, M. Tiejun, and J. Huai, “An Ensemble Approach to Link Prediction,” IEEE Trans. Knowl. Data Eng., vol. 10, no. 10, pp. 1–14, 2017.
[9] X. Teng and Y. Gong, “Research on Application of Machine Learning in Data Mining,” in IOP Conference Series: Materials Science and Engineering, 2018, vol. 392, no. 6.
[10] S. Kumar, V. & Minz, “Feature Selection: A literature Review,” Smart Comput. Rev., vol. 4, no. 3, pp. 211–229, 2014.
[11] M. Shardlow, “An Analysis of Feature Selection Techniques,” Univ. Manchester, vol. 14, no. 1, pp. 1–7, 2016.
[12] N. Krishnaveni and V. Radha, “Feature Selection Algorithms for Data Mining Classification: A Survey,” Indian J. Sci. Technol., vol. 12, no. 6, pp. 1–11, 2019.
[13] M. Doshi, S. K. Chaturvedi, and D. Ph, “CORRELATION BASED FEATURE SELECTION (CFS) TECHNIQUE TO PREDICT STUDENT PERFROMANCE,” Int. J. Comput. Netw. Commun., vol. 6, no. 3, pp. 197–206, 2014.
[14] M. B. Imani, T. Pourhabibi, M. R. Keyvanpour, and R. Azmi, “A New Feature Selection Method Based on Ant Colony and Genetic Algorithm on Persian Font Recognition,” Int. J. Mach. Learn. Comput., vol. 2, no. 3, pp. 278–282, 2012.
[15] K. Sheena, Krishan, K., & Gulshan, “Analysis of Feature Selection Techniques : A Data Mining Approach,” in International Conference on Engineering & Technology, 2016, pp. 17–21.
[16] H. Polat, H. Danaei Mehr, and A. Cetin, “Diagnosis of Chronic Kidney Disease Based on Support Vector Machine by Feature Selection Methods,” J. Med. Syst., vol. 41, no. 4, p. 55, Apr. 2017.
[17] R. S. Wahono, N. Suryana, and S. Ahmad, “Metaheuristic Optimization based Feature Selection for Software Defect Prediction,” J. Softw., vol. 9, no. 5, pp. 1325–1333, 2014.
[18] S. Beniwal and J. Arora, “Classification and Feature Selection Techniques in Data Mining,” Int. J. Eng. Res. Technol., vol. 1, no. 6, pp. 1–6, 2012.
[19] A. Tripathi, A. Nadaf, and A. K. Yadav, “Identification of the Stages of Chronic Kidney Disease Using Data Mining Approach,” Int. Res. J. Mod. Eng. Technol. Sci., vol. 2, no. 8, pp. 463–467, 2020.
[20] N. Oladeji, F A, Idowu, P A, Egejuru, “Model for Predicting the Risk of Kidney Stone using Data Mining Techniques,” Int. J. Comput. Appl., vol. 182, no. 38, pp. 36–56, 2019.
[21] M. K. Subhashini, R. & Jeyakumar, “E-Anfis to Diagnose the Progression of Chronic Kidney Disease,” Clin. Pract., vol. 16, no. 5, pp. 1235–1244, 2019.
[22] M. D. Basar and A. Akan, “Detection of Chronic Kidney Disease by Using Ensemble Classifiers,” in 10th International Conference on Electrical and Electronics Engineering, ELECO 2017, 2018, pp. 544–547.
[23] M. Alshammari and M. Mezher, “A comparative analysis of data mining techniques on breast cancer diagnosis data using WEKA toolbox,” Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 8, pp. 224–229, 2020.
[24] S. Gopika and M. Vanitha, “Efficiency of Data Mining Techniques for Predicting Kidney Disease,” Int. J. Eng. Technol., vol. 9, no. 5, pp. 3586–3591, 2017.