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ORIGINAL RESEARCH

A Model for Predicting Chronic Kidney Diseases Based on Medical Data Using Reinforcement Learning

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Abstract
Kidney diseases (KD) are a global public health concern affecting millions. Early detection and prediction are crucial for effective treatment. Artificial intelligence (AI) techniques have been used in KDP to analyze past medical records, applying patients' Electronic Medical Record (EHR) data. However, conventional statistical analysis methods conflict with fully comprehending the complexity of EHR data. AI algorithms have helped early KDP learn and identify complex data patterns. However, challenges include training heterogeneous historical data, protecting privacy and security, and developing monitoring system regulations. This study addresses the primary challenge of training heterogeneous datasets for real-world evaluation. Early detection and diagnosis of chronic kidney disease (CKD) is crucial for improved outcomes, reduced healthcare costs, and reliable treatment. Early treatments are crucial for CKD, as it often develops without apparent symptoms. Predictive models, particularly those using reinforcement learning (RL), can identify significant trends in complex healthcare information, which standard techniques may struggle with. The study makes KDP more accurate and reliable using RL methods on clinical data. This lets doctors find diseases earlier and treat them better by looking at static and changing health measurements. Machine learning (ML) algorithms can enhance the accuracy of AI systems over time, enhancing their effectiveness in detecting and diagnosing diseases. In the current investigation, the RL-ANN model is implemented for performing enforceable CKD by assessing the outcomes of multiple neural networks, which include FNN, RNN, and CNN, according to parameters such as accuracy, sensitivity, specificity, prediction error, prediction rate, and kidney failure rate (KFR). The recommended RL-ANN method has a lower failure rate of 70% based on the KFR data. Further, the proposed approach earned 95% in PR and 70% in analysis of errors. However, the RL-ANN approach obtained superior results of 97% accuracy, 95% sensitivity, and 90% specificity.

Keywords Chronic kidney disease · Medical history · Machine learning · RL-ANN · Alerting systems and diagnostic assistance

Introduction

The kidneys are two bean-shaped organs positioned in the posterior part of the abdomen [1]. Their main job is to filter waste materials and extra blood fluids, which the body excretes as urine. Kidney disease (KD) occurs when the kidneys are damaged and can no longer perform their filtering function (FF) accurately. There are many types of KD, but some of the most common are included in Fig. 1. The importance of early identification and chronic kidney disease prediction (CKD) rests in its ability to optimize patient outcomes, lower healthcare expenses, and improve the overall treatment of this standard and severe ailment. CKD frequently advances without noticeable symptoms and only becomes evident in the latter stages when therapies may have reduced effectiveness. Timely identification using predictive models can provide prompt therapies, impeding or ceasing the advancement of the disease and diminishing the likelihood of consequences such as cardiovascular disease and kidney failure.

Depending on the sort and degree of the condition, KD symptoms might vary; however, they may include swelling

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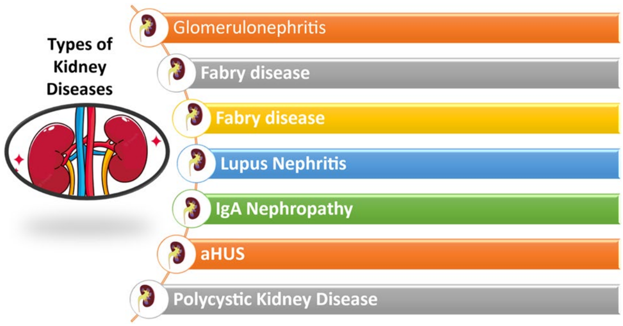

Fig. 1 Types of kidney diseases

in the legs or ankles, fatigue, difficulty sleeping, high blood pressure, decreased appetite, and changes in urination. Treatment for KD depends on the underlying cause and may include lifestyle changes, medication, dialysis, or a kidney transplant. Early detection and treatment are essential for preventing further kidney damage and improving patient outcomes [2–5].

Artificial intelligence (AI), a *state-of-the-art* science technology, is widely used in early detection, disease diagnosis, and management to progress medical research. KD endures as a global health issue because of the large patient population. The diagnosis and treatment of it still present difficulties. AI has the probability to consider individual cases, provide proper recommendations and make significant developments in the management of KD [6–10].

The author of this study recommends a novel method for the early prediction of chronic noncommunicable diseases (NCD) called the short sequential medical data-based prior prediction method (SSEPM), which encompasses pair-level sub-networks intended for multilevel augmentation. Every sub-network employs long short-term memory (LSTM) and concentration layers for recovering temporal information and has no temporal embedded features [11]. This effort aims to advance a machine learning (ML)-based diagnostic approach that efficiently identifies risk factors for chronic renal diseases [12]. The author contributed to the logical development of the article throughout its preparation or editing of the applications developed with AI for diagnostics and prognostics for high-prevalence disorders [3]. This study aims to provide a narrative assessment of the ML research used to calculate the polygenic risk score, emphasizing recent application advancements [13].

The Pima Indian Diabetes Dataset (PIDD) from the UCI-ML repository is used in this research to describe and build a general intelligent framework for accurate diabetes mellitus health management [14].

The study of CKD prediction using artificial intelligence (AI) methods is mainly driven by the need to address significant practical difficulties in managing KD. This is of world health significance, as CKD frequently develops without symptoms, and uncertainties in diagnosis prevent successful treatments. To minimize costs associated with healthcare, enhance patients' health, and reduce the probability of outcomes such as kidney failure and heart disease, detection at an early stage is essential. Complex information about patients, unpredictable health labels, and constraints imposed by standard diagnostic techniques all help explain the challenging task of CKD management. A feasible method for thoroughly assessing intricate EHR is to use AI techniques, such as ML and reinforcement learning (RL). The result is that it was achievable for researchers to identify minute correlations and patterns, enabling more incredible precision predictions and autocue responses. The primary objective of the present study is to enhance CKD management and healthcare resource usage by using AI in order to overcome the disadvantages of present diagnostic methods.

The requirement for reliable and adaptable use of AI in CKD is the primary aim of the present investigation, which attempts to deal with the emphasized issues of generalizability and robustness. Model performance ranges between population size, medical environments, and demographics; this research proposes to train heterogeneous datasets to resolve this unpredictability issue. A heterogeneous dataset allows the model to be trained for various scenarios and changes in health indices because it encompasses a wide range of patient features. This analysis makes the model more adaptable and more capable of predicting results for various patients. For applications in health care in the real world, it provides a more reliable and feasible approach for discovering information and making predictions.

Research Contribution

- Applied to medical data, RL offers a promising approach for CKD prediction, especially in the early stages, considering both static and dynamic health indicators.
- The research uniquely contributes by utilizing RL techniques on medical data, improving accuracy and adaptability in CKD. The model considers fixed and changing health indicators, providing a robust early disease identification and treatment enhancement tool.
- The study implements a reinforcement learning-based artificial neural network (RL-ANN) model for effective CKD, comparing it with fuzzy neural networks (FNN), recurrent neural networks (RNN), and convolutional neural networks (CNN).

The overview of this paper is as follows: a detailed review of the topic is presented in "Literature Review" section as the literature review. The review is followed by a brief description of the proposed model, which includes the flowchart in "Proposed Reinforcement Leaning-Based Artificial Neural

Network (RL-ANN) Model" section, ANN architecture, and algorithms with mathematical modeling implemented in this work. "Results and Discussion" section is the proposed model, the results, and the discussion to highlight the outcome of the implemented model towards CKD prediction, and "Conclusion and Future Work" section concludes with a short conclusion specifying the overall results.

Literature Review

The author of this study works to advance the inspection and measurement of the human body, focusing on the development of devices that support therapies for illnesses. Some of the most spectacular technical advancements may be found in developing non-invasive procedures [15–20]. In all areas of nephrology, this analysis aims to deliver a general overview of medical AI pertinent to practicing nephrologists [21]. The authors used published data gathered from 12 top-tier conferences and 9 top-tier papers in this discipline to assess the evolution of AI at the start of the twenty-first century [22]. The merging of AI with virtuality is examined in this article, with an application to AI agents in addition to the inferences for human-level AI [23]. In order to provide a realistic implementation model for AI ethics, this study uses ethical conceptualization as a framework. Find, challenge, and compare pertinent ideas used in the current AI ethical conversation; a keyword-based Systematic Mapping Study (SMS) on the words used in AI besides ethics was performed [24]. This work aims to prove and compare how well the different KLR-Bagging (Kernel Logistic Regression) and MARS-Bagging (Multivariate Adaptive Regression Splines) ensembles work at predicting the risk of landslides [25]. This work employs a unique III-Step-Hybrid Intelligent Model (III-Step-HIM), a prediction that integrates a Feature Extraction (FE) method with many intelligent modeling approaches [9, 26–29].

According to the authors [30], recent developments in ICT, particularly with the Internet of Things (IoT), big data, and Chronic Pelvic Pain Syndrome (CPPS), make it possible to adopt the flexibility, responsiveness, and intelligence needed to deal with business problems. This paper uses AI modeling to understand the relationships between the risk factors for low back pain and radiologic data. The authors concluded that Industrial Artificial Intelligence (IAI) had been used to solve various challenges for the industry. In addition, they recommended the IAI approach of Privacy-Enhanced Federated Learning (PEFL). This study aims to show how AI and cloud computing enhance the adaptability, reliability, and insight of systems in smart factories. To do this, we provide a thorough review and defense of the use of AI in a Cloud-assisted Smart Factory (CaSF). This article explains why AI is developing rapidly, what uses it may serve, and how it incorporates human behavior. The study identifies a complicated mechanical system crucial to industry—the vehicle wheel suspension system—using Q2 (Qualitatively Truthful Quantitative Learning). The authors have suggested the EPTs-TL-II-level system to predict events in the healthcare sector accurately. The research findings have shown that AI-assisted Customized Manufacturing (CM) may increase manufacturing's flexibility and effectiveness. AI's application to CM presents both advantages and challenges.

The goal of Inflammation and Autoimmunity (IAI) in healthcare is to streamline administrative processes, optimize resource allocation, and potentially improve the overall efficiency of healthcare delivery, specifically in the identification and prediction of CKD. Although the text does not explicitly state that IAI can be directly applied to identify CKD, its mention implies an acknowledgement of the wider range of AI uses in healthcare settings beyond clinical decision-making. Industrial Artificial Intelligence can indirectly aid in improving patient outcomes by enhancing the efficiency and management of healthcare systems, hence indirectly facilitating the early diagnosis and prediction of CKD through improved operational skills.

In the article [14], the authors analyze urinary infections using the XGBoost algorithm. The authors have highlighted the importance of the analysis, which may lead to kidney dysfunction and improper functioning of the related organs. However, the authors have proposed a hybrid ML approach with Random Forest [RF] and AdaBoost [AB] algorithms on the CKD dataset and compared it with several parameters of different algorithms. The authors perform a detailed assessment of the sensors and devices for health monitoring. Newton's Divide Difference Model [NDDM] is proposed to solve the issue of irregularities in electronic datasets. This NDDM model is a polynomial approximation method that implements the Euclidean Distance (ED) parameter. Regular patient health monitoring is performed with wearable sensors, which are highlighted. Like the kidneys in the human body, the liver also plays a significant role in processing the different chemical components in the human body. Improper functioning of the liver may lead to cancer. Table 1 provides a comparison of the existing system explained in this section.

The research highlights a significant deficiency in AI methods for forecasting KD, particularly CKD. Although there have been several studies investigating the use of AI in healthcare and illness prediction, there is a notable absence of research dedicated explicitly to utilizing sophisticated AI techniques for the early identification and prediction of CKD. The current body of literature primarily addresses different medical ailments such as CKD, genetic disorders, diabetes, dialysis, and low back pain. However, there is a noticeable lack of focus on CKD. This study seeks to address this deficiency by introducing an innovative AI model that utilizes RL to predict CKD at an early stage accurately. This

Table 1 Comparison of the existing models

References	Methodology	Outcome of study	Test data
[15]	Sequential medical data analysis	Early prediction of chronic diseases	Medical data
[31]	Prediction techniques	Chronic CKD data analysis	Chronic KD data
[32]	AI	Augmenting nephrologists' intelligence	N/A
[33]	ML	Prediction of genetic diseases	Genetic disease data
[34]	AI	Early prediction of diabetes mellitus	Diabetes-related data
[35]	AI	Application of AI in dialysis	Dialysis data
[36]	AI	Predicting imminent hospitalization with nursing notes	Nursing notes
[37]	N/A	Overview of AI in the twenty-first century	N/A
[38]	N/A	AI in virtual worlds	N/A
[39]	N/A	Key concepts of ethics of AI	N/A
[40]	Hybrid ML	Spatial prediction of landslide hazards	Kurseong Himalayan region data
[41]	Hybrid financial time series	Financial time series prediction	Financial time series data
[42]	Industrial AI	Industrial AI in Industry 4.0	Industrial AI applications
[43]	AI modeling	Prediction of low back pain	Low back pain data
[44]	Privacy-enhanced federated learning	Efficient and privacy-enhanced federated learning	Industrial AI applications
[45]	AI	Cloud-assisted smart factory	Smart factory data
[46]	N/A	Human behavior prediction	N/A
[47]	Qualitatively faithful prediction	Qualitatively faithful quantitative prediction	N/A
[48]	Two-level approach	Event prediction in healthcare	Healthcare event data
	AI-driven customized manufacturing	Key technologies, applications, and challenges	Customized manufacturing data
[49]	XGBoost ensemble model	Early urine infection prediction in IoT-Fog environment	IoT-Fog environment data
[50]	Hybrid analytic model	Effective prediction of distinct stages in CKD	Chronic kidney ailment data
[51]	Survey	Sensors and smart devices for IoT-enabled healthcare	IoT-enabled healthcare system
[52]	ML techniques	Predictive analysis and prognostic approach to diabetes	Diabetes-related data
[53]	Hybrid deep learning (DL)	Real-time patient activity recognition	Body wearable sensor network
[54, 55]	Ultrasound image analysis	Liver cancer classification	Ultrasound images
[56, 57]	Shape descriptor algorithm	Identification of immunity-boosting medicinal plants	Medicinal plant shape descriptors

research will contribute to the existing but limited understanding of AI applications in nephrology.

Proposed Reinforcement Leaning-Based Artificial Neural Network (RL-ANN) Model

A greater significant percentage of researchers are considering applying innovative ML methods to the field of CKD due to the substantial number of individuals suffering from CKD, variations in the severity of their problems, and even deaths that may ensue from them. AI is an integrated field to model human thought processes and actions on computers. Related fields of study include linguistic psychology, mental health, and computer science.

A systematic study into the particular contributions of various factors in the ANN model has been included in the radiation therapy experiment for the ANN used for CKD. To achieve this, particular parts of the model, such as hidden layers, nodes, activation functions, and learning rates, are actively eliminated or changed to demonstrate how they impact prediction accuracy. This study aims to invent key features and configurations that significantly impact ANN's performance to predict CKD accurately. Clinical experimentation changes these components and measures their impact on performance metrics. Regarding ANN decision-making for CKD prediction, this research investigation provides valuable information. As a result, it contributes to improving the predictive model.

ML, robots, DL, and NLP are changing healthcare by developing autonomous machines that can usually perform tasks humans perform. This technology can transform CKD detection and treatment for early detection and enhanced patient results.

The integration of AI with CKD encompasses several therapeutic activities, as demonstrated in Fig. 2. These procedures include improving medical care and treatment approaches, finding and diagnosing CKD early, and more. AI algorithms integrated into Electronic Healthcare Records (HER) can identify subtle CKD risk factors, enabling prompt and accurate diagnoses. This work aims to improve treatment outcomes for patients with CKD by integrating AI,

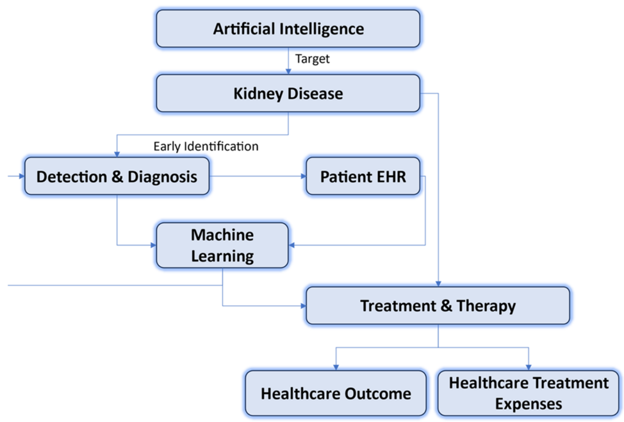

Fig. 2 Workflow of the proposed system

EHR, ML, and CKD, using a comprehensive understanding of a patient's overall health. Data drive the technique and focus on patients, predicting CKD change, treatment effectiveness, and probable results using ML models trained on the massive dataset.

AI-integrated CKD includes early detection, accurate diagnosis, and improved treatment. AI systems and EHRs can find risk factors, refine signs, and propose amended medicines. Combining AI, CKD, EHR, and ML can predict CKD developments, treatment responses, and results, improving patient results by highlighting their requirements.

AI can support KD findings and treatment in several ways. Find trends and show people who are most likely to get KD or experience the course of the illness; ML algorithms may analyze vast volumes of patient data, including laboratory results, EHRs, and imaging examinations. AI can also help healthcare providers make more precise diagnoses, create personalized treatment plans, and check patient responses to therapy. Overall, AI can potentially improve the accuracy, efficiency, and effectiveness of KD diagnosis and treatment, improving patient outcomes and reducing healthcare costs. This complete process of intelligent KDP is projected in Fig. 2.

One of the most fundamental components of ML is ANN. This mathematical model uses nonlinear statistical data modeling methods to account for the complicated interactions between inputs and outputs. It mimics the human brain's ability to analyze distinct input types and discover patterns in decision-making. An ANN has input, potentially hidden, and output layers. Since every neuron in one layer is linked to every neuron in the following layer, these networks are fully connected ANNs. The method analyzes data by passing it from one layer of linked nodes to another, resulting in each layer's neurons fetching the input for the neurons in the next layer. Information is shared across nodes, and the contributions of each node's outputs are considered. ANN can improve the number of correct answers compared to a reference by changing the weights on each node based on the error seen in each forward propagation. The mathematical answer gets closer to the truth with each repetition. Figure 3 shows the architecture of the ANN.

During forward propagation in an ANN, regulating the weights on each node entails altering the parameters

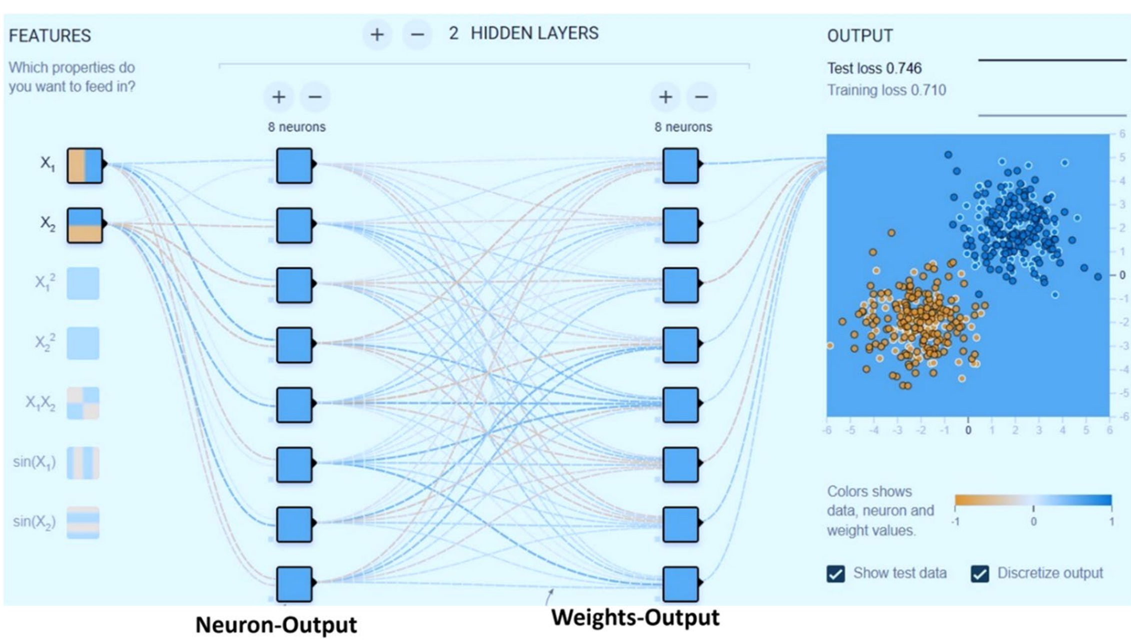

Fig. 3 Proposed RL-ANN model

according to the estimated error at each step. This iterative approach aims to enhance the model's output by aligning it more accurately with the desired reference. By periodically updating the number of weights, the mathematical model gets closer to an accurate prediction, decreasing the variation between the actual and predicted values. This approach helps the ANN improve its volume to generate accurate responses by frequently enhancing its performance.

In the ANN structure, the input layer is depicted in Fig. 3. It is responsible for collecting raw data as well as input data. In this layer, every node symbolizes a unique attribute or feature. The hidden layers between the input and output layers perform preliminary data processing. In these hidden layers, nodes process data received at the input layer, implementing any required deviations before sending it to higher levels. The level of complexity and specifications for the network dictate the number and layout of hidden layers and the total number of nodes in each network layer. Essential tasks such as classification and regression depend on the output layer, which uses processed data to provide predictions or results. The network's design, architecture, and purpose determine the layout of nodes in each layer.

The ANN approach with back-propagation has been used for data prediction. Neural networks (NNs) employ forward propagation during their training phase. After the forward pass, the nodes in the output layer generate a value. The node's complete input is initially named during the forward pass, and the activation function (AF) is then used to identify the node's output. Each neuron's total input in a FFNN is calculated using Eq. (1):

$$\textit{Total Input} = m_1 * e_1 + m_2 * e_2 + \ldots + m_n * e_n + 1 * e_v \tag{1}$$

where $m_1, m_2, \ldots .m_n$ are the input neurons, and $e_1, e_2, \ldots e_n$ are the weight of the input neuron. e_v is the bias-related weighting of the AF that is used to compute the neuron's output.

The AF calculates the neuron's output and is represented in Eq. (2):

$$\textit{Activation function} = 1/\left(1 + w^{(-\textit{Total Input})}\right) \tag{2}$$

where total input is the total input to the neuron.

It is a frequent practice to train ANNs using a method known as back-propagation in conjunction with an optimization method like gradient descent. The two stages of the algorithm's two-step cycle are propagation and weight updates.

Some risk factors for chronic KD include becoming older, having a low birth weight, being overweight, smoking, having high blood pressure, having diabetes, and having a history of renal disease in the family. The two conditions that contribute to kidney failure more often than any other are high blood pressure and diabetes. Algorithm 1 is the complete procedure applied for data collection for CKD prediction using ANN, presented and followed by the definitions for the variables applied in this algorithm.

Algorithm 1 for ANN for CKD prediction

Step 1: Collect and pre-process the EHR. It involves collecting data on relevant EHR variables such as age, sex, blood pressure, diabetes status, and cholesterol levels. The data is then normalized and pre-processed, for example, by converting categorical variables to one-hot encodings and scaling continuous variables to have a zero mean and unit variance.

Step 2: Data division into training, validation, and testing sets.

Step 3: Define the NN architecture, including the number of layers, the total count of neurons in every layer, and the AF used for each neuron. Let $'X'$ be the input matrix of the shape. (m, n), where $'m'$ is the number of examples and $'n'$ is the number of input features and let 'Y' be the output matrix of the shape $(m, 1)$ representing the binary class labels (0 for no KD, 1 for KD).

Step 4: Randomly initialize the weights in addition to the network's biases, for example, by sampling from a normal distribution. Let $W(p)$ be the Weight Matrix (WM) for layers p and $b(p)$ be the bias vector for layer p.

Step 5: Define the forward pass of the network. For a given input $x(p)$, compute the output $\hat{y}(i)$ using the following EQU (3) and EQU (4).

$$z(p+1) = W(p)a(p) + b(p) \quad (3)$$

$$a(p+1) = g\big(z(p+1)\big) \quad (4)$$

where, $z(p)$ is the pre-activation vector of layer$l$, $a(p)$ is the activation vector of layer l, and g is the AF, such as the sigmoid function.

Step 6: Define the Cost Function (CF), which measures the PR and true output. A commonly used CF for binary classification is the binary cross-entropy loss calculated using EQU (5).

$$J = -1/m * Sum\big(y(i) * \mathrm{Log}\big(\hat{y}(i)\big) + \big(1 - y(i)\big) * \mathrm{Log}\big(1 - \hat{y}(i)\big)\big) \quad (5)$$

Step 7: Define the network's backward pass, which determines the gradients of the CF concerning the weights and biases. In order to minimize the CF, the gradients were previously used to update the weights and biases in the contradictory direction of the gradient. EQU (6) to EQU (9) are used to update.

$$dZ(p+1) = dA(p+1) * g'\big(Z(p+1)\big) \quad (6)$$

$$dW(p) = 1/m * dZ(p+1) * A(p).T \quad (7)$$

$$db(p) = 1/m * np.sum(dZ(p+1), axis = 1, keepdims = True) \quad (8)$$

$$dA(p) = W(p).T * dZ(p+1) \quad (9)$$

Step 8: Train the network using mini-batch gradient descent with back-propagation. In each training iteration, randomly select a mini-batch of examples, perform a forward pass, calculate the cost function and gradients, and update the weights and biases.

Step 9: To make sure the network is not overfitting to the training set, validate it using the validation set.

Step 10: Test the network using the testing set to evaluate its performance on new, undetected data.

Step 11: Adjust the network architecture or training parameters to improve performance.

- X: The input matrix of the shape (m, n), where 'm' is the number of examples and 'n' is the total input features. Each row 'X' represents a single patient's EHR, and each column represents a different feature such as age, sex, blood pressure, diabetes status, or cholesterol levels.
- Y: The output matrix of the shape $(m, 1)$ representing the binary class labels. Each element of 'Y' is either 0 (indicating no KD) or 1 (indicating KD) for the corresponding patient in X.
- $W(p)$: The WM for layer p. The shape of $W(p)$ is $(n(p), n(p-1))$, where $n(p)$ is the sum of neurons in layers p and $n(p-1)$ is the total neurons in the previous layer. The weights determine the strength and sign of the connections between neurons in adjacent layers.
- $b(p)$: The bias vector for layer 'p'. The shape of $b(p)$ is $(n(p), 1)$, where $n(p)$ is the number of neurons in layer 'p'. The biases provide a constant offset to the pre-activation values of neurons in each layer.
- $z(p)$: The pre-activation vector of the selected layer 'p'. The shape of $z(p)$ is $(n(p), 1)$, in which $n(p)$ is the total number of neurons in a given layer 'p'. $z(p)$ is computed as a linear combination of the activations of the previous layer using the weights and biases.
- $a(p)$: The activation vector in the given layer 'p'. The shape of $a(p)$ is $(n(p), 1)$, in which $n(p)$ is the total number of neurons in a selected layer 'p'. $a(p)$ is the output of the AF applied to the pre-activation vector $z(p)$.
- g: The AF used for each neuron. Common choices include the sigmoid function, the ReLU function, or the hyperbolic tangent function.
- J: The CF, which measures the error between the predicted output and the true output. In this case, the CF is the binary cross-entropy loss.
- $dZ(p+1)$: The gradient of the CF concerning the pre-activation vector of layer $p+$. This is computed in the backward pass of the network and used to update the weights and biases.
- $dW(p)$: The gradient of the CF concerning the WM of layer 'p'. This is computed in the backward pass of the network and used to update the weights.
- $db(p)$: The gradient of the CF regarding the bias vector of layer 'p'. This is computed in the backward pass of the network and used to update the biases.
- $dA(p)$: The gradient of the CF about the activation vector of layer 'p'. This is computed in the backward pass of the network and used in computing the gradients for the previous layer.

Algorithm 2 for the proposed RL-ANN model

Step 1. Initialize the weights of the ANN to random values.

Step 2. Define the state space, action space, and reward function for the problem.

Step 3. Repeat for a fixed number of episodes:

a) Set the environment to its initial state.
b) Repeat for a fixed number of time steps:
   - Compute the current state of the environment.
   - Use the ANN to select an action based on the current state, using either an exploration or exploitation strategy.
   - Execute the selected action and observe the resulting state and reward.
   - Store the (state, action, next state, reward) tuple in a memory buffer.
   - Sample a batch of tuples from the memory buffer and use them to update the weights of the ANN using the RL algorithm (*e.g.,* Q-learning or policy gradient).
c) Update the target policy (if applicable) based on the current weights of the ANN.
d) Evaluate the performance of the current policy on a validation set.
e) If the performance is satisfactory, stop the training and deploy the policy in the real world. Otherwise, adjust the ANN model, RL algorithm, or hyper-parameters and repeat steps 3 to 4 until satisfactory performance is achieved. Initialize the weights of the ANN to random values.

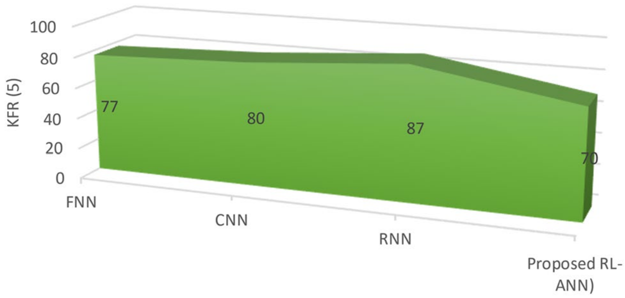

Fig. 4 KFR

Table 2 Results of KFR

Algorithms	KFR (%)
FNN	77
CNN	80
RNN	87
Proposed RL-ANN)	70

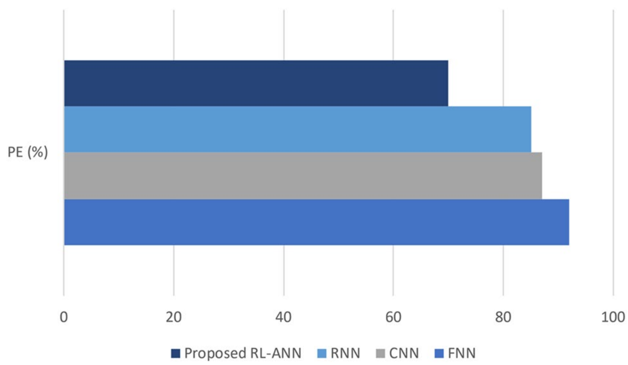

Fig. 5 Analysis of PE

Table 3 Results of PR and PR

Algorithms	PR (%)	PE (%)
FNN	78	92
CNN	82	87
RNN	86	85
Proposed RL-ANN	95	70

Note that this algorithm assumes a batch learning approach, where the weights of the ANN are updated using a batch of tuples rather than online learning. In addition, the specific implementation details of the RL algorithm may vary depending on the problem statement and the chosen RL algorithm.

Hyperparameters in ML models are predetermined settings external to the training process. These settings have

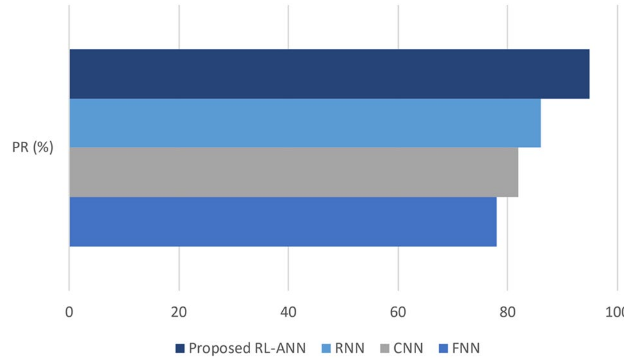

Fig. 6 Analysis of PA

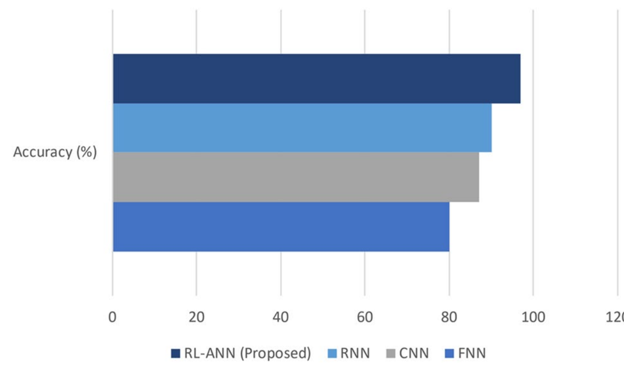

Fig. 7 Analysis of accuracy

Table 4 Accuracy analysis

Algorithms	Accuracy (%)
FNN	80
CNN	87
RNN	90
RL-ANN (proposed)	97

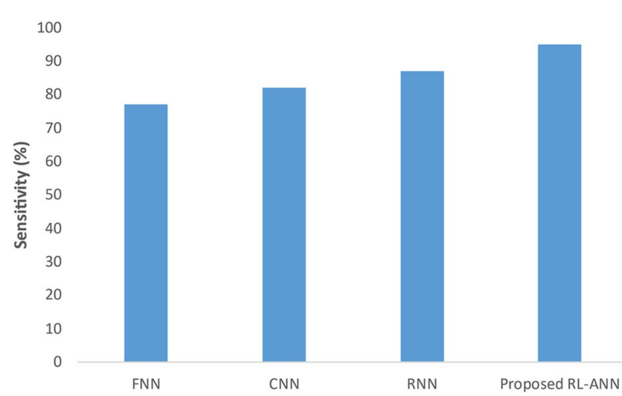

Fig. 8 Analysis of sensitivity

Table 5 Results of sensitivity and specificity for existing and proposed methods

Algorithms	Sensitivity (%)	Specificity (%)
FNN	77	70
CNN	82	78
RNN	87	82
Proposed RL-ANN	95	90

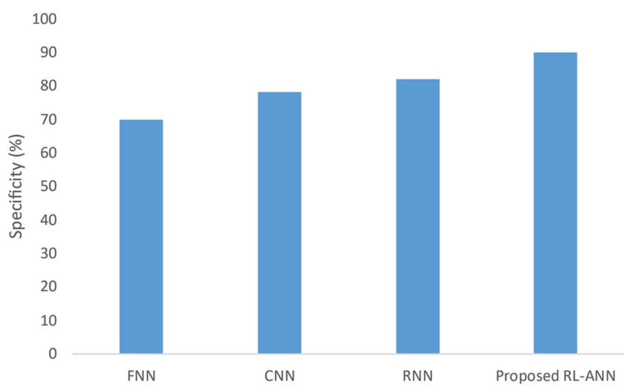

Fig. 9 Analysis of specificity

a direct impact on the structure and behavior of the model. These parameters, which are not derived from the data but established by practitioners, encompass vital elements such as the learning rate, which determines the magnitude of each training step; the number of hidden layers and neurons, which define the complexity of the network; the activation functions that influence the outputs of each node; the batch size; the epochs that determine the number of training iterations; and the regularization parameters that control model overfitting. The primary objective of improving ML models is to tune these hyperparameters since their proper setup drastically impacts performance and the capacity of the model to adapt to new data.

Results and Discussion

About Simulation

Researchers employ MATLAB 2021a to perform the implementation and comparison study of the presented RL-ANN model with the existing models. The findings of the simulation are then addressed. To achieve the test results, we will be using a grouping of the web tool Jupyter Notebook and the programming language Python 3.3. Many SCIKET-learning libraries were included; SCIKET-learning stands as an acceptable structure for AI systems built on Python.

Data description: with 24 features collected from 400 individuals, the data set provides an ample number of features related to the predicted size of the input. There are 24 features in the data set, with 10 representing absolutes and 14 being analytical. A maximum of 25 features have been produced by identifying a class label with each test input. Age, cholesterol levels, and biochemical tests are among the most health-related data mentioned in the statistical data. High blood pressure, diabetes, insulin resistance, and hunger are signs of specific illnesses that can be understood from their definite features. The dataset provides a wealth of information for comprehensive investigations due to its multidimensional nature, which includes real statistical and definite variables. The dataset's various numbers across its 25 features can help identify some instances. In health-related investigations, this provides enormous information for exploratory and predictive analyses [58]. This dataset is multivariate, featuring a mix of real statistical and definite data—the instances number 400 each feature by the values of these 25 values.

The dataset consists of various health-related features for individuals, including statistical and *definite* information. The statistical features consist of the individual's age in years, blood pressure measured in *mm/Hg*, and several biochemical parameters such as blood glucose random, blood urea, serum creatinine, sodium, potassium, hemoglobin, packed cell volume, white blood cell count, and red blood cell count. The nominal features consist of *definite* information, including specific gravity values (1.005, 1.010, 1.015, 1.020, 1.025), albumin values (0, 1, 2, 3, 4, 5), sugar values (0, 1, 2, 3, 4, 5), presence of red blood cells (normal, abnormal), pus cell status (normal, abnormal), presence of pus cell clumps (present, not present), bacteria presence (present, not present), hypertension status (yes, no), diabetes mellitus status (yes, no), coronary artery disease status (yes, no), appetite assessment (good, poor), pedal edema status (yes, no), anemia status (yes, no), and the class label with values (ckd, notckd). These qualities together offer a complete range of information for each person in the dataset, enabling thorough exploration and analysis in health and medical research.

Simulation Parameter

The existing methods, such as FNN, CNN, and RNN, were compared with the proposed method of RL-ANN. The parameters include kidney failure rate (KFR), prediction rate (PR), prediction error (PE), accuracy, specificity, and sensitivity.

In the medical condition known as kidney failure, sometimes called end-stage renal disease, the kidneys cannot filter trash materials effectively from the blood and instead function at levels less than 15% of what is measured as normal.

Figure 4 depicts the KFR. KFRs are higher for existing methods and lower for proposed methods. Table 2 depicts the results of KFR for existing and proposed methods.

Within the uncertainty due to statistical variations and noise in the input data values, A specifies whether or not the predicted values coincide with the target field's actual values. Figure 5 indicates the PR of the proposed and existing models. PR is higher for proposed methods and lower for existing methods. Table 3 depicts the results of the PR and PR.

When a predicted event does not occur, there is a PE. When predictions are incorrect, people may use metacognitive processes to look back at previous PR to investigate if there are any links or patterns, such as a chronic inability to predict outcomes in particular contexts accurately. The proposed work has a lower PR than existing methods, with less than 70%, and the highest PR is observed in the FNN model, with 92.8% (Fig. 6).

Accuracy is the proportion of accurately predicted occurrences to all expected instances. Figure 7 depicts the comparative evaluation of accuracy in proposed and existing models. Compared with the existing work, the proposed work shows greater accuracy. Table 4 highlights the values obtained for the accurate KDP for different models.

The degree to which a diagnostic test identifies a patient as having a condition is referred to as its sensitivity. A susceptible test indicates that there are fewer instances of false negative findings, and therefore, there are fewer instances of illness that go unrecognized. Figure 8 indicates the sensitivity. Sensitivity is lower in existing methods and higher in proposed methods, with 77% obtained by FNN, 82% by CNN, 87% by RNN, and the highest of 95% by RL-ANN with back-propagation, respectively.

Table 5 shows the sensitivity and specificity results for existing and proposed methods. The capability of a test to identify as "*negative*" a person who is not recorded with the ailment being evaluated is defined as "*specificity.*" Fig. 9 shows the specificity. Specificity is higher in proposed methods and lower in existing approaches. According to the graph, the proposed RL-ANN model achieves higher sensitivity with 90%, a minimum variance of 8% from RNN.

Different approaches, such as FNN, CNN, and RNN, along with the recommended RL-ANN, led to valuable results in several areas, as exposed in Table 2. The proposed RL-ANN model showed a significant development in the KFR compared to existing approaches such as FNN, CNN, and RNN. The KFR of the RL-ANN model was 70%, which is lower than the rates of 77%, 80%, and 87% achieved by FNN, CNN, and RNN, respectively. The RL-ANN model proved its superiority by having a better PR of 95% and a reduced PE of 70% compared to the previous models. The examination of PE (Fig. 5) verified the impacts of inaccurate predictions, underscoring the need for accuracy in medical assessments.

Accuracy, the ratio of correctly predicted occurrences to the total expected instances, has been identified as a crucial performance parameter. The RL-ANN model achieved a higher accuracy rate of 97%, outperforming other methods such as FNN (80%), CNN (87%), and RNN (90%). This information is visually represented in Fig. 7 and further elaborated in Table 4. The analysis of diagnostic test performance included the examination of sensitivity and specificity, which are important markers. This analysis used Figs. 8 and 9, and Table 5. RL-ANN showed superior sensitivity (95%) and specificity (90%) compared to FNN, CNN, and RNN. This indicates its enhanced capability to accurately distinguish true positive and negative results in predicting CKD. After everything was said and done, the suggested RL-ANN model with back-propagation showed promising results, demonstrating that it could be a valuable tool for making CKD predictions even more accurate and reliable.

Conclusion and Future Work

Artificial intelligence (AI) in urology ranges from the detection of diseases to the interpretation of diagnostic images to the prediction of prognosis. Its main goal is to support doctors in their decision-making without, in any technique, looking to replace them. From a human perspective, the doctor's presence is still necessary for developing a robust doctor–patient connection of trust that can improve the efficacy of any therapies and treatments and a responsible and ethical stance for diagnosis. This research implements the reinforcement learning-based artificial neural network (RL-ANN) model based on back-propagation to predict kidney disease. The proposed model is compared with the existing FNN, CNN, and RNN models. The findings from the kidney failure rate (KFR) study demonstrate that the failure rate has decreased by 7% in the recommended RL-ANN model. When contrasted with different approaches that exist in use, the proposed approach attains a prediction rate (PR) of 15% and a prediction error (PE) of 9%. In addition, for accuracy, sensitivity, and specificity parameters, the RL-ANN model has obtained higher difference values of 7%, 12%, and 12%, respectively. As a future enhancement, the analysis will be performed with the multi-modal dataset to obtain improved accuracy and lower PR.

Furthermore, research on predicting CKD using RL-ANN should look into how to combine different types of data to get a more complete picture of the patient. Applying longitudinal data analysis and real-time prediction can improve the model's ability to adapt to dynamic clinical situations. It ensured collaboration between AI and healthcare practitioners by prioritizing explainability and implementing human-in-the-loop frameworks. Deploying trustworthy and fair models necessitates the careful evaluation of ethical factors, the reduction of prejudice, and the conduct of cost–benefit analyses. In order to ensure that a solution can be effectively applied and have a significant effect in real-world scenarios, it is crucial to validate it using a variety of datasets, make iterative adjustments, and collaborate with healthcare organizations.

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Declarations

Conflict of interest Not applicable.

References

1. Wu C, Zhou T, Tian Y, Wu J, Li J, Liu Z. A method for the early prediction of chronic diseases based on short sequential medical data. Artif Intell Med. 2022;127:102262.
2. Shanmugarajeshwari V, Ilayaraja M. intelligent prediction techniques for chronic kidney disease data analysis. Int J Artif Intell Mach Learn. 2021;2:19–37.
3. Xie G, Chen T, Li Y, Chen T, Li X, Liu Z. Artificial intelligence in nephrology: how can artificial intelligence augment nephrologists' intelligence? Kidney Dis. 2019;1:1–6.
4. Mena Mamani N. Machine learning techniques and polygenic risk score application to prediction genetic diseases. Adv Distrib Comput Artif Intell J (ADCAIJ). 2020;9(1):5–14.
5. Ganie SM, Malik MB, Arif T. Early prediction of diabetes mellitus using various artificial intelligence techniques: a technological review. Int J Bus Intell Syst Eng. 2021;1(4):325.
6. Paul J, Bhukya R. Forty-five years of International Journal of Consumer Studies: A bibliometric review and directions for future research. Int J Consum Stud. 2021;45(5):937–63.
7. Sengan S, Khalaf OI, Vidya Sagar P, Sharma DK, Arokia Jesu Prabhu L, Hamad AA. Secured and privacy-based IDS for healthcare systems on e-medical data using machine learning approach. Int J Reliable Qual E-Healthc. 2022;11(3):1–11.
8. Sahu AK, Swain G. Reversible image steganography using dual-layer LSB matching. Sens Imaging. 2020. https://doi.org/10.1007/s11220-019-0262-y.
9. Saba SS, Sreelakshmi D, Sampath Kumar P, Sai Kumar K, Saba SR. Logistic regression machine learning algorithm on MRI brain image for fast and accurate diagnosis. Int J Sci Technol Res. 2020;9(3):7076–81.
10. Neal Joshua ES, Bhattacharyya D, Chakkravarthy M, Byun Y-C. 3D CNN with visual insights for early detection of lung cancer using gradient-weighted class activation. J Healthc Eng. 2021;2021:1–11.
11. Sridhar C, Pareek PK, Kalidoss R, Jamal SS, Shukla PK, Nuagah SJ. Optimal medical image size reduction model creation using recurrent neural network and GenPSOWVQ. J Healthc Eng. 2022;2022:1–8.
12. Banchhor C, Srinivasu N. Integrating cuckoo search-grey wolf optimization and correlative naive bayes classifier with map reduce model for big data classification. Data Knowl Eng. 2020;127:1017880.
13. Sengan S, Rao GRK, Khalaf OI, Babu MR. Markov mathematical analysis for comprehensive real-time data-driven in healthcare. Math Eng Sci Aerosp. 2021;12(1):77–94.
14. Talasila V, Madhubabu K, Mahadasyam MC, Atchala NJ, Kande LS. The prediction of diseases using rough set theory with recurrent neural network in big data analytics. Int J Intell Eng Syst. 2020;13(5):10–8.
15. Kumar V, et al. addressing binary classification over class imbalanced clinical datasets using computationally intelligent techniques. Healthcare (Switzerland). 2022;10(7):1293.
16. Sharma P, Moparthi NR, Namasudra S, Shanmuganathan V, Hsu C-H. Blockchain-based IoT architecture to secure healthcare system using identity-based encryption. Expert Syst. 2022. https://doi.org/10.1111/exsy.12915.
17. Gorla US, Rao K, Kulandaivelu US, Alavala RR, Panda SP. Lead finding from selected flavonoids with antiviral (Sars-cov-2) potentials against covid-19: an in-silico evaluation. Comb Chem High Throughput Screen. 2021;24(6):879–90.
18. Bandi V, Bhattacharyya D, Midhunchakkravarthy D. Prediction of brain stroke severity using machine learning. Revue d'Intelligence Artificielle. 2020;34(6):753–61.
19. Chithaluru P, Al-Turjman F, Stephan T, Kumar M, Mostarda L. Energy-efficient blockchain implementation for Cognitive Wireless Communication Networks (CWCNs). Energy Rep. 2021;7:8277–86.
20. Mubarakali A, Ashwin M, Mavaluru D, Kumar AD. Design an attribute-based health record protection algorithm for healthcare services in cloud environment. Multimed Tools Appl. 2020;79(5–6):3943–56.
21. Krishna BV, et al. Design and development of graphene FET biosensor for the detection of SARS-CoV-2. SILICON. 2022;14(11):5913–21.
22. Rao KS, et al. Design and sensitivity analysis of capacitive MEMS pressure sensor for blood pressure measurement. Microsyst Technol. 2020;26(8):2371–9.
23. Dharmadhikari SC, Gampala V, Rao CM, Khasim S, Jain S, Bhaskaran R. A smart grid incorporated with ML and IoT for a secure management system. Microprocess Microsyst. 2021;83:103954.
24. Rajendra Prasad K, Mohammed M, Noorullah RM. Visual topic models for healthcare data clustering. Evolut Intell. 2021;14(2):545–62.
25. Achanta SDM, Karthikeyan T, Kanna RV. Wearable sensor-based acoustic gait analysis using phase transition-based optimization algorithm on IoT. Int J Speech Technol. 2021. https://doi.org/10.1007/s10772-021-09893-1.
26. Thota MK, Shajin FH, Rajesh P. Survey on software defect prediction techniques. Int J Appl Sci Eng. 2020;17(4):331–44.
27. Hira S, Bai A, Hira S. An automatic approach based on CNN architecture to detect Covid-19 disease from chest X-ray images. Appl Intell. 2021;51(5):2864–89.
28. Ramesh KKD, Kiran Kumar G, Swapna K, Datta D, Suman Rajesh S. A review of medical image segmentation algorithms. EAI Endorsed Trans Pervasive Health Technol. 2021;7(27):e6.
29. Naik A, Satapathy SC, Abraham A. Modified Social Group Optimization—a meta-heuristic algorithm to solve short-term hydrothermal scheduling. Appl Soft Comput J. 2020;95:106524.
30. Kumar EK, Kishore PVV, Kiran Kumar MT, Kumar DA. 3D sign language recognition with joint distance and angular coded color topographical descriptor on a 2—stream CNN. Neurocomputing. 2020;372:40–54.

31. Kumar S, Jain A, Kumar Agarwal A, Rani S, Ghimire A. Object-based image retrieval using the U-net-based neural network. Comput Intell Neurosci. 2021;2021:1–14.
32. Sengan S, Vidya Sagar P, Ramesh R, Khalaf OI, Dhanapal R. The optimization of reconfigured real-time datasets for improving classification performance of machine learning algorithms. Math Eng Sci Aerosp. 2021;12(1):43–54.
33. Routray S, Malla PP, Sharma SK, Panda SK, Palai G. A new image denoising framework using bilateral filtering based non-subsampled Shearlet transform. Optik. 2020;216:164903.
34. Reddy AVN, Krishna CP, Mallick PK. An image classification framework exploring the capabilities of extreme learning machines and artificial bee colony. Neural Comput Appl. 2020;32(8):3079–99.
35. Eali SNJ, Bhattacharyya D, Nakka TR, Hong S-P. A novel approach in bio-medical image segmentation for analyzing brain cancer images with U-NET semantic segmentation and TPLD models using SVM. Traitement du Signal. 2022;39(2):419–30.
36. Mandhala VN, Bhattacharyya D, Vamsi B, Thirupathi Rao N. Object detection using machine learning for visually impaired people. Int J Curr Res Rev. 2020;12(20):157–67.
37. Mohammed M, Kolapalli R, Golla N, Maturi SS. Prediction of rainfall using machine learning techniques. Int J Sci Technol Res. 2020;9(1):3236–40.
38. Ganesan V, Sobhana M, Anuradha G, Yellamma P, Devi OR, Prakash KB, Naren J. Quantum inspired meta-heuristic approach for optimization of genetic algorithm. Comput Electr Eng. 2021;94:107356.
39. Prakash KB. Quantum meta-heuristics and applications, cognitive engineering for next generation computing: a practical analytical approach. 2021. p. 265–297.
40. Ismail M, Prakash KB, Rao MN. Collaborative filtering-based recommendation of online social voting. Int J Eng Technol (UAE). 2018;7(3):1504–7.
41. Prakash KB. Information extraction in current Indian web documents. Int J Eng Technol (UAE). 2018;7(2):68–71.
42. Prakash KB. Content extraction studies using total distance algorithm. In: Proceedings of 2nd international conference on applied and theoretical computing and communication technology, no. 7912085. 2017. p. 673–9.
43. Prakash KB, Rangaswamy MAD. Content extraction of biological datasets using soft computing techniques. J Med Imaging Health Inform. 2016;6(4):932–6.
44. Prakash KB, Rajaraman A. Mining of bilingual indian web documents. Procedia Comput Sci. 2016;89:514–20.
45. Prakash KB, Dorai Rangaswamy MA. Content extraction studies using neural network and attribute generation. Indian J Sci Technol. 2016;9(22):1–10.
46. Prakash KB. Mining issues in traditional Indian web documents. Indian J Sci Technol. 2015;8(32):1–11.
47. Prakash KB, Dorai Rangaswamy MA, Ananthan TV, Rajavarman VN. Information extraction in unstructured multilingual web documents. Indian J Sci Technol. 2015;8:16.
48. Prakash KB, Rangaswamy MAD, Raja Raman A. ANN for multilingual regional web communication. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7667 LNCS (PART 5). 2012. p. 473–8.
49. Prakash KB, Rangaswamy MAD, Raman AR. Statistical interpretation for mining hybrid regional web documents. Commun Comput Inf Sci (CCIS). 2012;292:503–12.
50. Kolla BP, Dorairangaswamy MA, Rajaraman A. A neuron model for documents containing multilingual Indian texts. In: International Conference on Computer and Communication Technology, ICCCT-2010, art. no. 5640489. 2010. p. 451–4.
51. Prakash KB, Dorai Rangaswamy MA, Raman AR. Text studies towards multi-lingual content mining for web communication. In: Proceedings of the 2nd International Conference on Trendz in Information Sciences and Computing, TISC-2010, no. 5714601. 2010. p. 28–31.
52. Jaiprakash SP, Desai MB, Prakash CS, Mistry VH, Radadiya KL. Low dimensional DCT and DWT feature-based model for detection of image splicing and copy-move forgery. Multimed Tools Appl. 2020;79(39–40):29977–30005.
53. Rachapudi V, Talapaneni CH, Kolluri D, Akthar AN, Anjali Devi S. Improved convolutional neural network for classification of white blood cells. Int J Control Autom. 2020;13(2):883–8.
54. Srinivas M, Pavan Kumar T, Sai Vivek U, Bala Narasimha Rao R, Avinash A. Exploratory study for data visualization on Internet of things. J Adv Res Dyn Control Syst. 2020;12(2):2286–97.
55. Doppala BP, Midhunchakkravarthy, Bhattacharyya D. Premature detection of cardiomegaly using hybrid machine learning technique. J Adv Res Dyn Control Syst. 2020;12(6):490–8.
56. Mandhala VN, Somesekhar G, Kumar GA. Image classification using advanced convolutional neural networks (Acnn). J Adv Res Dyn Control Syst. 2020;12(6):632–6.
57. Sai Sudha G, Praveena M, Sandhya Rani G, Harish TNSK, Charisma A, Asish A. Classification and detection of diabetic retinopathy using deep learning. Int J Sci Technol Res. 2020;9(4):3186–92.
58. https://archive.ics.uci.edu/dataset/336/chronic+kidney+disease.

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