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Research Article

Effective analysis of chronic kidney disease prediction using HRNN algorithm

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ABSTRACT

Chronic Kidney Disease is a catch-all phrase for a variety of kidney illnesses. Chronic Renal Disease is another name for it. The illness affects 5 to 10% of the world's population. Chronic Kidney Disease is a worldwide health issue. Often these instances of Chronic Kidney Disease get underdiagnosed or are eventually diagnosed in developing and underdeveloped countries; it is one of the main reasons why a greater percentage of these kinds of cases come from underdeveloped and developing countries as opposed to developed countries where most people have regular check-ups and diagnosis. Machine-learning systems could be used to identify Chronic Kidney Disease in what seems like a quick and accurate manner, allowing doctors to verify their test results in a relatively short period, going to allow a doctor to respond and recognise more sick people in less time than if he or She must go through the full diagnosis procedure by hand. Machine learning algorithms can be used for prediction, and exactness is determined by comparing various algorithms such as Hybrid-Recurrent Neural Networks (HRNN). This method is used to forecast a dataset derived from a patient's medical history.

Key words: Chronic kidney disease, Machine learning, HRNN, IoT

INTRODUCTION

Chronic kidney disease has rapidly become the leading cause of death worldwide. Anticipating cardiovascular disease is a difficult task since it involves both intuitive and analytical understanding (Khan, 2020). An Internet of Things (IoT) is recently been adopted in current clinical structures can gather device information for Kidney disease assessment and determination. Numerous experts have focused on identifying coronary vein infection; however, the accuracy of the results is low (Al-Makhadmeh & Tolba, 2019). The most recent advancements in IoT and detecting technologies can also be used for virtual healthcare administrations. To give exceptional support to customers who utilize online medical care services, a new Cloud & IoT-based Healthcare software to screen and assess genuine diseases has been developed (Ganesan & Sivakumar, 2019). In this study, a realistic strategy for infection is created utilizing the UCI Repository database along with clinical consideration sensors to predict the public who suffer from kidney disease (Jabeen *et al.,* 2019). Patients suffering from distant cardiovascular infections can profit from a fog-based IoT solution. A specialist cardiologist is frequently unavailable in such distant places. There are a few methods available to organize coronary infection and provide recommendations; however, these structures now only use plans for recommendations (Golande *et al.,* 2019). We provide an IoT-based clever neighborhood is an accessible system that investigates cardiovascular illness and its treatment and offers ideas related to physical and nourishment defensive strategies insight into this field of studies. The original segment's anticipation was that biosensors will be used to acquire information from the patient across a great distance (Arulanthu & Perumal, 2020).

The Internet of Things (IoT) seems to be a system of interconnected devices that interact with one another through different organizational processes. The Internet of Things idea is destined to take off become the next great thing. ECG sensors are being used to assess the efficacy of medical therapies. Those ECG sensors, as these are necessary for remote patient monitoring, reveal several significant flaws. To properly predict cardiac disorders, a varied application perspective is used to continue scanning for patient's ECG, and different data extraction procedures are done on the ECG wave to retrieve credits. The huge volume of data created by IoT devices inside the healthcare area may be examined in the cloud instead of being constrained by the capacity and capabilities of portable electronics. This study proposes a dynamic clinical choice emotionally supportive network for CKD expectations to provide robust restorative administrations (Hosseinzadeh *et al.,* 2020). CKD is frequently regarded as a debilitating illness, particularly in developing nations where access to appropriate treatments is too expensive. IoT, as a variety of values in which simple body sensors and astute predominant communication clinical gadgets are used to consider giving virtual verification of kidney work, plays an important role, — especially where simply a symptom and regenerative intellect places are not effectually accessible to the majority of people (Abdelaziz *et al.,* 2010). This IoHT (Internet of Health Things) technology has a variety of applications in medical care, including the combination of health-monitoring devices like sensors & clinical machines to remotely observe patient data as well as provide perceptive and perceptive federally medical care client administration. In this study, an IoT combination cloud services clinically choice economically supportive Chronic Kidney Disease Network for Prediction and Diagnosis (CKD) through all severity levels are offered to benefit optimal medical care presentations to clients via e-wellness applications.

RELATED WORKS

Detecting sickness at a preliminary phase is the most challenging task. Online information sets for various diseases are available, each with a unique collection of disease-specific features. To decrease the number of items in a dataset as well as select the ones that are most relevant, several image enhancement and component extraction approaches are applied. The variations in performances of a few AI models that used the Part-Based complexities decrease technique on a dataset on Chronic Kidney Disease & Cardiovascular Disease (Lakshmanaprabu *et al.,* 2019) are investigated in this study. The authors compared the outcomes with and without PCA using K Nearest Neighbour, Regression Techniques, SVM (Support Vector Machine), HRNN and Random Forest Model on the datasets. In the area of information, mine and AI, developing the right and economically productive classifiers for clinical applications is a hot topic. The KNN classifier and strategic relapse were shown to be the most reliable strategies for anticipating renal and chronic disease, with a specificity of 100 percent on chronic kidney illness and 85 percent on chronic illness, respectively (Chimwayi *et al.,* 2017). Chronic Kidney Disease is a pro disease that affects the vast majority of individuals worldwide. The key risk factors for CKD include diabetes and hypertension. There are no early signs of CKD, as well as the majority of the cases are discovered after they have progressed. This causes the patient's therapy to still be postponed, which might be fatal. Machine learning algorithms are quite good at predicting Chronic Kidney Disease in its early stages. In this article, four aggregation techniques are used to identify a patient with Chronic Kidney Disease (Chandra *et al.,* 2021). Among the seven performance measures being used to examine machine learning models are accuracy, sensitivity, specificity, F1-Score, and Mathew Correlation Coefficient. AdaBoost and Random Forest outperformed Ensemble Learning and Bagging in terms of effectiveness, precision, and sensitivity. Both the Mathew Correlation Coefficient and the Areas underneath the Curve values with AdaBoost and Random Forest were 100%. The proposed machine learning model used in this study will provide an effective method for avoiding Chronic Kidney Illness by enabling medical practitioners to recognise the chronic disease in its early stages (Zubair Hasan & Hasan, 2019).

CKD occurs when the kidneys are unable to eliminate extra water and waste from the circulation to produce urine adequately. Since this destruction to the kidney takes place gradually over time, the pollution is described as "chronic". As a response to this damage, squanders might form in the body. The aetiology of CKD is uncertain, and several elements influence this illness. Diabetes and high blood pressure are two of the most prevalent causes of CKD (Yaramalla & Singh, 2021). It may be feasible to slow or stop the course of kidney disease if it is treated adequately in the early stages of infection/damage. We are seeking to collect explanatory illustrations from patient reports and present explanations that are commonly comprehended by both experts and laypeople in this study. The projected values obtained from whatever machine learning model are typically correct in most circumstances. However, because the data are ambiguous, an explanation for some instances, such as which reasons are impacting the illness, is necessary. The LIME (Local interpretable model-agnostic explanations) approach is used to accomplish this (Parab *et al.,* 2021).

Diabetes mellitus, as well as its consequences such as heart disease, stroke, renal failure, as well as other comorbidities, is a worldwide public health issue. As a result, it is vital to monitor numerous critical blood signs non-invasively and precisely. This study covers a technique developed in-house for monitoring blood urea and glucose levels in diabetics suffering from Chronic Kidney Disease (CKD). The spectra of 57 research lab samples representing essential blood components were measured (Hasan *et al.,* 2021).

Diabetes is a disease that is affecting people all over the world. It happens when the blood glucose levels are too high, causing kidney, heart and eye issues. Diabetic Retinopathy (DR) was undeniably a retina illness caused by the destruction of retinal veins as diabetes advances. It is considered the leading form of myopia since it develops without causing any symptoms in its beginning phases. It is crucial to detect and characterise DR episodes as quickly as possible to receive appropriate medical assistance. Machine learning algorithms have advanced quickly, and they now play an essential role in clinical applications such as machine diagnostics. Massive volumes of thermal pictures and retina fundus from numerous publically existing datasets are used to train and analyse these systems. These methods are effective at detecting warning signals and determining the severity of DR. The ResNet50 deep learning model was deemed the best approach for performance measures in the targeted frameworks (Ramyea *et al.,* 2021). The Resnet50 features several extractions of elements sections that may be used to extract abundance data from retina images. We believe that our machine learning methods might assist clinicians in making accurate diagnoses and treating DR patients.

Hyperglycemia is a chronic illness characterised by persistently elevated blood sugar levels. Hyperglycemia makes people more vulnerable to illnesses including cardiovascular disease, renal disease, brain haemorrhage, and organ damage. To assess this in the early stages, an AI-based expectation model is developed. The data sets utilised for prediction are frequently insufficient and contain outliers, making it challenging to create an acceptable model. If the precise early prediction is possible, the increased risk and symptoms of hyperglycemia may always be significantly reduced. It is advised to use a suitable emotionally supporting network based on Random Forest with Gradient Boosting classifiers. Arbitrary Forest is a Decision Tree extension that takes information at midpoints and transfers it to a neighbouring tree if it is large part. A modified Random Forest offers 91% expectation exactness. In different random woods, K-cross crease approval was guided by evaluating the 90 percent of the preparation set and 10 percent of the testing set. Hyperparameter tweaking or splitting hubs to determine the number of trees reduces overfitting. The accuracy is enhanced to 90.6 percent by changing the calculation. This disarray grid is being used to count how many accurate and wrong hypotheses there are. The gradient boosting approach reduces the prior tree's error rate. The average accuracy of gradient boosting is enhanced to 89 percent by using N estimators.

METHODOLOGY

Our objective is to utilise a machine learning technique to anticipate chronic kidney illness. CKD occurs when your tissues become damaged and unable to purify the blood as effectively as they should. Because the damage to your kidney happens progressively over time, the strategy is referred to this as "chronic." Wastes may collect in the body as just a result of a disaster. Other health issues might arise as a result of CKD. It affects 10% of the world's population and millions die every year doctors are unable to detect the condition. The system predicts CKD by automation. This program is a great browser programme that numerous hospitals may employ. Based on the HRNN theorem, HRNN is a classification method. On the premise that parameters were independent of one another, it is based on the results of the experiment. The technique is straightforward to implement and performs well when dealing with huge data sets. It has been used because it is capable of estimating the parameters required for classification using just a little quantity of data during the training phase. It excels in multiple class projection. When the requirement of independence is met, an HRNN classifier outperforms conventional models such as logistic regression and requires less training data as shown in Figure 1.

Hybrid-Recurrent Neural Networks (HRNN)

Nonlinear changes are included in deep learning, which is a form of Machine Learning. The input data utilized in various levels with sophisticated architecture is interpreted and examined in a variety of ways. Deep autoencoders, Hybrid-recurrent neural networks (HRNN) and convolutional neural networks are examples of deep learning models (CNN). The approaches outlined above can be used for a variety of purposes, including language modelling, voice recognition, and medical applications. The HRNN modifies the prior input by modifying the character of the current forward process. Some areas in the histopathological photographs are spread over many nearby slices, resulting in a succession of similar slices. The HRNN approach, which consists of four distinct layers, is being used to solve complex problems and classify enormous datasets. A subclinical picture of 32 32 M classes is sorted using an HRNN in Figure 2, where A, B, and C are ascribed.

At this phase, the equivalent size from both the component map is reduced and transferred to the following stage, presuming the deep learning model delivers the outcome to fairly estimate the class.

EXPERIMENTAL RESULTS AND DISCUSSIONS

Dataset Description

CKD from the University of California, Irvine Repository was used in this study. This dataset has 400 occurrences with 25 characteristics, 14 of which would be classified and 11 of which are statistics. There are 14 category attributes and 11 numerical attributes in total. There are just two values in the output variable: "CKD" indicates successful identification of Chronic Kidney Disease and "notckd" for null identification of Chronic Kidney Disease.

Dataset Pre-Processing

First, an uncontrolled attribute filter known as 'Numeric Cleaner' was employed to classify the missing values across all

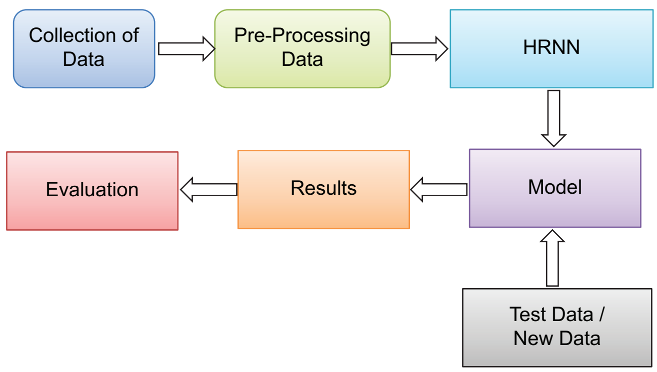

Figure 1: Architecture of Proposed Methodology.

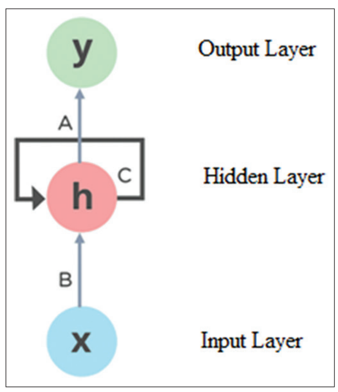

Figure 2: Proposed System of HRNN Classification.

attributes. If the number of missing values was significantly less than the total number of instances, the instances with missing values were destroyed using the unattended instance filter's 'Remove Values' rule. Whenever the number of unknown entries in an attribute exceeds a certain threshold, the attribute is destroyed. The missing values in the dataset were replaced with attribute mean values in this case.

Task of Feature Selection

Strategies of feature as well as attribute selection are being used to detect and remove unwanted and redundant features from the dataset that do not contribute to prediction accuracy or may reduce model accuracy. There are two broad methods for the job of feature selection:

Wrapper Technique

The wrapper technique is used in this article to determine the most precise collection of the 24 characteristics capable of producing high quality detection of CKDs. The induction algorithm, which operates as a black box, is used to pick the subset attribute in the wrapper method. The wrapper's strategy is that it searches for feasible parameters and, because of its robustness, uses 'best first search' as a tool in this study. The goal is to choose the most promising group. The best initial search ends when the objective is achieved. Because it is an optimisation issue, the searching can be stopped at any moment and the best solution identified so far is returned.

Embedded Technique

This project uses the embedded technique to create and score CKD detection features, resulting in good prediction while also eliminating unnecessary and obsolete attributes. Embedded approaches determine whether features contribute to model correctness during the development process.

Algorithm for HRNN with Implementation steps:

Step 1: Analyze the Dataset

Step 2: Calculate the probability of each attribute value. [m, m z, n, Q]

Using the following formula, we determine the probability of recurrence for each attribute. The equations should be used for each ailment.

Step3:Usetheformulae: $Q\frac{(attribute\,value\;(xj))}{subject\;value\,bk}=\frac{(m\_z+nq)}{(m+n)}$

Where:
m = the amount of training instances for which b = bk
m_z= amount of instances for which b = bk and x = xj
q = a preliminary estimate for Q(xjkbk)
n = the corresponding sample size

Step 4: Divide the probability by q.

Step 5: Comparing the findings, assign each parameter value to one of the class categories generated.

As demonstrated in Figure 3 and 4, it is expected to result in increased predictive value and is also described as the average likelihood of relevant retrieval.

The recommended model's confusion matrix is provided for a given dataset in Figure 5, that are based upon epoch durations of 1800 and 2000, accordingly. It's worth noting that the accuracy achieved also with 2000 epoch size is significantly better than the accuracy recorded only with 1800 epoch size.

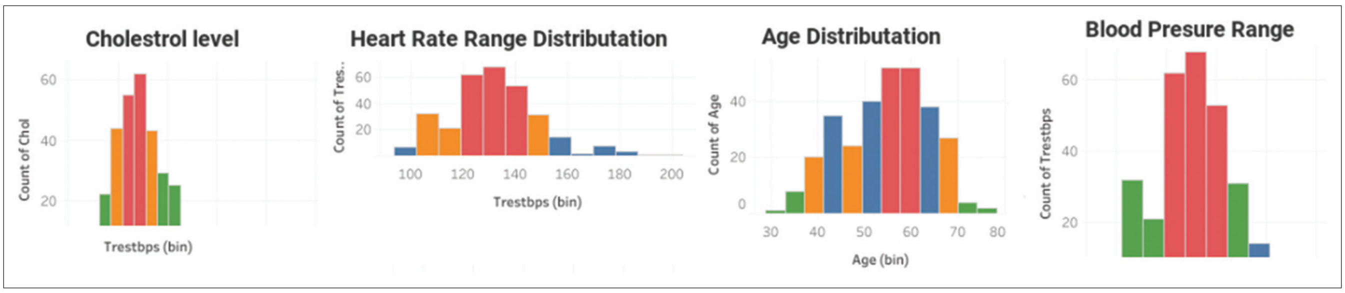

Figure 3: CKD vs heart disease dataset attribute descriptions.

```
Confusion matrix :
 [[2 2]
 [1 5]]
Outcome values :
 2 2 1 5
Classification report :
              precision    recall  f1-score   support

           1       0.67      0.50      0.57         4
           0       0.71      0.83      0.77         6

   micro avg       0.70      0.70      0.70        10
   macro avg       0.69      0.67      0.67        10
weighted avg       0.70      0.70      0.69        10
```

Figure 4: Classification Output.

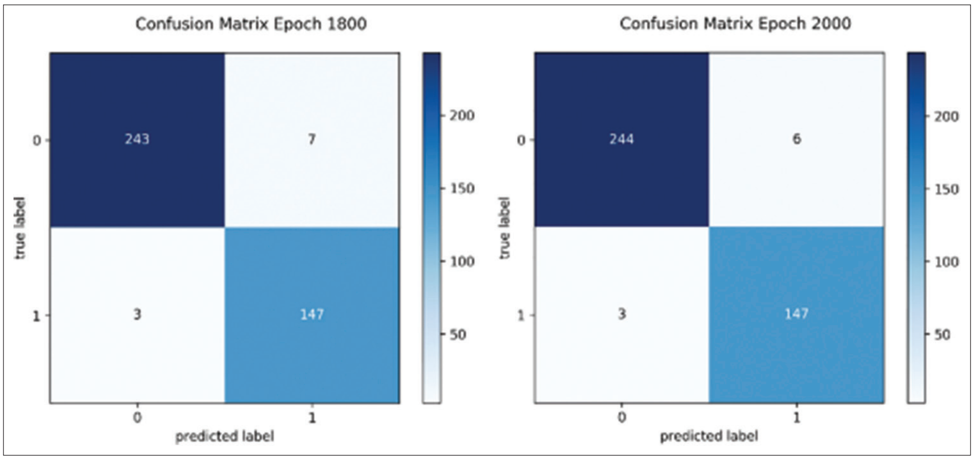

Figure 5: Confusion matrix for given dataset.

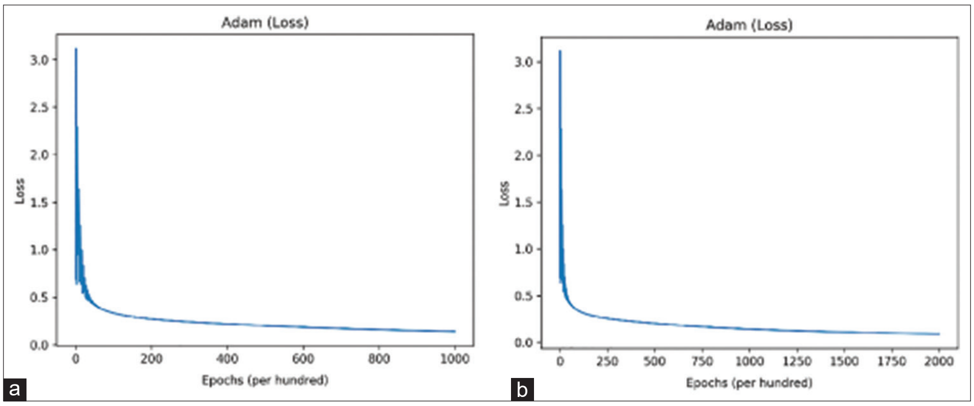

Figure 6: (a and b) Loss rate evaluation of 1800 Epochs and 2000 Epochs.

Figure 6 shows the loss rate analysis of the proposed model for epoch sizes of 1800 & 2000, respectively. The loss rate achieved with a value of 2000 epoch is substantially lesser when compared with simply an 1800 epoch size, showing a considerable improvement.

CONCLUSION

We have developed a unique approach to CKD identification using a combination of machine learning methods such as the HRNN algorithm. We assessed a cohort comprising 400 patients, 250 of whom had early stage CKD. This data set has some noisy values that are missing. As a result, classification algorithms now have the capacity to deal with missing and noisy inputs. We utilized two strategies for feature reduction: the Wrapper Method as well as LASSO Regularisation. These methods assisted in reducing overfitting and identifying the most relevant predictive variables for CKD. Notably, the outcomes of this experiment introduce additional factors that classifiers will utilise to identify CKD more effectively than current formulae and FRNN have the highest prediction accuracy rates. Machine Learning has filled in the clinical field to make instruments and assess information connecting with sicknesses. As a result, machine learning techniques play a critical role in achieving illness diagnosis in advance.

REFERENCES

Abdelaziz, A., Salama, A. S., Riad, A. M., & Mahmoud, A. N. (2019). A machine learning model for predicting of chronic kidney disease based internet of things and cloud computing in smart cities. In Security in Smart Cities: Models, Applications, and Challenges (pp. 93-114). Springer, Cham.

Al-Makhadmeh, Z., & Tolba, A. (2019). Utilizing IoT wearable medical device for heart disease prediction using higher order Boltzmann model: A classification approach. *Measurement, 147*, 106815. https://doi.org/10.1016/j.measurement.2019.07.043

Arulanthu, P., & Perumal, E. (2020). An intelligent IoT with cloud centric medical decision support system for chronic kidney disease prediction. *International Journal of Imaging Systems and Technology, 30*(3), 815-827. https://doi.org/10.1002/ima.22424

Chandra, R., Kapil, M., & Sharma, A. (2021). Comparative Analysis of Machine Learning Techniques with Principal Component Analysis on Kidney and Heart Disease. In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1965-1973). IEEE.

Chimwayi, K. B., Haris, N., Caytiles, R. D., & Iyengar, N. C. S. (2017). Risk level prediction of chronic kidney disease using Neuro-fuzzy and hierarchical clustering algorithm (s). *International Journal of Multimedia and Ubiquitous Engineering, 12*(8), 23-36. https://doi.org/10.14257/ijmue.2017.12.8.03

Ganesan, M., & Sivakumar, N. (2019). IoT based heart disease prediction and diagnosis model for healthcare using machine learning models. *IEEE International Conference on System, Computation, Automation and Networking (ICSCAN-2019)* (pp. 1-5). IEEE. https://doi.org/10.1109/ICSCAN.2019.8878850

Golande, A., Sorte, P., Suryawanshi, V., Yermalkar, U., & Satpute, S. (2019). Smart hospital for heart disease prediction using IoT. JOIV. *International Journal on Informatics Visualization, 3*(2-2), 198-202. https://doi.org/10.30630/joiv.3.2-2.251

Hasan, D. A., Zeebaree, S. R., Sadeeq, M. A., Shukur, H. M., Zebari, R. R., & Alkhayyat, A. H. (2021). Machine Learning-based Diabetic Retinopathy Early Detection and Classification Systems-A Survey. In 2021 1st Babylon International Conference on Information Technology and Science (BICITS) (pp. 16-21). IEEE.

Hosseinzadeh, M., Koohpayehzadeh, J., Bali, A. O., Asghari, P., Souri, A., Mazaherinezhad, A., Bohlouli, M.,& Rawassizadeh, R. (2020). A diagnostic prediction model for chronic kidney disease in internet of things platform. *Multimedia Tools and Applications*, *80*, 16933–16950 (2021). https://doi.org/10.1007/s11042-020-09049-4

Jabeen, F., Maqsood, M., Ghazanfar, M. A., Aadil, F., Khan, S., Khan, M. F., & Mehmood, I. (2019). An IoT based efficient hybrid recommender system for cardiovascular disease. *Peer-to-Peer Networking and Applications, 12*(5), 1263-1276. https://doi.org/10.1007/s12083-019-00733-3

Khan, M. A. (2020). An IoT framework for heart disease prediction based on MDCNN classifier. *IEEE Access, 8*, 34717-34727. https://doi.org/10.1109/ACCESS.2020.2974687

Lakshmanaprabu, S. K., Mohanty, S. N., Krishnamoorthy, S., Uthayakumar, J., & Shankar, K. (2019). Online clinical decision support system using optimal deep neural networks. *Applied Soft Computing, 81*, 105487. https://doi.org/10.1016/j.asoc.2019.105487

Parab, J., Sequeira, M., Lanjewar, M., Pinto, C., & Naik, G. (2021). Backpropagation Neural Network-Based Machine Learning Model for Prediction of Blood Urea and Glucose in CKD Patients. *IEEE Journal of Translational Engineering in Health and Medicine, 9*, 1-8. https://doi.org/10.1109/JTEHM.2021.3079714

Ramyea, R., Preethi, S., Keerthana, K., Keerthana, R., & Kavivarman, J. (2021, November). An intellectual supervised machine learning algorithm for the early prediction of Hyperglycemia. In 2021 Innovations in Power and Advanced Computing Technologies (i-PACT) (pp. 1-7). IEEE.

Yaramalla, D., & Singh, T. (2021). A Machine Learning Paradigm for Explanatory Cases with CKD. In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-7). IEEE.

Zubair Hasan, K. M., & Hasan, Z. (2019). Performance evaluation of ensemble-based machine learning techniques for prediction of chronic kidney disease. In Emerging research in computing, information, communication and applications (pp. 415-426). Springer, Singapore.