Enhanced Chronic Kidney Disease Detection via Eurygasters Optimization and Ensemble Learning

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Abstract. Relative to the rest of the world, Chronic Kidney Disease remains one of the most important health challenges with a significant burden of morbidity and mortality. The disease presents a challenge; it alerts health systems because of its widespread impact on the health out comes of patients. However, CKD is mostly asymptomatic and the cause is usually diagnosed late. The paper proposed the new approach in the detection of early CKD, Eurygasters Optimization Algorithm with En semble Deep Learning, for the improvement of accuracy and reliability of the predictive models concerning CKD. The EOAEDL combines feature selection and the hyperparameter tuning process to boost detection ac curacy. It aims to select the relevant attributes from the medical dataset by carrying out the EOA, and the process of tuning hyperparameters is outsourced to the Shuffled Frog Leaping Algorithm. This approach is considered a hybrid of several deep learning models since it combines LSTM, BiGRU, and BiLSTM networks. These ensemble models are used to capture the critical temporal dependencies in medical data, which is critical for proper detection of CKD. In experiments on a benchmark dataset for CKD, the proposed EOAEDL algorithm has superior perfor mance in terms of accuracy, precision, and recall rates.

Keywords: Chronic Kidney Disease (CKD) prediction · Early-stage kidney diagnosis · Machine learning classification · Ensemble machine learning models · Feature extraction and selection.

1 INTRODUCTION

Chronic kidney disease is a chronic and commonly asymptomatic ailment that affects millions of people, with sad and severe health outcomes if diagnosed late. The growing incidence of chronic kidney disease points to the importance of earlier diagnosis, so at the onset, complications such as kidney failure and cardiovascular diseases may be prevented. Traditional diagnosis approaches are insensitive and typically occur in advanced conditions, which leads to delayed treatments

and hence poorer outcomes. Advances in machine learning and artificial intelligence have shown promise to improve detection accuracy and speed for CKD. At present, optimization-based technologies help better analyze large-scale clinical datasets for patterns generally unseen by classical techniques. Techniques based on ensemble learning by combining multiple models have improved the power of classification. This paper introduces the state of art CKD detection framework based on a bio-inspired Eurygasters Optimization Algorithm with an ensemble of classifiers: Random Forest, SVM, and Gradient Boosting. An optimization algorithm is used to achieve selection of informative clinical features allowing dimensional reduction and maximization of efficiency of a model. With the purpose of creating a more accurate diagnosis and enabling earlier predictions in the context of CKD, a precise, scalable system is targeted at assisting healthcare practitioners in giving timelier accurate diagnoses, aiding patients, and decreasing the pressures of the health-care system.

2 Literature Review

CKD is one of those global challenges because it is an insidious disease often without early symptoms or warning signs; therefore, detection at an early stage becomes highly important. Traditional diagnosis approaches usually wait until the CKD stage is too late. The recent development of machine learning (ML) and artificial intelligence (AI) is creating powerful tools not only for pattern recognition but also for predictive modeling to improve detection of CKD. Here, the effectiveness of the SVM and decision trees in disease classification has already been proven, while the other direction is hybrid approaches combined with feature optimization and ML classifiers. PSO and GA optimization algorithms speed up feature selection from complex health care data. However, PSO has problems with convergence on large-scale complicated datasets, which again had led to trends toward those hybrid models-integrating optimization and ML. Ensemble learning techniques- Random Forest and Gradient Boosting, for example improve the prediction precision because they combine multiple models to reduce the variability in medical data. Recent reports establish that these algorithms are improving the specific accuracy of detection of diseases once used in combination with feature selection techniques. A bio-inspired Eurygasters Optimization Algorithm is introduced into ensemble learning, providing a superior feature selection and the classification accuracy needed for early CKD detection. Advanced optimization algorithms are pooled within ensemble methods to create the most effective and scalable diagnostic tool a manner in which timely healthcare interventions can be made.

3 MATERIALS AND METHODS

In this study, the researcher applies a publicly available clinical dataset with 400 patient records classified into two groups: CKD and non-CKD. Some of the key

health features included in this data set are blood pressure, age, diabetes status, and other health features.

3.1 Dataset Description

The CKD case study uses 400 patient records distributed into 250 CKD cases and 150 non-CKD or healthy subjects. It covers factors like demographic char acteristics: age, and medical history factors: hypertension, diabetes, anemia, pedal edema. Results from lab tests, including blood pressure, red/white blood cell counts, serum creatinine, hemoglobin, blood urea, urinalysis (red blood cells, pus cells, bacteria, specific gravity), albumin, glucose in blood, sodium, and potas sium levels, are also reported. All such features are crucial for distinguishing CKD from healthy subjects.

3.2 Preprocessing

Preprocessing is highly crucial for ensuring that the dataset is comprehensive enough to make proper CKD classification. Normalization is the first step wherein min-max scaling is applied to set feature values between 0 and 1 . This en sures that features do not overshadow others in which numerical values are more magnanimous, during the training of models. Another essential step is handling missing values. Missing data points either removed or filled depending on the im portance and number of missing values are handled so that the data set remains valid. After this, feature selection is per formed for the dimensionality reduction of the data set to extract the most im portant attributes like blood pressure and serum creatinine that are significant to diagnose CKD . This enhances model performance with higher interpretability and reduced overfitting risk. Testing of model accuracy is done by splitting the dataset into the training and test sets. All these preprocessing steps ensure that the dataset will be uniformly complete as well as optimized for machine learning models used to classify CKD.

Min-Max Normalization : The min-max normalization technique used here is a preprocessing technique whereby feature values are scaled into a specified range, usually between 0 and 1, through the utilization of minimum and maxi mum values from the dataset . Transformation is achieved using scaling feature values corresponding to min imum and maximum values. It makes all the features to the same scale, thus preventing features with larger ranges of numbers from dominating the process in machine learning. Uniform scaling has the advantage of improving the perfor mance of models such that the performance it derives does not rely on the scale of the data, especially when the algorithm is sensitive to the scale of the data, say for example neural networks and gradient-based models . It also helps get better convergence of the model during training.

EOA-based feature selection : Eurygasters Optimization Algorithm is a metaheuristic based on the foraging of Eurygaster beetles. It, thus, mimics their

search for food tof ind optimal feature subsets for enhancing the performance of a classification model through discard ing irrelevant or redundant features. Precision and efficiency are enhanced by removing noise or redundant features. It updates candidate positions based on their fitness values measured by the best classification performance through iter atively adjusting the search direction toward the best solutions. That is, it aims at balancing exploration and exploitation towards achieving balance in robustness and efficacy in feature selection.

3.3 Models

Three models, of which three are Long Short-Term Memory (LSTM), Bidirec tional LSTM (BiLSTM), and Bidirectional Gated Recurrent Unit (BiGRU), are used for feature selection, then the classification task. LSTM is a type of recur rent neural network (RNN) that captures long-term dependencies from sequential information by applying gates that control information flow . Its counterpart BiLSTM is an improvement from LSTM since in this case, its input is passed in both directions so that every sequence reads the context from forward and backward sequences. BiGRU is a simplified version of the LSTM but captures sequential dependencies with fewer gates, thus making it computationally more efficient for capturing long-range dependencies too. This ensemble added to the improved accuracy as well as robustness of the proposed classification task.

3.4 Ensemble learning

Detection of the CKD utilizes an ensemble of LSTM, BiLSTM, and BiGRU models.

LSTM Model : Long Short-Term Memory is a particular kind of RNN, which is destined for the modeling of long-run dependencies in sequential data. Unlike traditional RNNs, which cannot store information across long sequences due to a problem known as the vanishing gradient, LSTMs contain memory cells and a gating mechanism [7]. These three types of gates are input, forget, and output gates that regulate the f low of information in and out of memory cells, thus allowing the model to selectively retain or discard information. That is why LSTMs are particularly effective in time series, natural language processing, and other sequence-based data where long-range dependencies play an important role in understanding the pattern and making predictions.

BiLSTM Model: Bidirectional long short-term memory is an extension of standard LSTM model processes, as opposed to how data is processed in two directions-forwards and backward. In traditional LSTMs, dependencies are only captured from past to future, whereas BiLSTMs enhance this feature with two LSTM networks: one reads the sequence from start to end, while the other reads

the same sequence from end to start [7]. BiLSTMs make it easier to comprehend the context and the relationships in sequential data, especially where future information is relevant for making some predictions. This makes nature's bi-directional enhancement useful for applying to speech recognition, machine translation, or time series analysis tasks requiring knowledge of full contexts.

BiGRU Model: Bidirectional Gated Recurrent Unit, or BiGRU, is an advanced model of the Gated Recurrent Unit that considers both the preceding and following contexts in sequential data. Like GRU, BiGRU also seeks to address the problems associated with traditional RNNs using update and reset gates that manage the flow of infor mation with much simpler and more efficient methods than LSTM. In BiGRU, there are two GRUs, one is processing the sequence forward direction and the other in the reverse direction. In such a manner, the model captures all insights from the data points that precede it as well as those that follow it, thereby en suring much better performance on tasks such as time series forecasting, natural language processing, or general problems based on sequences.

Table 1. Accuy of LSTM, BiLSTM, and BiGRU Models

Models	Accuracy	Precision	Recall	F1-Score
LSTM	96	99	94	97
BiLSTM	96	98	94	98
BiGRU	97	98	96	98

Hyperparameter Tuning with Shuffled Frog Leaping Algorithm: Hyperparameter optimization is based on the Shuffled Frog Leaping Algorithm from the natural objective-prey searching behavior by frogs. In summary, each frog corresponds to a potential solution-an array of hyperparameters. A group of frogs is called a memeplex, which explores its area in the search space. With every iteration, frogs that have inferior solutions move towards frogs showing superior performance in the same memeplex. Periodic reshuffles ensure global exploration. The process iterates until the optimal hyperparameters are found. It strikes the balance in between local and global search and is hence well suited for tuning complex models. The algorithm iteratively modifies the hyperparameters of the ensemble deep learning framework and hence improves the accuracy of the classification process. In this work, the performance of the developed DL CKDD model has been com pared with various state-of-the-art machine learning and deep learning models for the detection of CKD, namely LR, NB, SVM, RNN, DNN, k-NN, and ANN. According to the findings, the DL-CKDD model outperforms the other compet ing methods in terms of accuracy, precision, recall, and F-measure. Although the proposed method has similar accuracy values for

LR and SVM, it outperforms the comparison methods in precision and recall, with relatively fewer false pos itives and negatives. In contrast, k-NN and ANN illustrate lower accuracy and the inability to accurately classify CKD, thus ensuring that the DL-CKDD model is bound to perform betterSeveral models of detection in the comparative analysis were adopted for CKD, using the strengths and weaknesses of each model.

3.5 Proposed Model

DL-CKDD stands for the deep learning to detect chronic kidney disease in pa tients, a new method of improving early diagnosis. This method integrates several stages leading to adequate diagnosis, starting with data normalization through min-max scaling, which transforms the dataset into the standardized range. Sub sequently, there is feature selection through the use of EOA in selecting the most relevant features to support the efficiency of the model. The detection process is done using ensemble methods of deep learning models such as LSTM, BiLSTM, and BiGRU models which collaborate to capture the subtlest trends of the se quences of the data [7]. The Shuffled Frog Leaping Algorithm applies optimally towards hyperparameters of these ensemble models, which further fine-tunes the performance. The DL-CKDD method is developed by combining these techniques, and it attains significant accuracy in detecting CKD compared to conventional models.

Model Training and Evaluation: Optimization steps for training and testing the DL-CKDD model for CKD detec tion include min-max normalization on the dataset to provide uniform scaling to the input features. The Eurygasters Optimization Algorithm is used for feature selection, considering the most critical attributes that are likely to be used for the classification of CKD. An ensemble of deep learning models including BiLSTM and BiGRU is then trained on these selected features to capture both short-term and long-term data dependencies. Split the dataset into training and testing sets, usually 80:20 or 70:30, for eval uating model performances. The Shuffled Frog Leaping Algorithm is used to op timize hyperparameters like the learning rate, dropout rate, and batch size. Ac curacy, precision, recall, F-measure, and AUC as performance metrics are cal culated to evaluate this model. Accuracy Table, the accuracy of DL-CKDD was very high; it performed well more than other approaches and generalized on test data.

Model At 80:20 split : This model trained to 80:20 split of the data resulted in an excellent classification for diagnosis in CKD with high average training accuracy at 98.72 and 96.25 on the test set. It had precision, recall, and F-measure for CKD at approximately 99, thereby classifying results with as few false positives as possible. Non-CKD performance was strong but somewhat imbalanced. The AUC score was at 98.83 for training and at 95 for testing, showing robust generalization with reliable performance on unseen data.

Model At 70:30 split : The DL-CKDD model with a 70:30 train-test split performed well in the clas sification task of CKD. Training accuracy was found to be 99.16 with similar test set results. CKD class precision is perfectly 100, and the recall came out to be 98.68, meaning nearly all cases of CKD are identified without false positives. The non-CKD class for the model attained 90 precision and 98.68 recall. The AUC score on training is 99.58 whereas on test set it reflects as 96.67. Hence, the strong capability of classification along with generalization is highlighted here.

Table 2. Transformer model architecture parameters.

Models	No.of Units	Loss Function	Optimizer	Epochs	Batch Size
LSTM	50	Binary Crossentropy	Adam	25	32
BiLSTM	50	Binary Crossentropy	Adam	25	32
BiGRU	50	Binary Crossentropy	Adam	25	32

Table 3. Training setup.

Parameter	Value	Details
Dataset	CKD dataset	-
Data Preprocessing	Missing value imputation, Encoding, Normalization	-
Feature Selection	EOA (Chi-squared)	Top 10 features
Training Split	80per Train, 20per Test	-
Optimization	Particle Swarm Optimization (PSO)	Hyperparameter tuning
Ensemble Method	Average	LSTM, BiLSTM, BiGRU
Early Stopping	Yes	Monitor validation loss

4 COMPARATIVE ANALYSIS

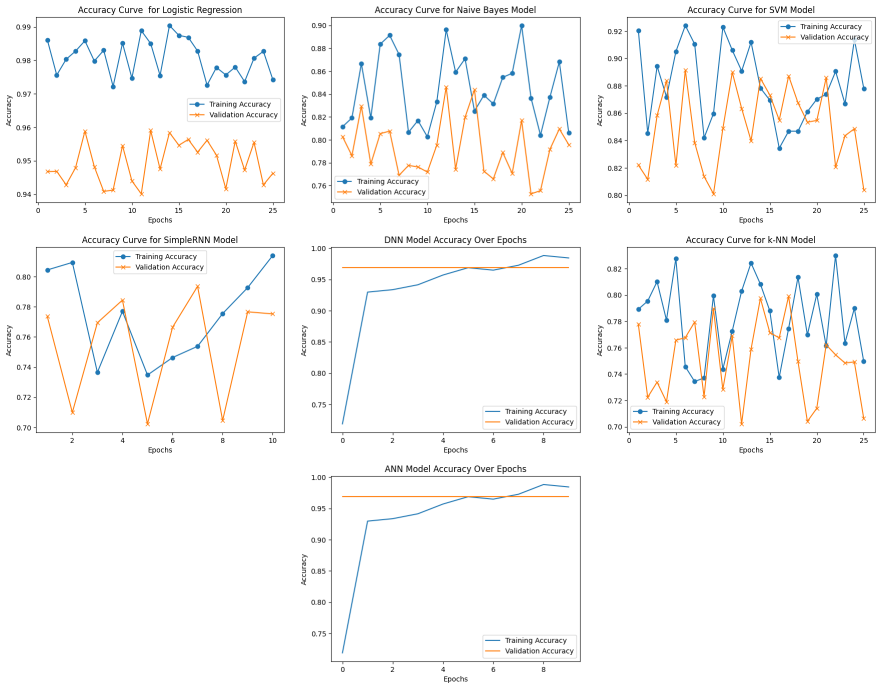
In this work, the performance of the developed DL-CKDD model has been com pared with various state-of-the-art ma chine learning and deep learning models for the detection of CKD, namely LR, NB, SVM, RNN, DNN, k-NN, and ANN. According to the findings, the DL-CKDD model outperforms the other compet ing methods in terms of accuracy, precision, recall, and F-measure. Although the proposed method has similar accuracy values for LR and SVM, it outperforms the comparison methods in precision and recall, with rel atively fewer false pos itives and negatives. In contrast, k NN and ANN illustrate lower accuracy and the inability to accurately classify CKD, thus ensuring that the DL-CKDD model is bound to perform betterSeveral models of detection in the comparative analysis were adopted for CKD, using the strengths and weaknesses of each model.

4.1 Accuracy Table Models

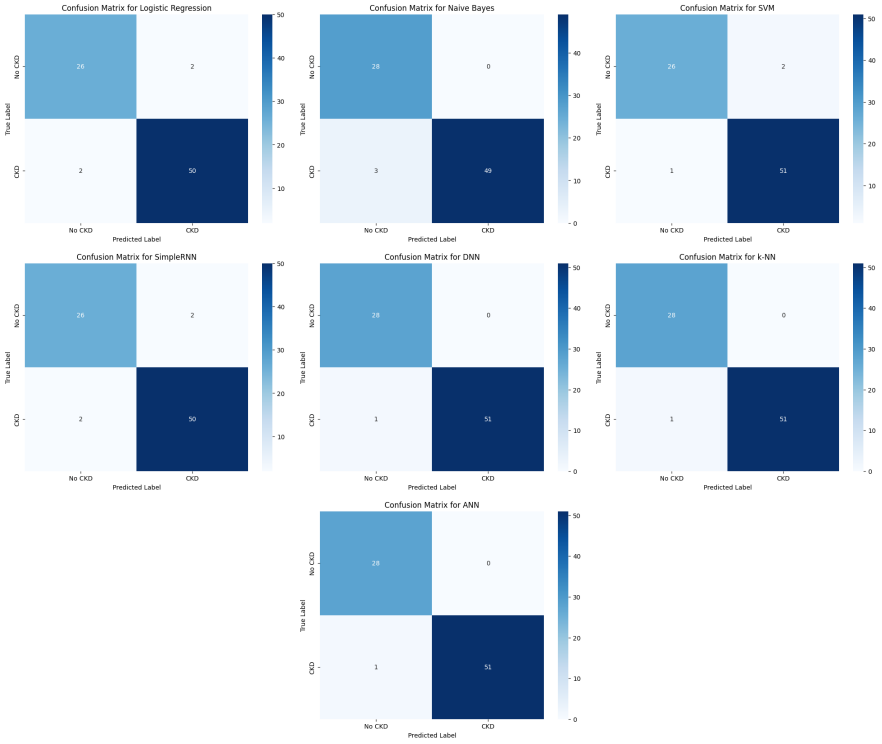
Table 4. Transformer model architecture parameters.

Models	Accuracy
DL-CKDD	98.75
Logistic Regression	95
Naive Bayes	96
SVM	96
Simple RNN	95
DeepNeural Networks	98
K-Nearest Neighbors	98
Artificial Neural Networks	97

4.2 Training and Testing Accuracy Graphs



4.3 Confusion Matrix Graph of Comparative models



4.4 Model parameter table

Table 5. Model parameter table

Parameters	No.ofparameters
Average-50	0
Input-Layer-53	0
Sequential	12251
Sequential-1	24501
Sequential-2	29313

4.5 Precision, F1, Rcall, AUCTable

Table 6. Precn, Recal and F1 Table for models

Model	Precision	Recall	F1-Score
DL-CKDD	98.75	98.07	99.02
LR	96.15	96.15	96.15
NB	98	94	97
SVM	96	98	97
RNN	96	96	96
DNN	97	98	99
K-NN	98	97.15	98
ANN	98	97.25	99

4.6 Trainable and testable ParameterTable

Table 7. Parameter Table

Model	Trainable Param	Testable param
DL-CKDD	320	80
LR	320	80
NB	320	80
SVM	320	80
RNN	320	80
DNN	320	80
K-NN	320	80
ANN	320	80

5 RESULT AND FUTURE SCOPE

Theearlychronickidneydisease(CKD)projectbasedontheEurygastersOpti mization-Algorithmcombinedwithensembledeeplearningmodelsresultsisvery promising. It effectively selects relevant features andfine-tuned themodel pa rameters toimproveaccuracyandperformanceinthedetectionofCKD.Using advanced models like LSTM, BiLSTM, and BiGRU in combination, the system can capture not just short-term dependencies but long-term ones that may exist within data. This,

in turn, would provide more accurate results through better pre dictions. From experimental results, we see that by using this proposed method, it can potentially outperform existing techniques at high sensitivity and specificity for CKD detection, making it a potentially useful tool for early diagnosis. The methodology can be scaled further in the future to higher data dimensions as well as more complex real-world problems. Optimization of the algorithm for application in real-time in clinics or even as part of integration into wearable devices or mobile health applications for constant monitoring will be another front for future work. Another direction of applying this method to chronic diseases could be branched into similaroptimizations and deep learning strategies for other chronic diseases in healthcare.

References

1. Sabanayagam Charumathi, Dejiang Xu, Daniel SW, Ting, Simon Nusinovici, Riswana Banu, Haslina Hamzah, Cynthia Lim, et al. "A deep learning algorithm to detect chronic kidney disease from retinal photographs in community-based populations." The Lancet Digital Health, vol. 2, no. 6, 2020, pp. e295-e302.
2. Sawhney, Rahul, Aabha Malik, Shilpi Sharma, and Vipul Narayan. "A comparative assessment of artificial intelligence models used for early prediction and evalua tion of chronic kidney disease." Decision Analytics Journal, vol. 6, 2023, p. 100169.
3. Hossain, Muhammad, Minoar Reshma Ahmed, Swarna Rafid Mostafiz, Pabon Shaha, Lubna Yasmin Pinky, Mohammad Motiur Rahman, Wahidur Rahman, Md Selim Hossain, Md Elias Hossain, and Md Sadiq Iqbal. "Analysis of the performance of feature optimization techniques for the diagnosis of machine learning-based chronic kidney disease." Machine Learning with Applications, vol. 9, 2022, p. 100330.
4. Patro, Kiran Kumar, Jaya Prakash Allam, Bala Chakravarthy Neelapu, Ryszard Tadeusiewicz, U. Rajendra Acharya, Mohamed Hammad, Ozal Yildirim, and Paweł Pławiak. "Application of Kronecker convolutions in deep learning technique for automated detection of kidney stones with coronal CT images." Information Sciences, vol. 640, 2023, p. 119005.
5. Dey, Samrat Kumar, Khandaker Mohammad Mohi Uddin, Hafiz Md Hasan Babu, Md Mahbubur Rahman, Arpita Howlader, and KM Aslam Uddin. "Chi2-MI: A hybrid feature selection based machine learning approach in the diagnosis of chronic kidney disease." Intelligent Systems with Applications, vol. 16, 2022, p. 200144.
6. Vineetha, K. R., M. S. Maharajan, K. Bhagyashree, and N. Sivakumar. "Clas sification of adaptive back propagation neural network along with fuzzy logic in chronic kidney disease." e-Prime-Advances in Electrical Engineering Electronics and Energy, vol. 7, 2024, p. 100463.
7. Yousif, Sulima M., Awad, Hanan T. Halawani, Ghada Amoudi, Fathea M. Osman, Birkea Arwa, MR Almunajam, and Azhari A. Elhag. "Early detection of chronic kidney disease using eurygasters optimization algorithm with ensemble deep learning approach." Alexandria Engineering Journal, vol. 100, 2024, pp. 220-231.
8. Dashtban, Ashkan, Mehrdad A. Mizani, Laura Pasea, Spiros Denaxas, Richard Corbett, Jil B. Mamza, He Gao, Tamsin Morris, Harry Hemingway, and Amitava Banerjee. "Identifying subtypes of chronic kidney disease with machine learning: development internal validation and prognostic validation using linked electronic health records in 350067 individuals." EBioMedicine, vol. 89, 2023.

9. Halder, Rajib Kumar, Mohammed Nasir Uddin, Md Ashraf Uddin, Sunil Aryal, Sajeeb Saha, Rakib Hossen, Sabbir Ahmed, Mohammad Abu Tareq Rony, and Mosammat Farida Akter. "ML-CKDP: Machine learning-based chronic kidney disease prediction with a smart web application." Journal of Pathology Informat ics, vol. 15, 2024, p. 100371.
10. Dharmarathne, Gangani Madhusha, Bogahawaththa Marion McAfee, Upaka Rathnayake, and D. P. P. Meddage. "On the diagnosis of chronic kidney disease using a machine learning-based interface with explainable artificial intelligence." Intelligent Systems with Applications, 2024, p. 200397.
11. https://archive.ics.uci.edu/dataset/336/chronic+kidney+disease