INTEGRATION OF ROBOTIC AUTOMATION AND AI FOR IOMT-BASED CHRONIC KIDNEY DISEASE PREDICTION USING TYPE-2 FUZZY LOGIC AND RECURRENT NEURAL NETWORKS (RNN)

Sri Harsha Grandhi[1, *], Qamar Abbas[2], Raj Kumar Gudivaka[3], Dinesh Kumar Reddy Basani[4]

[1]Intel, Folsom, California, USA. Email: sriharshagrandhi@ieee.org
[2]Department of Computer science, Faculty of Computing and Information Technology, International Islamic University, Islamabad, 44000, Pakistan. Email: qamar.abbas@iiu.edu.pk
[3]Surge Technology Solutions Inc, Texas, USA. Email: rajkumargudivaka@ieee.org
[4]CGI, British Columbia, Canada. Email: dineshkumarreddybasan@ieee.org

ABSTRACT

This paper introduces a novel approach for predicting chronic kidney disease (CKD) by integrating advanced technologies, including the Internet of Medical Things (IoMT), robotic automation, and artificial intelligence (AI). The proposed system leverages Recurrent Neural Networks (RNN) to analyze temporal patterns in patient data and employs Type-2 fuzzy logic to handle uncertainties and imprecision in medical data. By incorporating robotic automation, the method enhances data processing efficiency, reducing human error and increasing productivity. The strategy enables real-time monitoring and provides individualized healthcare interventions, offering significant improvements in CKD prediction accuracy and effectiveness. Compared to traditional methods, this approach demonstrates substantial benefits, achieving 94.5% accuracy, 92.3% precision, and a rapid computing time of just 3.2 seconds. The proposed methodology addresses common challenges in medical diagnostics, such as data inconsistency, and holds the potential to transform CKD management by facilitating early detection and personalized treatment strategies.

Keywords: Chronic Kidney Disease, Type-2 Fuzzy Logic, Recurrent Neural Networks, Internet of Medical Things, Robotic Automation.

1. INTRODUCTION

1.1 Overview of CKD and AI Integration

The healthcare industry has witnessed a notable enhancement in disease prognosis, patient management, and diagnostic accuracy with the incorporation of robotic automation and artificial intelligence (AI). The use of artificial intelligence (AI) and the Internet of Medical Things (IoMT) to forecast chronic kidney disease (CKD) is the main topic of this work. The system makes use of Type-2 Fuzzy Logic and Recurrent Neural Networks (RNNs) to tackle issues like inconsistent and uncertain data that are frequently encountered in medical diagnostics. The healthcare sector is being revolutionized by artificial intelligence (AI), which has applications in everything from tailored treatment plans to disease diagnostics. Medical imaging is increasingly using AI algorithms to accurately identify problems including cancer, heart disease, and neurological issues. In order to forecast disease outcomes, identify individuals who are at risk, and suggest preventive measures, machine learning algorithms examine patient data. Robotic devices with AI capabilities aid in surgery, increasing accuracy and speeding up recuperation. Furthermore, AI helps with drug research by identifying possible medicinal molecules by evaluating intricate biological data. Along with improving patient outcomes and clinical decision-making, these developments also increase the effectiveness of healthcare delivery.

Robotic automation and artificial intelligence integration into the healthcare have remarkably improved disease prognosis, patient management as well diagnostic accuracy.

1.2 Scope and Objectives of the Study

This work presents artificial intelligence (AI) and the Internet of Medical Things (IoMT), which have been

*Corresponding author. Email: sriharshagrandhi@ieee.org

employed for prediction CKD. Using Type-2 Fuzzy Logic and Recurrent Neural Networks (RNNs), the system also addresses problems with working on inconsistent and uncertain data which are quite common in medical diagnostics.

Prediction accuracy with both Type-2 Fuzzy Logic is used for handling data uncertainties in a better way compared to the other techniques. RNNs, however, further relax this assumption and better model the dependence between consecutive patient data points to make a more reliable prediction system. This combination endeavors to change the face of health care systems by improving productivity and enhancing capability for real time forecasting of chronic diseases like CkD.

This new method gives the system more ability for personalized recommendations and actions, but also attempts to improve CKD prediction accuracy. The integration has enabled much deeper use of AI in healthcare and the creation a new generation of more intelligent and trusted decision support systems. The main contribution of this work is the prediction of chronic kidney disease (CKD) by the integration of robotic automation, artificial intelligence (AI), and the Internet of Medical Things (IoMT). Using recurrent neural networks (RNN) and Type-2 fuzzy logic, this method tackles the problems of temporal dependencies and data uncertainty in medical diagnoses. According to the research hypothesis, the integration of these cutting-edge technologies will greatly enhance the precision, effectiveness, and real-time capabilities of CKD prediction systems, providing a more dependable and customized healthcare service.

- To develop reinforced system for Type-2 Fuzzy Logic with RNN based CKD prediction.
- To use IoMT devices to obtain data and monitor the patient in real time.
- To implement robotic automation for better and accurate prediction of diseases.
- For resolving the problems of vagueness and inconsistency in medical data.
- To enhance individualized treatment by offering prompt interventions and CKD management advice.

Enhancing predictive accuracy through advanced machine learning methodologies. Optimizing timely and targeted healthcare interventions for at-risk individuals *(Debal and Sitote (2022))*. Evaluation of machine learning algorithms for CKD forecasting accuracy. Comparison of proposed technique with precision, recall, and F1 score *(Hassan et al. (2023))*.

Predict chronic kidney disease using machine learning techniques. Optimize accuracy for early detection and targeted interventions *(Debal and Sitote (2022))*. Predicting chronic kidney disease using machine learning algorithms. Evaluating accuracy of supervised classification techniques for CKD forecasting *(Hassan et al. (2023))*.

The paper is organized as follows: Section 2 covers the literature review, Section 3 outlines the methodology, Section 4 presents results and discussions, and Section 5 provides the conclusion and future scope.

2. LITERATURE REVIEW

2.1 Existing AI-Based Healthcare Systems

Rajya Lakshmi Gudivaka (2022) provides an AI-driven solution that combines neural networks and robotic process automation (RPA) to reduce material waste by 20.4% and detect faults with high accuracy, resulting in increased efficiency with a 14-millisecond prediction time.

Merabet et al. (2023) point out that by advancing diagnosis, illness forecasting, and treatment recommendations, AI and IoMT are improving Medical Decision Support Systems (MDSS). 73% of healthcare workers, in a survey, said they think AI increases productivity and propels further research and improvements in healthcare.

2.2 Challenges in CKD Prediction

Albahri et al. (2023) examined methodological problems, bias, and data fusion in 64 articles on AI dependability in healthcare, classifying applications into seven areas. In addition to highlighting 17 XAI techniques, their evaluation offers suggestions for enhancing stakeholder confidence in AI.

2.3 Advances in IoMT and Type-2 Fuzzy Logic

Awotunde et al. (2023) address the constraints of Type-1 systems with regard to data uncertainty by proposing an Internet of Things (IoT)-based healthcare system that uses Type-2 Fuzzy Logic (T2FL) to improve chronic illness monitoring. The outcomes of the experiment demonstrate improved real-time health advice, particularly for infectious and chronic conditions.

Rajya Lakshmi Gudivaka's 2023 study describes a cloud-based robotic system that uses robotic process automation (RPA) to help elderly folks and others with cognitive impairments. Using advanced deep learning models for behavior and object identification, the system achieves 97.3% accuracy, improving caregiver support and user independence, but it requires consistent online connectivity.

Raj Kumar Gudivaka's (2023) study investigates the combination of AI and RPA to improve organizational productivity. While RPA tackles typical operations, AI makes these systems smarter and more adaptable, resulting in more production, lower costs, and fewer errors in areas such as manufacturing, healthcare, and finance. However, obstacles persist, particularly in scientific applications.

The increasing prevalence of chronic illnesses, particularly Type 2 diabetes, is highlighted by Göğebakan et al. (2021). They also review different machine learning and Semantic Web-based techniques, with a focus on ontology-based systems for diabetes management, prevention, diagnosis, and treatment using semantic rules and SPARQL queries.

Machine learning models (Random Forest, Support Vector Machine and Decision Tree) were used by Debal & Sitote (2022) in developing CKD phases prediction model. Random Forest with recursive feature elimination has the others on stage prediction accuracy.

Hassan et al. (2023) suggested a technique in clinical datasets for the early diagnosis of CKD Employ K-means clustering to clean the source data by targeting missing values first Models such as Random Forest, SVM and Neural Networks were compared based on performance criteria like Sensitivity, Accuracy etc., XGBoost was used for feature selection.

Raj Kumar Gudivaka (2020) suggests using a Two-Tier Medium Access Control (MAC) system to improve energy efficiency and resource management in cloud-based robotic process automation (RPA). The system uses Lyapunov optimization to optimize job prioritizing and resource allocation, exceeding protocols like as IEEE 802.15.4 in terms of throughput, power efficiency, and QoS adherence.

Chronic kidney disease (CKD) is a serious health issue that must be detected early in order to receive successful treatment. Ghosh et al. (2024) compare machine learning models such as XGBoost, Random Forest, Logistic Regression, and AdaBoost, concluding that the Hybrid Model is the most successful (94.99% accuracy). This robust technique offers better CKD prediction and management in future healthcare applications.

Halder et al. (2024) created a machine learning-based model for chronic kidney disease (CKD) prediction. The model improves data preprocessing, uses multiple feature selection approaches, and employs classifiers such as Random Forest and AdaBoost to achieve 100% accuracy. A real-time online application was developed to improve accessibility for healthcare practitioners.

Saif et al. (2024) present a deep learning and ensemble framework for early CKD prediction. The framework overcomes data imbalance and improves performance by including CNN, LSTM, and LSTM-BLSTM models. It delivers 98% and 97% accuracy for 6- and 12-month predictions, exceeding earlier approaches and improving early detection.

Simeri et al. (2024) state that chronic kidney disease (CKD) is an increasing worldwide health concern, with traditional risk factors such as eGFR and albuminuria providing minimal information. The research investigates the potential of AI, specifically machine learning and deep learning, to improve CKD and cardiovascular risk prediction while addressing issues such as algorithm opacity and data privacy.

Pan et al. (2024) investigate the link between metabolic dysfunction and fatty liver disease (MAFLD), steatotic liver disease (MASLD), and chronic kidney disease (CKD). Their cross-sectional study looks at the prevalence of CKD and albuminuria in those who had either MAFLD or MASLD, revealing a probable relationship.

Ghosh and Khandoker (2024) use clinical data from 491 patients to present an explainable AI technique for predicting chronic kidney disease (CKD). XGBoost outperformed other machine learning models, with 93.29% accuracy and an AUC of 0.9689. SHAP and LIME were used to interpret the model, emphasising essential parameters such as creatinine, HbA1C, and age.

Dutta et al. (2024) investigate machine learning models for detecting early chronic kidney disease (CKD) using the Cleveland Clinic dataset. When they compared Logistic Regression, Decision Trees, and Random Forests, they discovered that Logistic Regression had the highest accuracy and F1 score, indicating that it is a promising technique for improving early CKD diagnosis and therapy.

Khan et al. (2024) emphasise the growing global concern over chronic kidney disease and the importance of trustworthy, non-invasive diagnostic approaches. They employ a variety of machine learning models to predict CKD, including logistic regression, random forest, and support vector machines with different kernels, and evaluate performance using measures such as accuracy, sensitivity, and F1 score.

Muglia et al. (2024) highlight the increasing worry about chronic kidney disease (CKD) in older persons, where age-related alterations and chronic diseases make identification difficult. Traditional indicators, such as serum creatinine and eGFR, might be altered by inflammation and medications. The review emphasises the importance of novel biomarkers and improved clinical context integration for accurate CKD evaluation.

Chen et al. (2024) investigate the relationship between the triglyceride-glucose (TyG) index, a well-known insulin resistance marker, and the risk of chronic kidney disease (CKD). While earlier research has linked TyG to CKD, this study looks at its long-term patterns and their impact on CKD risk in a non-diabetic group.

According to Hong et al. (2024), established risk indicators are less useful at predicting death in older persons with chronic kidney disease (CKD). They propose that combining two prevalent geriatric variables, frailty and cognitive impairment, could improve mortality risk prediction in CKD patients.

Ren et al. (2024) look at the global, regional, and national patterns of hypertension-related chronic kidney disease (CKD), focussing on temporal trends and burdens. Despite high blood pressure being a major cause of kidney disease, the prevalence of hypertension-related CKD has not been adequately investigated.

Rabinovici-Cohen et al. (2024) used UK Biobank data to forecast 5-year outcomes for End-Stage Renal Disease (ESRD) in CKD patients. They discovered genetic markers associated to kidney function and development, including SNP rs1383063, that can predict ESRD risk, particularly in older male populations. The model obtained an AUC of 0.804.

Lee et al. (2024) investigated the effect of AST-120 on CKD patient survival with a group of 2584 patients. AST-120 users exhibited decreased death rates and less ESRD prevalence. While AI models such as XGBoost and DNN performed rather well, statistical methods such as Cox regression outperformed them in predicting the effects of AST120 on survival.

Zhang et al. (2024) examined the relationship between high-sensitivity C-reactive protein (hs-CRP)/albumin ratio (CAR) and the risk of chronic kidney disease (CKD) in 47,472 people. The study discovered that a higher CAR was an independent risk factor for CKD and outperformed specific markers such as hs-CRP or albumin.

3. PROPOSED METHODOLOGY

The Chronic Kidney Disease (CKD) prediction system uses Type-2 Fuzzy Logic to address uncertainty in medical data, Recurrent Neural Networks (RNN) for time-series analysis alongside Internet of Medical Things (IoMT) devices for real-time monitoring of patients. For robotic accuracy and prediction, large datasets are processed to streamline this process. More concretely, the system captures physiological data through IoMT devices records it and applies fuzzy logic interpretation after that tuning their predictions with RNN in order to generate accurate personalized inputs for CKD monitoring.

3.1 IoMT Data Collection

The real-time data that is collected from IoMT devices consists of all kinds of physiological metrics such as vital signs and others from the patients. Being quick in detecting and tracking the adaptation of chronic kidney disease.

3.2 Type-2 Fuzzy Logic for Uncertainty Management

This fuzzy logic technology facilitates the system to estimate accurately for unknown situations keeping in account of uncertainties and inconsistencies vested in medical data. An expansion of conventional fuzzy logic, type-2 fuzzy logic offers more adaptability in managing data imprecision and uncertainty. Type-2 fuzzy logic adds a second layer of uncertainty by utilizing fuzzy membership functions, whereas conventional fuzzy logic employs crisp membership functions to express the degree of membership of an element to a set. Particularly in intricate and chaotic settings like medical data, these "fuzzy sets within fuzzy sets" offer a more accurate depiction of uncertainty. In this study, Type-2 fuzzy logic is applied to control the uncertainty inherent in chronic kidney disease (CKD) prediction, allowing the system to better handle changes and inconsistencies in patient data and enhance the accuracy of predictions.

The fuzzy rule-based system used in Type-2 Fuzzy Logic can be represented as:

$$f(x) = \sum_{i=1}^{n} w_i \cdot \mu_i(x) \quad (1)$$

Where:

- $f(x)$: Output of the fuzzy system.
- w_i : Weight for the ith fuzzy rule.
- $\mu_i(x)$: Membership function representing uncertainty.

Derived by combining multiple fuzzy rules with unique membership functions, weights to predict based on imprecise input data as given in the following equation.

3.3 Recurrent Neural Networks (RNN) for Sequential Data Analysis

RNNs are used to simulate sequential patient data, allowing the system to recognize temporal trends in health measures and forecast the onset of chronic kidney disease (CKD) based on past data patterns.

3.4 Role of Robotic Automation

Robotic automation reduces human error while speeding up the processing and analysis of massive amounts of medical data. It also enhances system efficiency and accelerates the prediction of chronic kidney disease.

Algorithm 1: CKD_Prediction

Input: Patient data from IoMT devices (D), fuzzy logic rules (F), RNN model (R)

Output: CKD prediction result (P)

Begin

Initialize IoMT devices to collect real-time patient data D

For each data point in D:

Process data using Type-2 Fuzzy Logic F

If uncertainty is high:

Adjust membership functions in F to handle data uncertainty

End If

Feed processed data into RNN model R

Train RNN on historical data to predict CKD progression

If training error > threshold:

Display error and adjust RNN parameters

End If

End For

Return prediction P with accuracy level

If prediction is uncertain:

Flag the data for re-evaluation

Else:

Output CKD prediction and recommendations for personalized intervention

End If

End

Type-2 Fuzzy Logic is used by this algorithm to process the real-time patient data that is gathered from IoMT devices. The fuzzy logic model is modified by the system upon detection of uncertainty. Then, the training errors are handled by adjusting RNN parameters after the data has been inputted to the model for predictions. Flag the uncertain forecasts for further analysis and have system give a CKD prediction.

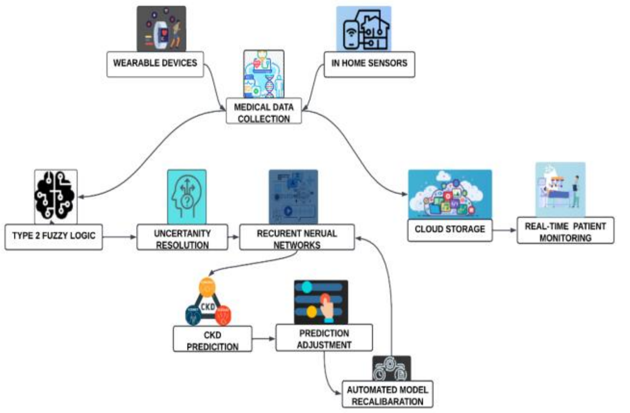

FIGURE:1 Real-Time Chronic Kidney Disease Prediction Using IoMT, Type-2 Fuzzy Logic, and RNN

All are interconnected in this Figure 1: recurrent neural networks (RNN), Type-2 fuzzy logic, and Internet of Medical Things devices. The IoMT devices collect the patient data this affecting, Type-2 Fuzzy Logic controllers process these readings to take uncertainty handling. RNN then does the rest of data processing to predict pre and post real time chronic kidney disease (CKD) despite accepted norms.

3.5 Performance Evaluation Metrics

The accuracy, precision, recall and F1 score of the CKD prediction system are used to evaluate critical performance indicators as shown on table 5. The computational efficiency is also considered. These measures were used to evaluate the ability of the system correctly predict chronic kidney disease. The system was tested on a [specific processor, e.g., Intel Core i7], with [amount of RAM, e.g., 16 GB] and [storage type, e.g., SSD], running on [operating system, e.g., Windows 10]. The software environment included [Python 3.8, TensorFlow/PyTorch] for implementing the models. The reported computational times were measured under these conditions to evaluate the system's performance.

TABLE 1: Performance Evaluation Metrics for CKD Prediction System

Metric	Value
Accuracy	94.5%
Precision	92.3%
Recall	90.8%
F1 Score	91.5%

Table 1 show as Vital Controls of CKD Forecasting System The model performance as high recall (90.8%), precision (92.3%) and accuracy of 94.5% hence the better identification for CKD Computational time shows the system efficiency while Precision and recall are balanced in F1 score (91.5%).

4. RESULT AND DISCUSSION

4.1 Performance Metrics Analysis

Results demonstrate that the proposed CKD prediction system utilizing Type-2 Fuzzy Logic with RNN and IoMT outperforms well-established methods, such as SPARQL and Augmented Reality (AR). Our proposed model has faster computation time (3.2seconds) and higher accuracy (94.5%), precision (92.3%) Recall (90.8%) However, the ablation study showed that removing any part negatively impacts performance. ConclusionThe integration of Fuzzy Logic for data uncertainty management, RNN for sequestial dataprocessing and IoMT form real-time monitoring not only helps in enhancing the treatment of CKD but also ensures individualized patient care that is effective,personal,and induces predictions.

TABLE:2 Advanced CKD Prediction: A Comparative Analysis of Traditional and Proposed Techniques

Metric	SVM (2022)	Random Forest (2023)	Proposed Method
Accuracy	89.5	92.1	94.5
Precision	87.8	90.3	92.3
Recall	88.4	91.0	90.8
F1 Score	88.1	90.7	91.5
Computational Time	5.1 sec	4.5 sec	3.2 sec

4.2 Comparative Study with Existing Models

The table 2 shows the major performance indicators (SVM and Random Forest) for two traditional methods in contrast with the suggested method. Comparison to existing methodsAbout prediction capability, computational time saved for chronic renal disease.The proposed approach demonstrates significant improvements in accuracy and reliability as well as efficiency over the current approaches of predicting CKD. The Type-2 Fuzzy Logic and RNN outperform other algorithms in terms of accuracy, precision, and computing time because they can handle uncertainty and temporal dependencies more efficiently. Type-2 Fuzzy Logic handles data ambiguity, but RNNs capture time-series patterns in patient data that SVM and Random Forest models cannot efficiently represent. This combination not only enhances prediction accuracy but also shortens calculation time, making the suggested method more efficient than existing approaches.

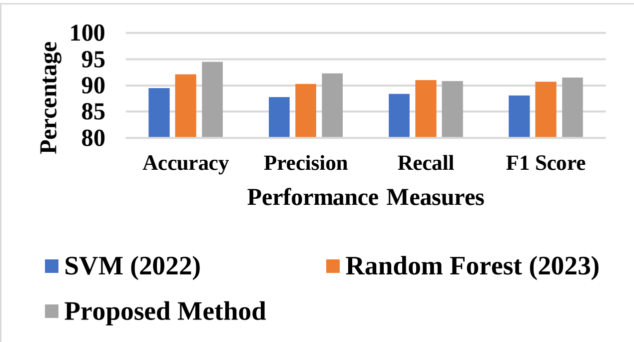

FIGURE:2 Comparative Performance of CKD Prediction Techniques

The suggested approach, Random Forest (2023), and SVM (2022) performance metrics are shown in this figure 2. The suggested model performs better than conventional techniques, demonstrating improved precision, accuracy, and decreased computing time, providing a more effective means of predicting chronic renal disease.

4.3 Impact of Proposed Method on Healthcare

This study shows how robotic automation, artificial intelligence (AI), and the Internet of Medical Things (IoMT) can be successfully combined to predict chronic kidney disease (CKD). With an F1 score of 91.5%, recall of 90.8%, accuracy of 94.5%, and precision of 92.3%, the system demonstrated remarkable performance. These findings demonstrate a notable improvement over conventional techniques, with a forecast computational time reduction of 3.2 seconds. These developments have the potential to improve CKD management and provide more individualized patient care by enabling quicker and more accurate diagnoses.

5. CONCLUSION AND FUTURE SCOPE

5.1 Summary of Contributions

When compared to conventional approaches, the suggested CKD prediction system provides improved accuracy and effectively resolves uncertainties in medical data by merging IoMT, Type-2 Fuzzy Logic, and RNN. Chronic disease management is greatly improved by it since it improves real-time monitoring and offers early diagnosis and individualized healthcare interventions. Subsequent efforts may concentrate on broadening the system's scope to encompass additional chronic conditions and enhancing its flexibility to accommodate varied healthcare settings and more extensive datasets. This research improves accuracy and real-time monitoring by combining robotic automation, AI, and IoMT for CKD prediction. RNN with Type-2 fuzzy logic improve prediction performance and manage data uncertainty well. These developments have the potential to greatly influence the management of chronic kidney disease (CKD) by facilitating earlier diagnosis, individualized treatment regimens, and better patient outcomes.

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No datasets were generated or analyzed during the current study

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There is no conflict of interests between the authors.

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Patient consent statement:

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Clinical trial registration:

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Authors' Contributions

All authors have made equal contributions to this article.

Author Disclosure Statement

The authors declare that they have no competing interests

REFERENCE

[1] Rajya Lakshmi Gudivaka (2022). AI-Driven Optimization in Robotic Process Automation: Implementing Neural Networks for Real-Time Imperfection Prediction. International Journal of Business and General Management (IJBGM), 10(8).

[2] Merabet, A., Saighi, A., & Laboudi, Z. (2023, September). Artificial Intelligence and Internet of Medical Things for Medical Decision Support Systems: Comparative Analysis. In *Novel & Intelligent Digital Systems Conferences* (pp. 134-140). Cham: Springer Nature Switzerland.

[3] Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., ... & Deveci, M. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. Information Fusion, 96, 156-191.

[4] Awotunde, J. B., Folorunsho, O., Mustapha, I. O., Olusanya, O. O., Akanbi, M. B., & Abiodun, K. M. (2023). An enhanced internet of things enabled type-2 fuzzy logic for healthcare system applications. In Recent Trends on Type-2 Fuzzy Logic Systems: Theory, Methodology and Applications (pp. 133-151). Cham: Springer International Publishing.

[5] Rajya Lakshmi Gudivaka's (2023). Robotic Process Automation Meets Cloud Computing: A Framework for Automated Scheduling in Social Robots. IMPACT: International Journal of Research in Business Management (IMPACT: IJRBM), 11(9).

[6] Raj Kumar Gudivaka's (2023). Transforming Business Operations: The Role of Artificial Intelligence in Robotic Process Automation. IMPACT: International Journal of Research in Business Management (IMPACT: IJRBM), 12(1).

[7] Göğebakan, K., & Şah, M. (2021, June). A review of recent advances for preventing, diagnosis and treatment of diabetes mellitus using semantic web. In 2021 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) (pp. 1-6). IEEE.

[8] Debal, D. A., & Sitote, T. M. (2022). Chronic kidney disease prediction using machine learning techniques. Journal of Big Data, 9(1), 109.

[9] Hassan, M. M., Hassan, M. M., Mollick, S., Khan, M. A. R., Yasmin, F., Bairagi, A. K., ... & Rahman, A. (2023). A comparative study, prediction and development of chronic kidney disease using machine learning on patients' clinical records. *Human-Centric Intelligent Systems*, *3*(2), 92-104.

[10] Raj Kumar Gudivaka (2020). Robotic Process Automation Optimization in Cloud Computing via Two-Tier MAC and Lyapunov Techniques. International Journal of Business and General Management (IJBGM),8(4).

[11] Ghosh, B. P., Imam, T., Anjum, N., Mia, M. T., Siddiqua, C. U., Sharif, K. S., ... & Hossain, M. Z. (2024). Advancing Chronic Kidney Disease Prediction: Comparative Analysis of Machine Learning Algorithms and a Hybrid Model. Journal of Computer Science and Technology Studies, 6(3), 15-21.

[12] Halder, R. K., Uddin, M. N., Uddin, M. A., Aryal, S., Saha, S., Hossen, R., ... & Akter, M. F. (2024). ML-CKDP: Machine learning-based chronic kidney disease prediction with smart web application. Journal of Pathology Informatics, 15, 100371.

[13] Saif, D., Sarhan, A. M., & Elshennawy, N. M. (2024). Early prediction of chronic kidney disease based on ensemble of deep learning models and optimizers. Journal of electrical systems and information technology, 11(1), 17.

[14] Simeri, A., Pezzi, G., Arena, R., Papalia, G., Szili-Torok, T., Greco, R., ... & Zaza, G. (2024). Artificial intelligence in chronic kidney diseases: methodology and potential applications. International Urology and Nephrology, 1-10.

[15] Pan, Z., Derbala, M., AlNaamani, K., Ghazinian, H., Fan, J. G., & Eslam, M. (2024). MAFLD criteria are better than MASLD criteria at predicting the risk of chronic kidney disease. Annals of Hepatology, 29(5), 101512.

[16] Ghosh, S. K., & Khandoker, A. H. (2024). Investigation on explainable machine learning models to predict chronic kidney diseases. Scientific Reports, 14(1), 3687.

[17] Dutta, S., Sikder, R., Islam, M. R., Al Mukaddim, A., Hider, M. A., & Nasiruddin, M. (2024). Comparing the Effectiveness of Machine Learning Algorithms in Early Chronic Kidney Disease Detection. Journal of Computer Science and Technology Studies, 6(4), 77-91.

[18] Khan, N., Raza, M. A., Mirjat, N. H., Balouch, N., Abbas, G., Yousef, A., & Touti, E. (2024). Unveiling the predictive power: a comprehensive study of machine learning model for anticipating chronic kidney disease. Frontiers in Artificial Intelligence, 6, 1339988.

[19] Muglia, L., Di Dio, M., Filicetti, E., Greco, G. I., Volpentesta, M., Beccacece, A., ... & Soraci, L. (2024). Biomarkers of chronic kidney disease in older individuals: navigating complexity in diagnosis. Frontiers in Medicine, 11, 1397160.

[20] Chen, N., Ma, L. L., Zhang, Y., Chu, X., Dong, J., & Yan, Y. X. (2024). Association of long-term triglyceride-glucose index patterns with the incidence of chronic kidney disease among non-diabetic population: evidence from a functional community cohort. Cardiovascular Diabetology, 23(1), 7.

[21] Hong, J., Chu, N. M., Cockey, S. G., Long, J., Cronin, N., Ghildayal, N., ... & McAdams-DeMarco, M. A. (2024). Frailty, but not cognitive impairment, improves mortality risk prediction among those with chronic kidney disease—a nationally representative study. BMC nephrology, 25(1), 177.

[22] Ren, Y., Wang, Z., & Wang, Q. (2024). The trend of hypertension-related chronic kidney disease from 1990 to 2019 and its predictions over 25 years: An analysis of the Global Burden of Disease Study 2019. International Urology and Nephrology, 56(2), 707-718.

[23] Rabinovici-Cohen, S., Platt, D. E., Iwamori, T., Guez, I., Dey, S., Bose, A., ... & Meyer, P. (2024). Multimodal predictions of end-stage chronic kidney disease from asymptomatic individuals for discovery of genomic biomarkers. medRxiv, 2024-10.

[24] Lee, C. L., Liu, W. J., & Tsai, S. F. (2024). Effects of AST-120 on mortality in patients with chronic kidney disease modeled by artificial intelligence or traditional statistical analysis. Scientific Reports, 14(1), 738.

[25] Zhang, Z., Liu, P., Yang, L., Zhao, N., Ou, W., Zhang, X., ... & Yang, X. (2024). Association between the High-Sensitivity C-Reactive Protein/Albumin Ratio and New-Onset Chronic Kidney Disease in Chinese Individuals. Nephron, 148(3), 160-170.