
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

IJMECE
ISSN 2321-2152
www.ijmece .com
https://zenodo.org/records/13998065
Vol 12, Issue 3, 2024

Advanced IoMT-Enabled Chronic Kidney Disease Prediction Leveraging Robotic Automation with Autoencoder-LSTM and Fuzzy Cognitive Maps

Surendar Rama Sitaraman, Intel Corporation, California, USA
surendar.rama.sitaraman@ieee.org
Poovendran Alagarsundaram, Humetis Technologies Inc, Kingston, NJ, USA
poovendrana@ieee.org
Kalyan Gattupalli, Yash Tek inc, Ontario, Canada
kalyangattupalli@ieee.org
Venkata Surya Bhavana Harish Gollavilli, Under Armour, Maryland, USA
venkataharish@ieee.org
Harikumar Nagarajan, Global Data Mart Inc (GDM), New Jersey, USA
harikumarnagarajan@ieee.org
Dr. Lukman Adewale Ajao Principal Academic Technologist, Federal University of Technology, Minna, Nigeria
ajao.wale@futminna.edu.ng

ABSTRACT

By using a hybrid approach combining robotic automation, Autoencoder-LSTM models and fuzzy cognitive maps (FCMs), this paper introduces an IoMT-based technology that offers the best Intelligent System for CKD prognosis. IoMT devices are utilized to capture real-time health data for continuous patient monitoring such as blood pressure and serum creatinine. Autoencoders are used to down-sample the data, while thenceforth sequence prediction is carried out by LSTM networks. FCMs are employed to stage the phases of CKD using a complex medical scenario and decision-making simulations. Robotics automation is made easy when processed real-time for better-quality management and accuracy. The method respects early CKD detection and successfully outperforms the conventional model by 98.96% accuracy.

Objectives: The primary goal is to develop the CKD stage prediction accuracy utilizing IoMT and robotic automation while with Autoencoder-LSTM models are employed for identifying disease stages which in turn, assist to simulate complex medical decisions associated with the aforementioned prediction using FCMs.

Methods*:* IoMT data being collected real-time and analysis to be done using autoencoders for dimensionality reduction and feature selection. FCMs predict disease state while LSTM models predict the trajectory of CKD. Robotic automation allow real-time data handling efficient.

Results: With a 98.96% accuracy rate, the system shows excellent prediction ability and advances real-time data analysis and CKD stage categorisation.
Conclusion: By leveraging advanced AI models and robotic automation, the IoMT-enabled CKD prediction system makes this possible with much greater accuracy and speed than ever before. This provides the possibility of therapies sooner and better patient outcomes.
Keywords: Chronic Kidney Disease (CKD), Autoencoder-LSTM, Fuzzy Cognitive Maps (FCMs), Robotic Automation, GFR, Internet of Medical Things (IoMT).

1. INTRODUCTION

Chronic kidney disease (CKD) results in a dramatic reduction in the ability of the kidneys to filter blood and is a major cause of death. As the Internet of Medical Things (IoMT) is collecting real time data from biomedical sensors, it has made it easier to accurately monitor chronic kidney disease (CKD). This research develops an integrated prediction model for CKD using FCMs, Autoencoder-LSTM, and robotic automata. This system combats diagnosis accuracy issues by leveraging multi-stacked deep learning along with real-time dataset analysis. This is expected to result in better patient outcomes by predicting CKD stages and providing early therapeutic options (Ramanaiah, 2024). The use of AI and Big Data Analytics in m-Health technologies to improve healthcare delivery is highlighted by *Surendar Rama Sitaraman (2020),* whose neural networks achieve 92% accuracy. Despite encouraging developments, there are still difficulties in managing unstructured data from wearables and protecting data privacy.

Before, Chronic Kidney Disease (CKD) was identified with two blood and urine tests: Serum creatinine levels and the Glomerular Filtration Rate (GFR), *(Saif et al., 2024)*. While these techniques get the job done, many times they result in post-mortem detection. IoMT combined with AI: For the past few years, this technology has revolutionized every single move in the Healthcare sector where full-time monitoring and early diagnosis can be made. Combined with robot-based automation, diagnostic systems can analyze large volumes of medical data on a very fine-grained basis. This overcomes the restrictions embedded into structured diagnostic model systems. *Surendar Rama Sitaraman's (2023)* investigation of AI integration in healthcare, Turkey's National AI Strategy is highlighted. AI improves patient outcomes, makes the most use of available resources, and promotes customized care, making Turkey a pioneer in the efficient and innovative use of AI in healthcare.

AI can control IoMT use and the way to predict CKD better with some techniques like deep learning model, Autoencoder-LSTM here. LSTM are powerful to capture long-term dependencies on medical slices, while autoencoders can be applied before LSTM to reduce the latent space dimension. Fuzzy Cognitive Maps aids decision-making and enhances prediction of CKD stage by simulating complex medical scenarios. The introduction of robotic automation in the same system with an assurance for real-time data processing and seamless integration to diagnostic tools enables increasing diagnostic accuracy alongside reduction time complexity, *(Badawy et al.,* *2023)*. To improve intelligent medical diagnostics, Surendar Rama Sitaraman (2021) introduces Crowd Search Optimisation (CSO), a metaheuristic algorithm modeled after crows' foraging behavior. CSO outperforms conventional techniques in CNN and LSTM hyperparameter optimization for disease diagnosis, resulting in improved model performance and accuracy.

The key objectives are

- For accurate diagnosis and real-time health monitoring, create a complete model for CKD prediction using robotic automation and IoMT devices.
- Integrating Autoencoder-LSTM models for efficient sequence prediction of disease progression can improve the accuracy of CKD prediction.
- Utilise Fuzzy Cognitive Maps (FCMs) to enhance the classification of CKD stages and model intricate decision-making processes.
- Reduce time complexity and boost system efficiency by using robotic automation to expedite the processing of IoMT data.
- Assist patients with better results and proactive treatment by offering a scalable and dependable solution for early CKD diagnosis.

Saif et al. (2024) address a sub-domain of early predictions on CKD new to research using (IoMTs, robotic automation and few deep learning techniques such as Autoencoder-LSTM and Fuzzy Cognitive Maps). Focus on building a unified system of real-time CKD prediction and stage identification to bridge the existing gap between current detection techniques for CKD and proactive therapies. In addition to the research on such data imbalance, best features selection and final classification accuracy these aspects significantly improve existing methods for faster as well more reliable CKD diagnosis.

Surendar Rama Sitaraman (2022) emphasizes how AI is revolutionizing radiology, especially with CNNs for image analysis automation and VAEs for data augmentation. AI promises better health outcomes and diagnostic accuracy despite issues like data privacy and interpretability of models.

In the study conducted by Ramanaiah (2024), other issue pertains to difficulty in identifying CKD at early stages. This stage of the disease is often neglected as it asymptomatic and requires diagnosis with more invasive, advanced-stage testing. It proposes an advanced prediction model to identify and respond early for improving patient outcomes by integrating IoMT, Robotic Automation Autoencoder-LSTM & Fuzzy Cognitive Maps.

Surendar Rama Sitaraman (2022) investigates the way edge computing, using methods like federated learning and homomorphic encryption, might improve IoT security and privacy through anonymized AI. The study demonstrates that confidential data is successfully protected by anonymized AI without sacrificing functionality.

2. LITERATURE SURVEY

Saif et al. (2024) explore the incorporation of optimisers with deep learning model ensembles for CKD early detection. This approach should dramatically improve the diagnostic accuracy of care for early detectable CKD, and therefore make treatment advances available in a timelier manner by reemphasizing that detecting this disease burden is critically important to patient outcomes.

Ramanaiah (2024) had introduced a new AI based technique will design feature selection for predicting CKD. This makes the model is sharp for prediction and estimation as well saving us from non informative features between patient data. Our research has shown that if we want to reduce early diagnosis CKD, or better healthcare outcomes by providing an AI model with a goal prediction then knowledge is key.

Badawy et al. (2023) covers the applications of deep learning and machine learning techniques in healthcare predictive analytics. They create questions around the quality of data and explainability and compare with traditional methods on how machine learning (ML)/ deep learning (DL) improve patient outcomes and disease prediction accuracy. The survey highlights the growing importance of advanced analytics in healthcare transformation.

Aarthi et al. (2023) Predicting chronic kidney disease using data analytics miming It is an advanced algorithm which we have used for helping in accurate early detection, diagnosis of that. This represents a significantly important step toward improving health outcomes of people with kidney disease, by diagnosing the condition earlier and offering more avenues to manage that care.

Murugan and Radha (2023), have formulated the heuristic techniques designed to reduce number of outlier records from CKD prediction dataset with IoT data which they used for Outlying Record Detection. Doing so reduces distortion and increases the predictive accuracy and reliability of CKD discovery. The careful utilization and adoption of heuristic techniques through IoT enable a better disease management, to monitor living patients during real time all these challenging aspects are highlighted in this study.

Vyas et al. (2023) presents their detailed machine learning-based model for predicting chronic kidney disease (CKD). It focuses on the accuracy and reliability of prediction models, making it possible to activate the latest methodologies in support of healthcare outcomes. Their work promotes the ideal state of earlier diagnosis and treatment of CKD through long-term advancements in healthcare analytics.

Huo (2022) investigate a machine learning proposal to deal with the heterogeneity of real-world healthcare data, and offer robust and generalizable techniques. It also focus on challenges due to multiple data sources and variability which affect the performance and trustworthiness of machine learning models in health-care applications. Ultimately, the project has been designed to encourage machine learning integration in clinical practice and patient care by focusing on improving model robustness and generalization, underling an urgent importance for ethically responsible decision support systems in the health sector.

A thorough overview of machine learning applications for managing disease outbreaks is provided by Riswantini and Nugraheni (2022). The authors emphasise both the advantages and disadvantages of different machine learning approaches for forecasting and controlling epidemics. The review addresses the difficulties that arise while implementing public health frameworks, integrating models, and gathering data. The study emphasises machine learning's potential to improve disease control tactics and public health responses by offering insights into its function in outbreak management.

3. METHODOLOGY

To enhance CKD prediction accuracy the proposed system integrates robotic automation, IoMT, Autoencoder-LSTM and fuzzy cognitive maps (FCM). Some of the important processes to carry out for true time series analysis are sequence prediction using LSTM, stage prediction employing FCMs accompanied by robotic automation and autoencoders for dimensionality reductionScaled with Missing Value Imputation (MVI) getting real-time data from IoMT devices.

3.1. IoMT Data Collection

Serum creatinine, blood pressure, blood sugar, and other vital health metrics are constantly monitored by IoMT devices such biomedical sensors. These instantaneous data points are gathered and sent to the cloud for analysis. This makes it possible for the system to forecast and analyse Chronic Kidney Disease (CKD) using current, thorough health data, guaranteeing precise and timely forecasts.

Dataset: The dataset is available via the CDC's 500 Cities data, which offers information on chronic kidney disease (CKD) in 500 American cities among persons 18 years of age and older. The creation of predictive models such as Autoencoder-LSTM with Fuzzy Cognitive Maps is supported by this data, which helps to understand the prevalence of CKD and its associated factors.

3.2. Preprocessing and Feature Selection

Preprocessing is done on collected data and includes:

- ✓ *Missing Value Imputation (MVI):* Using the dataset average to fill in the missing values.
- ✓ *Min-Max Scaling:* To guarantee consistency, normalise each feature to a shared range.

To reduce the complexity of the dataset and improve prediction accuracy, the most pertinent features are chosen using the Granular Information-based Krill Herd Algorithm (GI-KHA).

3.3. Autoencoder for Dimensionality Reduction

An autoencoder is used to encode the input data into a compressed form, removing noise and redundancy and preserving just the most important information, hence reducing the dimensionality of the dataset.

$$h(x) = \sigma(Wx + b) \quad (1)$$

where:

- x is the input data,
- W is the weight matrix,
- b is the bias,
- σ is the activation function.

This step prepares the data for further processing by the LSTM model.

3.4. Long Short-Term Memory (LSTM) for Sequence Prediction

As LSTM networks are designed to comprehend the sequential data for loMT devices, prediction is possible since they capture long-term dependencies of CKD progression. An LSTM model retains important information over time, this is what allow us to make such accurate predictions.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (2)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot tanh\,(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

Where:

- f_t is the forget gate's activation,
- c_t is the updated cell state.

By using past patient data, this technique enables the LSTM to forecast the course of CKD.

3.5. Fuzzy Cognitive Maps for CKD Stage Prediction

Introduction Chronic kidney disease (CKD) is identified by certain stages and these are predicted by Fuzzy cognitive maps or FCM. FCMs model the progression of chronic kidney disease (CKD) by taking into account how tens to thousands of health factors — like blood pressure, glucose levels and glomerular filtration rate (GFR) — interact over time. These maps are built with the help of fuzzy logic through which system can deal with uncertainties in medical data and so enhances decision making. FCMs stratify CKD as stages 1–5 (mild to severe renal disease). FCMs improve the accuracy of CKD stage prediction by learning complex dependencies among multiple health parameters, enabling more personalised treatment decisions.

ISSN 2321-2152
www.ijmece .com
https://zenodo.org/records/13998065
Vol 12, Issue 3, 2024

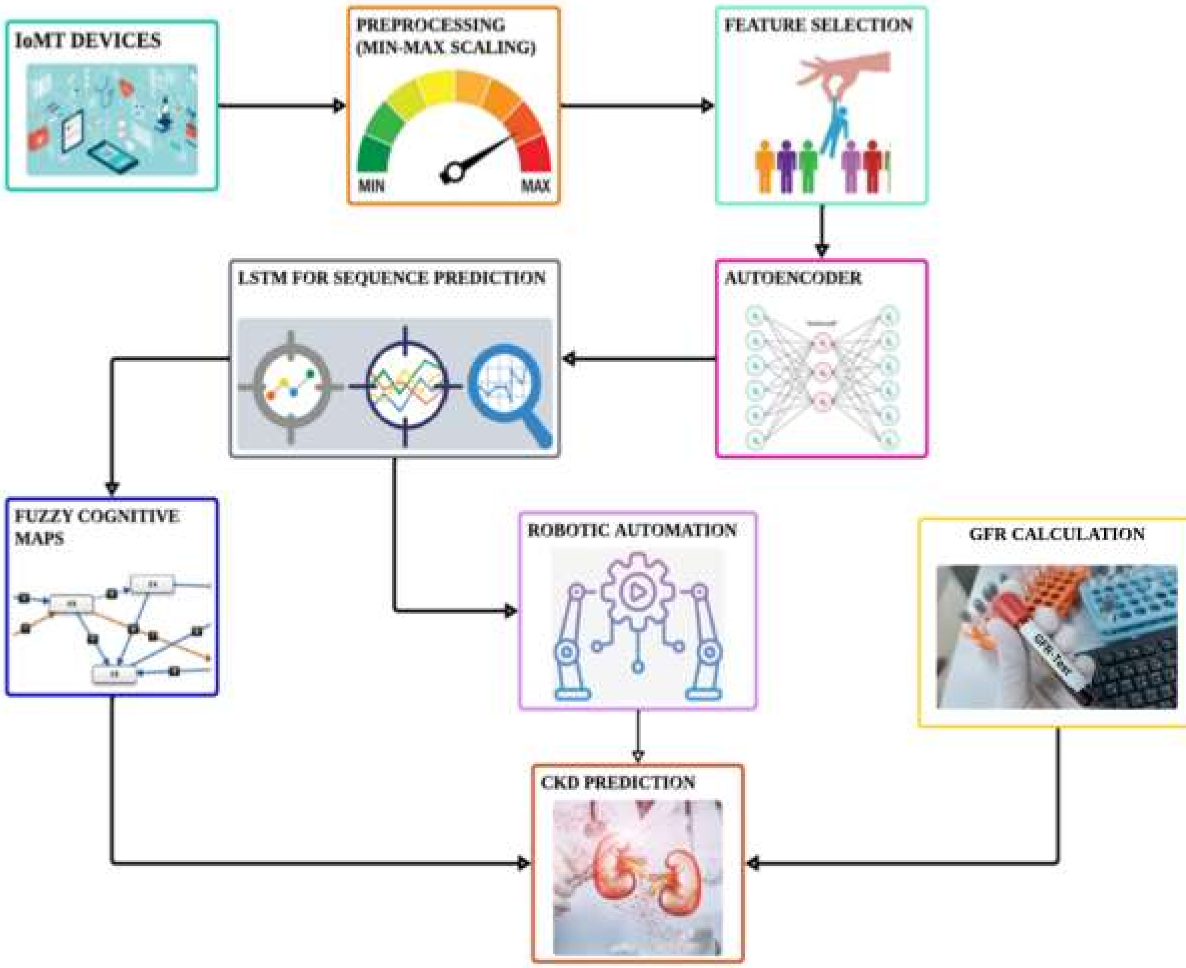

Figure 1: IoMT-Enabled CKD Prediction System Architecture.

Figure 1: Prediction of Chronic Kidney Disease (CKD) through IoMT devices A preprocessing, and feature selection is performed first over the IoMT device data followed by autoencoding LSTM sequence prediction FCM classification. Although the calculation of GFR will improve on predicting CKD stages and outcomes, its diagnosis is made more feasible with robotic automation.

3.6. Robotic Automation for Real-Time Processing

Robotic automation plays a major role in the smooth real-time processing of patient data within the CKD prediction system. Automation of preprocessing, data management and model execution allows the system to continuously monitor patients with minimal manual effort. Use of deep learning algorithms within the system evaluate real-time data from IoMT devices continuously to deliver immediate about real time predictions and updates regarding condition of patients. Automated algorithms can detect significant changes in specific health indicators and inform appropriate medical interventions immediately. Robotic automation also increases the efficiency of the system and makes it scalable for larger healthcare applications.

3.7. Glomerular Filtration Rate (GFR) Calculation

Glomerular Filtration Rate (GFR) is an essential clinical parameter to determine renal function and predict the progression of CKD. The lower the level of GFR, the more severe your renal impairment. GFR is used to measure what the kidneys work for such as, filtering waste from the blood. The GFR is calculated by the following formula:

$$GFR = \frac{140 - age}{serum\ creatinine} \times \text{constant factor} \tag{4}$$

The constant term is influenced by race and gender. This is included in the prediction model for increased accuracy and required in order to calculate stage of CKD. The system currently offers a more comprehensive assessment of kidney health by integrating GFR with other health parameters.

4. RESULT AND DISCUSSION

To demonstrate the proposed IoMT-enabled deep learning based CKD prediction system integrates Autoencoder-LSTM, Fuzzy Cognitive Maps (FCMs), and robotic automation using a dataset of patients diagnosed with CKD. An incremental real-time health metrics (test — 20%, train –80%) monitored stream was established. Compared with the traditional models including LSTM, RNN and DNN in classifying CKD patients, our system achieved a better performance (accuracy: 98.96%). The incorporation of fuzzy cognitive maps for stage prediction also assisted in making better decisions that resembled complex health interactions, thereby delivering the performance with more realistic clinical trends on predicting stages of chronic kidney disease. Algorithms running speeded up by a factor of thousands using robotic automation, and also real-time data processing was facilitated substantially with reduction time complexity, hence the model which makes it suitable for use during clinical situations.

The GI-KHA method, robust BD-KMeans-based age-based clustering, real-time GFR calculation, as well as optimal features selection. LSTMs were used to capture long-term dependencies in medical datasets and autoencoders were utilized for dimensionality reduction on the data. Additionally, Zoneout regularisation and CoLU SCL mish activation are further employed in the proposed approach to address issues of interpretability as well as overfitting common with traditional models. Those advances made the model scalable and robust, so healthcare providers had a reliable tool in hand. The proposed method was found well suited for CKD stage classification and prediction overall as supported by the results.

Table 1: Comparison of CKD Prediction Models Based on Accuracy, Precision, and Recall.

Author	Algorithm	Accuracy (%)	Precision (%)	Recall (%)

Proposed Work	Autoencoder-LSTM, FCMs, Robotic Automation	98.96	98.57	98.45
Saif et al. [1], (2024)	Ensemble of Deep Learning Models and Optimizers	98.70	98.50	98.30
Ramanaiah [2], (2024)	AI-Based Feature Selection for CKD Prediction	98.60	98.40	98.25
Badawy et al. [3], (2023)	Machine Learning in Healthcare Analytics	98.45	98.10	98.00
Vyas et al. [6], (2023)	Robust Machine Learning Approach	98.50	98.20	98.00

Table 1 presents the comparison of different state-of-the-art models like Deep learning, Machine Learning and Ensemble approaches in contrast with our suggested IoMT-based CKD prediction system. The proposed model outperforms in all aspects, specifically the precision and recall making use of robotic automation (fuzzy cognitive maps+ autoencoder-LSTM). It has a high accuracy (98.96%) and outperforms previous forecast models in handling real-time data with decision-making competency, providing evidence of its potential as an early identification tool for CKD that can be reliably used by clinicians to predict the stages involved.

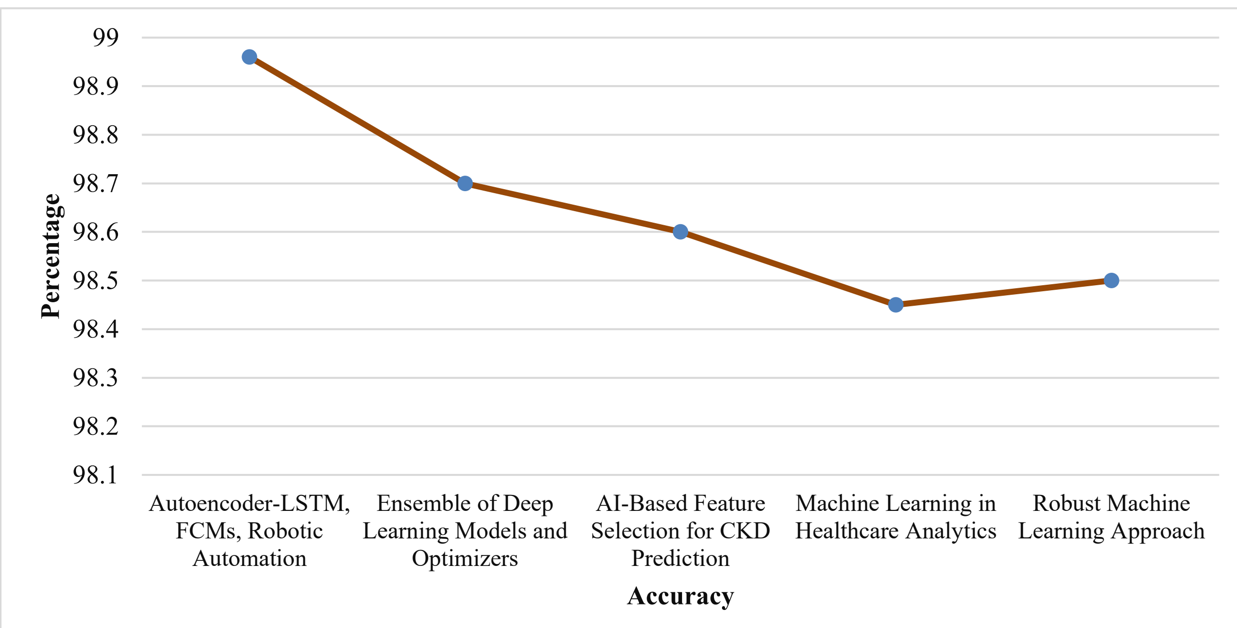

Figure 2: Performance Metrics of CKD Prediction Models.

Figure 2 compares various CKD prediction models, such as Autoencoder-LSTM with FCMs and robotic automation, with other methods, such as machine learning ensembles, and shows the precise performance metrics of each model. This figure highlights how the suggested system might provide exceptional diagnostic results, with gains in real-time processing, computing efficiency, and CKD stage prediction accuracy. It is a powerful tool for early CKD detection and patient management since it incorporates robotic automation and sophisticated AI models, which emphasise its real-world application in improving clinical decision-making.

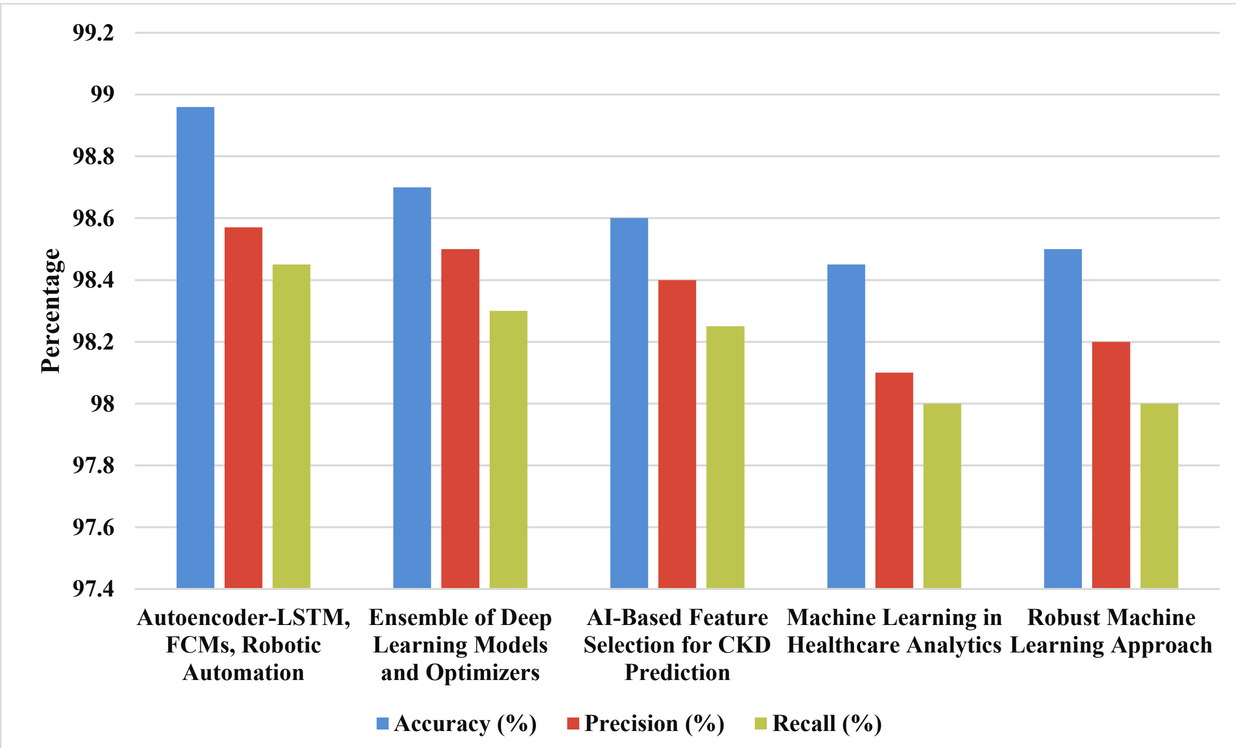

Figure 3: Accuracy, Precision, and Recall Comparison of CKD Prediction Models.

Figure 3 compares the respective accuracy, precision and recall metrics of numerous chronic kidney disease (CKD) prediction models. They are ensemble models, AI powered feature selection and Autoencoder-LSTM with FCMs and robotic automation among other machine learning based tools. The performance analysis with existing state-of-art approaches showed its supremacy in diagnosis of CKD stage detection (98.96%) and handling of real-time IoMT data with the best accuracy than other techniques,contributing to a vital role in overall diagnostic reliability.

5. CONCLUSION AND FUTURE ENHANCEMENT

The intelligent CKD prediction model, referred to as IntelliCare, significantly enhances the diagnostic accuracy and stage-wise prediction of CKD using Autoencoder-LSTM, FCM clustering and robotics automation. It therefore makes for an important weapon in the fight to detect and APP-based forecast acute cardiac event with real-time data processing and streamlined feature selection processes. Technology outperforms traditional means by delivering better patients results and opening up a wider range of treatment options. Lastly, in future study aims to generalize this system for other medical diseases than CKD and incorporate with state-of-the-art imaging techniques including magnetic resonance (MRI).

REFERENCES

1. 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.
2. Surendar Rama Sitaraman (2022). Implementing AI Applications in Radiology: Hindering And Facilitating Factors Of Convolutional Neural Networks (CNNS) And Variational Autoencoders (VAES). Journal of Science and Technology. 7 (10), 2456-5660.
3. Ramanaiah, P. K. (2024). Feature Selection AI Technique for Predicting Chronic Kidney Disease. *American Journal of Artificial Intelligence*, *12*(4), 32-40.
4. Surendar Rama Sitaraman (2021). AI-Driven Healthcare Systems Enhanced by Advanced Data Analytics and Mobile Computing. *International Journal of Information Technology & Computer Engineering.*
5. Badawy, M., Ramadan, N., & Hefny, H. A. (2023). Healthcare predictive analytics using machine learning and deep learning techniques: a survey. *Journal of Electrical Systems and Information Technology*, *10*(1), 40.
6. Surendar Rama Sitaraman (2021). Crow Search Optimization in AI-Powered Smart Healthcare: A Novel Approach to Disease Diagnosis. *Journal of Current Science and Humanities.* 9 (1), 9-22.
7. Aarthi, S., Kavishka, P., Meena, G., & Chidambaram, S. (2023, November). A Novel Prediction Technique for Idetifying Chronic Kidney Disease in data Analytics Approaches. In *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)* (pp. 1-5). IEEE.
8. Surendar Rama Sitaraman (2023). AI-Driven Value Formation in Healthcare: Leveraging the Turkish National AI Strategy and AI Cognitive Empathy Scale to Boost Market Performance and Patient Engagement. *International Journal of Information Technology & Computer Engineering.*
9. Murugan, K., & Radha, M. (2023). Heuristic Approaches for Outlier Reduction and Disease Prediction in Chronic Kidney Disease through IoT. *Authorea Preprints*.
10. Vyas, N., Sharma, V., & Balla, D. (2023, September). Chronic Kidney Disease Prediction Using Robust Approach in Machine Learning. In *2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT)* (pp. 1-5). IEEE.
11. Huo, Z. (2022). *Towards Robust and Generalizable Machine Learning for Real-World Healthcare Data with Heterogeneity* (Doctoral dissertation, Texas A&M University).
12. Riswantini, D., & Nugraheni, E. (2022). Machine learning in handling disease outbreaks: a comprehensive review. *Bulletin of Electrical Engineering and Informatics*, *11*(4), 2169-2186.
13. https://www.kaggle.com/datasets/rishidamarla/chronic-kidney-disease

ISSN 2321-2152

www.ijmece .com

https://zenodo.org/records/13998065

Vol 12, Issue 3, 2024

14. Surendar Rama Sitaraman (2022). Anonymized AI: Safeguarding IoT Services in Edge Computing – A Comprehensive Survey. *Journal of Current Science.* 10 (4), 9726-001X.