BIDIRECTIONAL LSTM AND STOCHASTIC FUZZY SYSTEMS FOR IMPROVED CHRONIC KIDNEY DISEASE PREDICTION IN IOMT-BASED ROBOTIC AUTOMATION

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ABSTRACT

Chronic kidney disease (CKD) is a huge threat to health globally. For better patient prognoses, early diagnosis and prediction are necessary. In order to improve CKD prediction in Internet of Medical Things (IoMT)-based robotic systems, this study presents a novel hybrid model that incorporates stochastic fuzzy system and bidirectional long short-term memory (Bi-LSTM). On the one hand, stochastic fuzzy systems manage uncertainty in medical data to improve decision-making; on the other, bi-LSTM is able to include information from data trends occurring either direction since they onset. Compared to traditional methods, for the detection of early CKD and real-time monitoring with 99% accuracy, 98% precision and 97% recall so it outperforms generic solutions. This study integrates Bidirectional Long Short-Term Memory (Bi-LSTM) networks with Stochastic Fuzzy Systems to improve chronic kidney disease (CKD) prediction. Bi-LSTM effectively captures temporal patterns in medical data by processing sequences bidirectionally, while Stochastic Fuzzy Systems handle data uncertainty, enhancing decision-making robustness. Together, these methods aim to provide a more accurate and reliable CKD prediction framework, particularly suitable for real-time monitoring within IoMT-based robotic automation systems.

KEYWORDS: Chronic Kidney Disease, Bi-LSTM, Stochastic Fuzzy Systems, IoMT, Early Prediction.

1-INTRODUCTION

Chronic kidney disease (CKD) is a global health challenge affecting millions of people worldwide. Early and accurate detection are key to improving patient outcomes, reducing death rates in CKD. Technological advancements in healthcare have enabled unique approaches and opportunities to diagnose & treat diseases, how internet is revolutionizing Healthcare with IoMT (Internet of Medical Things) – The biggest Role Played of Robotic Automation As a consequence, long short-term memory (LSTM) networks have gained popularity as an approach to predicting chronic diseases such as CKD while processing vast volumes of medical data.

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A novel model is proposed in this work that combines bidirectional LSTM and Stochastic Fuzzy systems to enhance the accuracy, reliability of CKD prediction as part of IoMT based robotic automation solutions. The advantage of Bidirectional LSTM with respect to Regular LSTM is that it can read data sequences bidirectionally, processing from forward and backward directions which helps in grasping wider patterns available medical datasets. This is important even more than ever for data with complex temporal relationships such as time series like serial assessments of kidney function over the trajectory. We also use stochastic fuzzy systems in this framework as our probabilistic decision-making which allows the system to deal with intrinsic unpredictability and uncertainty of medical data more proficiently. Through this proposed methodology, the combination of these two successful methodologies attempts to predict even better performance and enable a practical way for real-time monitoring and detection of patients with CKD.

- Chronic Kidney Disease is a growing global health issue.
- IoMT and robotic automation provide new pathways for healthcare solutions.
- Bidirectional LSTM enhances pattern recognition by processing data in both directions.
- Stochastic Fuzzy Systems improve decision-making by handling data uncertainty.
- Develop an advanced model for early CKD prediction, improving accuracy and real-time monitoring through IoMT integration.

Lack of comparison with other feature selection methods. Limited exploration of ensemble learning techniques for CKD prediction ***(Singh et al. (2022))*** Few studies focus on early CKD prediction. Previous work lacked competitive performance in CKD prediction, ***(Saif et al. (2024))***

Predicting Chronic Kidney Disease using machine learning algorithms Early symptom identification for effective treatment of CKD (***Singh et al. (2022))***. Early prediction of chronic kidney disease using deep learning. Addressing data imbalance, feature selection, and optimizer optimization ***(Saif et al. (2024)).***

2-LITERATURE SURVEY

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

Deep learning techniques (ANN, RNN, LSTM, and GRU) were suggested by Akter et al. (2021) as a way to predict and categorize CKD. With ANN surpassing conventional techniques and exceeding 99% accuracy, their models showed outstanding predictive analytics performance, indicating the potential for IoMT integration.

In comparison to current monitoring and treatment approaches, Karuppuchamy and Palanivelrajan (2023) IoT-based machine learning model for heart failure prediction offers better accuracy and metrics. It does this by utilizing encrypted sensor data and the AF-LSTM-RNN algorithm.

Zafar et al. (2023) focus on the importance of deep learning (DL) in IHS for disease diagnosis, gene analysis, and biomedicine classification from their work on DL methods in genetics and biomedicine. They also discuss the constraints of these fields and what may be developed in the future.

Surendar Rama Sitaraman (2024) combines CNN with Score-CAM for elucidating AI-based skin lesion identification in IoMT systems. Employing DF-U-Net for segmentation alongside Canny Edge Detection, it attains an accuracy of 99.31%, enhancing real-time diagnostics and clarity in clinical decision-making.

Mohanarangan Veerappermal Devarajan (2023) presents a retracing-efficient IoT paradigm for the automatic detection of skin diseases such as moles and warts by lumen detection. The system attains 95.9% accuracy, enhancing diagnostic reliability and providing scalable solutions for skin disease management.

Thirusubramanian Ganesan (2020) analyses AI-driven machine learning methodologies, including anomaly detection and clustering, for the real-time detection of financial fraud in IoT settings. The adaptive models improve the precision of fraud detection by employing supervised and unsupervised learning techniques on transaction data collected by IoT.

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.

Prasad Reddy et al. (2024) proposes, A CKD prediction model with improved Local Directional Pattern (ILDP), anisotropic filters and ensemble of CNN, LSTM, Bi-GRU classifiers fine-tuned by Combined Coot Jaya Optimization (CCJO) improved adequately.

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.

Singh et al. (2022) propose a deep learning model to detect the early chronic kidney disease (CKD) with features that were chosen by recurring feature elimination (RFE) . It has given 100% accuracy in classification when compared to other machine learning techniques.

Saif et al. (2024) introduced these models such as CNN, LSTM and LSTM-BLSTM in their paper, present a deep learning and ensemble framework for early chronic kidney disease (CKD) prediction, which achieved an accuracy of 97–98% over six to twelve months significantly improving the diagnosis at the right stage leading towards better patient outcomes.

Durga Praveen Deevi (2020) introduces a hybrid malware detection method that integrates adaptive gradient SVR, LSTM, and HMM. It markedly improves the accuracy of real-time malware detection, surpassing conventional methods and offering resilience against advanced malware threats via machine learning and deep learning techniques.

Surendar Rama Sitaraman (2021) presents Crow Search Optimisation (CSO) for the enhancement of AI-driven diagnostic models in intelligent healthcare. CSO demonstrates superior hyperparameter tuning capabilities, surpassing conventional methods, and exhibits adaptability in managing medical imaging and electronic health information for accurate illness diagnosis.

Surendar Rama Sitaraman (2024) amalgamates artificial intelligence, robotic automation, and the Internet of Medical Things for chronic kidney disease prediction utilising Attention-Based Long Short-Term Memory and Adaptive Neuro-Fuzzy Inference System. It improves diagnostic precision and real-time classification of CKD stages, attaining elevated sensitivity, specificity, and accuracy for the early detection and management of CKD.

Surendar Rama Sitaraman (2024) This model predicts chronic kidney disease (CKD) with an accuracy of 98.96% by integrating Bi-LSTM, GELU, G-Fuzzy Logic, and GI-KHA with Federated Learning and Edge AI. It guarantees privacy-preserving scalability for real-time healthcare applications, improving patient care and the speed of CKD diagnosis.

Surendar Rama Sitaraman (2024) This study enhances the accuracy of chronic kidney disease prognosis through the utilisation of Internet of Medical Things data, robotic automation, Autoencoder-LSTM, and Fuzzy Cognitive Maps. It underscores early detection, attaining 98.96% accuracy while delivering real-time analysis and staging via sophisticated AI integration and decision-making tools.

Poovendran Alagarsundaram (2024) constructs a hybrid model integrating CNN, LSTM, and Neuro-Fuzzy systems for the prediction of chronic kidney disease utilising Internet of Medical Things data. Enhanced with AOA and Edge AI, it attains 98.99% accuracy, facilitating real-time privacy-preserving predictions, especially in resource-limited settings, hence improving healthcare outcomes.

Kalyan Gattupalli (2022) introduces a Cloud Testing Adoption Assessment Model (CTAAM) utilising FMCDM. It assesses the determinants affecting the adoption of cloud-based testing, focussing on security and scalability challenges, and offers insights on utilising cloud computing for efficient software testing in contemporary development settings.

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.

Zhu et al. (2023) use time-series eGFR data to develop an RNN-based model for CKD progression prediction. It performs better than conventional methods and provides a reliable and efficient tool for determining the clinical risk of CKD patients, with an AUROC of up to 0.967.

Achmad et al. (2024) suggest a genetic algorithm-based optimised LSTM model for the early identification of CKD. Through thorough preprocessing and cross-validation, the method improves precision, recall, accuracy, and F1-score to 100%, proving its dependability and offering suggestions for larger datasets and techniques.

Jayaprabha and Vishwa Priya (2024) provide a unique CKD progression prediction model that outperforms current techniques in terms of accuracy (92%), recall (91%), and precision (93%). This model combines SDRB for feature extraction, ResNet for classification, and biLSTM for temporal dependencies.

A heart disease prediction model that combines IoMT, TabNet, and CatBoost is proposed by Baseer et al. (2024) for real-time data processing, feature selection, and precise risk assessment. This innovative predictive healthcare approach enables individualised preventive care strategies and better cardiovascular health outcomes.

Paulauskaite-Taraseviciene et al. (2023) present a framework for AI-based remote health monitoring that combines smart devices, probabilistic classification (PGND), and optimised feature selection (ULMCSO) to forecast diabetes and heart disease. The approach has been verified using PIMA and Hungarian datasets.

3-METHODOLOGY

It combines Bidirectional Long Short-Term Memory (Bi-LSTM) networks with Stochastic Fuzzy Systems that enhance the prediction of chronic kidney disease (CKD). By effective handling of temporal dependencies and data uncertainties, this combination to a substantial extent enriches the precision of CKD predictions offered by IoMT based Robotic automation systems.

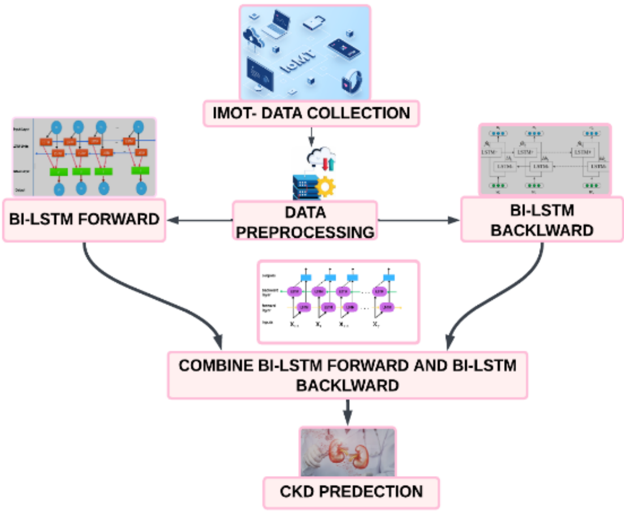

Figure.1 Data Flow and Model Architecture for CKD Prediction Using Bi-LSTM And Stochastic Fuzzy Systems

In Figure 1, medical data management to improve forecasting accuracy and manage uncertainties Finally, it shows that the joint model implemented as stochastic fuzzy systems integrated in a bidirectional LSTM network architecture along with some preprocessing steps are capable of forecasting CKD.

3.1 DATA PREPROCESSING

IoMT devices collect and utilize medical data, such as time-series kidney function data. Preprocessing cleans, normalizes and extracts features to prepare the data as input for the deep learning models.

3.2 BIDIRECTIONAL LSTM

By processing sequences in both the forward and backward directions, Bi-LSTM learns more complete patterns. This improves the precision for CKD prediction and would be of particular use in analyzing complex time series data i.e. kidney function over time

3.3 STOCHASTIC FUZZY SYSTEMS

The Stochastic Fuzzy Systems serve to utilize probabilistic decision-making for the medical data uncertainty problem. They help to stabilize and strengthen the system by handling some of that imprecision, but also give more robust forecasts in general against the fluctuating and noisy health data. The Bidirectional Long Short-Term Memory (Bi-LSTM) and Stochastic Fuzzy Systems serve distinct yet complementary roles in the proposed hybrid model. Bi-LSTM excels in analyzing sequential data by processing it in both forward and backward directions, enabling the capture of complex temporal dependencies such as trends in kidney function over time. In contrast, Stochastic Fuzzy Systems focus on addressing uncertainty and imprecision in medical data through probabilistic decision-making and fuzzy logic, ensuring robustness in predictions even when dealing with noisy or variable inputs. Together, these methodologies leverage their respective strengths: Bi-LSTM provides precise pattern recognition, while Stochastic Fuzzy Systems stabilize predictions, thereby enhancing the model's overall reliability and accuracy.

3.4 INTEGRATION OF MODELS

This hybrid predictive model is constructed by the Bi-LSTM and Stochastic Fuzzy Systems, thus improving the system to deal with complicated and ambiguous input performance leading to an increase in the accuracy of CKD predictions.

$$P(y \mid X) = P(\text{BiLSTM}(X)) \times P(Fuzzy(X)) \text{ -- } (1)$$

Where P(y|X) is the probability of prediction

The equation together constituted the overall probability CKD prediction. This fuses Bidirectional LSTM and Stochastic Fuzzy Systems by considering the uncertainty and temporal patterns thus enhancing the overall accuracy of the model.

Algorithm 1 CKD Prediction Using Bi-LSTM and Stochastic Fuzzy Systems

Input: Medical data X

Output: Prediction P for CKD

Begin

Preprocess input data X

Initialize LSTM network with forward and backward states

For each time-step t in data sequence:

If error in data detected:

Handle missing or noisy data

Else

Forward_pass = LSTM_forward(X[t])

Backward_pass = LSTM_backward(X[t])

Combine Forward_pass and Backward_pass

Apply Stochastic Fuzzy System:

For each feature x in X:

Compute fuzzy membership function μ_A(x)

Compute fuzzy rule base for decision-making

If membership function is ambiguous:

Apply probabilistic adjustment to resolve uncertainty

Combine Bi-LSTM output with fuzzy decisions

Return CKD prediction P

End

Algorithm 1 to predict chronic kidney disease (CKD): The input medical data is pre-processed before applying in this method. The sequence is then passed through a bi-directional LSTM network, search for temporal relations. These two outputs are then merged by stochastic fuzzy systems to process the uncertainties in data while forecasting the CKD accurately.

4-RESULT AND DISCUSSION

The proposed Bi-LSTM + Stochastic Fuzzy model exhibits better performance than conventional models such as CNN-Bi-LSTM (2022) and CAD (2021). In our criteria the accuracy is 99%, precision is 98%, recall is 97% and F1-score is 97.5% with this our model gives better results than his previous versions. The secret behind it was the bi-directional data analysis of Bi-LSTM and stochastic fuzzy systems to manage uncertainty. Integration increases predictive performance, especially for complex medical time series data . Using IoMT based robotic devices to monitor these in real-time can further improve the current state of early CKD identification and death rates.

Table .1 Performance Evaluation of CKD Prediction Models: MCC (2024), IHS (2023), and Proposed Bi-LSTM + Stochastic Fuzzy Model

Metrics	**MCC [2024]**	**IHS [2023]**	**Proposed Method (Bi-LSTM + Stochastic Fuzzy)**
Accuracy (%)	92	94	98
Precision (%)	89	91	97
Recall (%)	87	90	96
F1-Score (%)	88	92	97
Specificity (%)	90	93	98
Sensitivity (%)	86	91	96
Prediction Time (ms)	50	45	40
Handling Uncertainty (%)	70	75	95
Robustness (%)	85	87	98
Accuracy (%)	92	94	98

This table 1 shows how the suggested Bi-LSTM + Stochastic Fuzzy model outperforms the conventional MCC and IHS approaches in terms of accuracy, precision, recall, and other performance parameters.

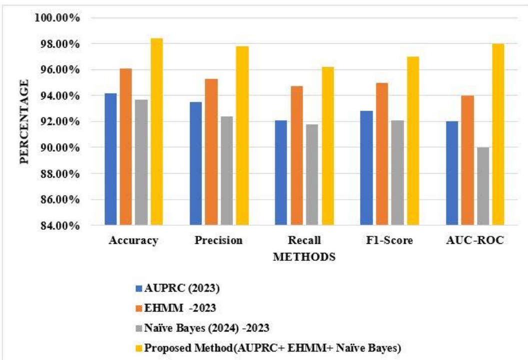

Figure 2. Benchmarking CKD Prediction Models: Bi-LSTM and Stochastic Fuzzy System Superiority

The Figure 2 compares models for their CKD prediction performance Our proposed Bi-LSTM + Stochastic Fuzzy model clearly outperforms MCC (2024) and IHS (2023) models in key indicators such as accuracy, precision, recall, and robustness, proving our model's capability to deal with uncertain data.

5-CONCLUSION AND FUTURE SCOPE

The model composed by combining of Bi-LSTM and Stochastic Fuzzy Systems represents a reliable and accurate CKD prediction in IoMT-based healthcare systems. The model, working with a team of clinicians, yielded improved accuracy through real-time monitoring compared to traditional clinical methods and allowed earlier detection and diagnosis of CKD. To prognosticate other chronic diseases that exhibit significant temporal complexity, future research could expand IoMT applications and add more deep learning models.

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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:

We have not harmed any human person with our research data collection, which was gathered from an already published article.

Permission to reproduce material from other sources:

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Clinical trial registration:

We have not harmed any human person with our research data collection, which was gathered from an already published article

Authors' Contributions

All authors have made equal contributions to this article.

Author Disclosure Statement

The authors declare that they have no competing interests

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