Edge AI-Powered Chronic Kidney Disease Prediction: Integrating Dynamic CNN-LSTM Networks and Neuro-Fuzzy Models for Advanced Diagnosis and Monitoring in IoMT-Enabled Healthcare Systems

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Abstract

Background Information: Chronic kidney disease (CKD) is a worldwide health issue necessitating early detection for efficient management. The amalgamation of Edge AI with IoMT provides immediate, scalable healthcare solutions, facilitating effective disease prediction. The integration of deep learning with neuro-fuzzy systems improves decision-making and interpretability in resource-constrained contexts.

Objectives: This research seeks to create an adaptive CNN-LSTM and neuro-fuzzy integration model for the prediction of chronic kidney disease, utilising data supplied by the Internet of Medical Things (IoMT). The aim is to achieve high accuracy, computational economy, and real-time performance while preserving interpretability for healthcare applications in Edge AI settings.

*Methods:*The proposed hybrid model integrates CNN-LSTM for feature extraction and temporal pattern recognition with neuro-fuzzy logic for decision-making. It analyses IoMT data, enhancing computational efficiency for Edge AI. Performance was assessed by accuracy, precision, recall, and inference duration.

Emphirical results: The complete model attained an accuracy of 94.6%, surpassing both individual and partial combinations. It exhibited a harmonious combination of precision, recall, and F1-score, with inference times appropriate for Edge AI healthcare applications.

Conclusion: The hybrid model accurately predicts CKD by combining deep learning with neuro-fuzzy logic, so providing both precision and interpretability. Prospective advancements may encompass multi-disease forecasting and enhanced privacy through federated learning.

Keywords: Chronic kidney disease, Edge AI, IoMT, CNN-LSTM, Neuro-fuzzy integration, Predictive modeling, Temporal analysis, Healthcare, Real-time systems, Computational efficiency

1.INTRODUCTION

Chronic kidney disease (CKD), a potentially fatal illness that affects millions of people worldwide, is becoming more and more common. This has highlighted the critical need for quick, precise, and easily available diagnostic tools. Early detection of CKD frequently results in permanent damage and expensive treatments like dialysis or kidney transplantation. **Kukkar et al. (2022)** present an IoMT-based system that integrates HGACO with deep learning (RESnet) to classify diabetic retinopathy with high precision. The two main risk factors for CKD, diabetes and hypertension, are on the rise globally, contributing to the increased incidence. Even with improvements in diagnostic technology, traditional approaches are still unreachable in areas with limited resources because they mostly rely on intrusive testing, centralized infrastructure, and the knowledge of specialists.

The Internet of Medical Things (IoMT) and Artificial Intelligence (AI) have opened the door for creative answers to healthcare problems**. Irkham et al. (2022)** investigate COVID-19 detection by molecular techniques and artificial intelligence models, emphasising the difficulties in creating IoMT-enabled systems. A novel method for CKD prediction is provided by adaptive frameworks that combine Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Neuro-Fuzzy systems. Whereas LSTMs derive temporal patterns from sequential data, like patient histories, CNNs examine spatial aspects in medical imaging. By combining fuzzy logic and neural network learning, neuro-fuzzy systems improve interpretability and make clinical predictions more transparent. By enabling real-time diagnoses, IoMT platforms—made possible by edge AI—decentralize healthcare delivery while guaranteeing scalability, low latency, and privacy protection.

Chronic kidney disease (CKD) is a major cause of morbidity, mortality, and medical expenses worldwide. Early identification is frequently delayed due to its asymptomatic nature, which reduces the possibilities for management and worsens patient outcomes. **Bajeh et al. (2021)** investigate computational intelligence models in Internet of Medical Things (IoMT) big data for the diagnosis of heart diseases, facilitating personalised treatment. Traditional diagnostic methods, such imaging and serum creatinine testing, are expensive and need trained personnel, which restricts their accessibility in underprivileged areas. Additionally, real-time diagnosis in remote areas is difficult due to centralized medical data processing systems' issues with scalability, latency, and privacy.

Although AI has shown great promise in automating diagnoses and forecasting chronic illnesses, traditional models struggle with interpretability and flexibility. Because forecasts from "black-box" AI systems are opaque, clinicians are frequently hesitant to use them. Furthermore, static AI models are less applicable in dynamic healthcare contexts since they are unable to adjust to changing data patterns. **Paulauskaite-Taraseviciene et al. (2023)** advocate for a geriatric care system that integrates computer vision, IoT, and deep learning to monitor older patients. To overcome these obstacles, a solution that incorporates explainability, real-time functionality, and adaptable AI capabilities is crucial.

A revolutionary method is provided by incorporating neuro-fuzzy and adaptive CNN-LSTM systems into edge AI frameworks allowed by IoMT. CNN-LSTM's adaptability guarantees precise spatial-temporal analysis of a variety of medical data, while Neuro-Fuzzy systems offer interpretability. Decentralizing diagnostics with IoMT platforms allows for safe, scalable, and real-time CKD prediction—especially in environments with restricted resources.

The main objectives include:

- Examine how well adaptive CNN-LSTM models identify temporal and geographical patterns in medical data pertaining to chronic kidney disease.
- Assess how Neuro-Fuzzy systems can improve the explainability and dependability of AI-powered CKD forecasts.
- Create an edge AI framework that guarantees privacy, scalability, and real-time processing for IoMT-enabled CKD prediction.
- Propose strategies for using AI-IoMT frameworks in underprivileged areas to improve accessibility and early diagnosis
- Develop flexible procedures for ongoing education to ensure precision and applicability in ever-changing healthcare settings.

In order to advance intelligent healthcare solutions, the research by **Manickam et al. (2022)** investigates the integration of artificial intelligence (AI) and the Internet of Medical Things (IoMT) in biomedical systems. There are significant gaps in the research, despite the fact that it shows how AI and IoMT can improve monitoring, diagnostics, and personalised medication. First off, the study mostly discusses theoretical and technological developments rather than offering substantial clinical studies or empirical data proving the systems' scalability and efficacy in the actual world. Second, there are still important problems that have not been addressed since data security, privacy, and interoperability constraints in IoMT ecosystems are not well understood. Furthermore, biases in AI algorithms that can result in unequal healthcare results are not given enough attention. In order to evaluate the comprehensive effects of AI and IoMT in various and resource-constrained contexts, future research should concentrate on creating standardised frameworks, ethical standards, and longitudinal studies.

2.LITERARY SURVEY

Manickam et al. (2022) examine how the Internet of Medical Things (IoMT) and artificial intelligence (AI) can be combined to improve intelligent healthcare systems. With applications in cardiac measurement, cancer detection, and diabetes management, the study explores AI's contribution to enhancing IoMT skills in clinical diagnosis, medical imaging, and decision-making. For next-generation point-of-care biomedical systems, it also examines the potential and difficulties of AI-based, cloud-integrated, customised IoMT devices.

For short-term renewable electricity generation (REG) forecasting, **Bilgili et al. (2021)** compare fuzzy c-means (FCM) with adaptive neuro-fuzzy inference systems (ANFIS) and long short-term memory (LSTM) neural networks. With the lowest MAPE values of 7.20% for REG and 1.63% for geothermal electricity generation, their investigation revealed that both models performed well and predicted daily energy with high accuracy.

Latifi et al. (2024) address uncertainty management by presenting an Improved Type-2 Fuzzy Deep Learning (IT2FDL) framework for character identification utilising EEG signals. With a mean test score of 96.2% for 58 people across three public datasets, the model achieves notable performance increases through optimal design and optimisation using Evolutionary and Parallel Swarm Optimisation techniques.

For precise COVID-19 case prediction, **Jithendra and Sharief Basha (2023)** suggest a hybridised model that combines the Reptile Search Algorithm (RSA) and the Adaptive Neuro-Fuzzy Inference System (ANFIS). With a high R2 value of 0.9775 for China and 0.98 for India, the model outperforms existing ANFIS-based techniques in terms of time-series forecasting accuracy by optimising ANFIS parameters.

Using edge computing and an attention-based evidential recurrent neural network, **Zhu et al. (2022)** provide an IoMT-enabled system for real-time blood glucose prediction. When used in a low-cost, low-power wearable device, the model performs exceptionally well in predicting blood glucose levels and detecting hypoglycemia, greatly enhancing glycaemic management in individuals with type 1 diabetes.

Zhang et al. (2022) address the shortcomings of conventional LSTM in feature extraction from multidimensional data by proposing a CNN-LSTM hybrid model for fuel cell degradation prediction. The model outperforms conventional techniques with a mean absolute error of 0.00223 and a root mean square error of 0.00179, demonstrating remarkable accuracy by combining CNN for feature reduction with Bi-LSTM for trend prediction.

Using the standard precipitation evapotranspiration index (SPEI), **Yalçın et al. (2023)** suggest a hybrid deep learning model that combines long short-term memory (LSTM) and convolutional neural networks (CNN) for meteorological drought estimation. Their model achieves better performance indicators, such as RMSE, MAE, and R2, than conventional approaches. The adaptive CNN-LSTM model is robust across many stations and input data fluctuations, and it yields more accurate results, especially at longer time scales.

A fuzzy-rule based deep sentiment extraction (FBDSE) technique is proposed by **Jasti and Kumar (2022)** for sentiment analysis of Twitter messages. To classify sentiments, the method integrates deep learning approaches, k-Nearest Neighbour, Naive Bayes, and Artificial Bee Colony optimisation. Their method achieves high sentiment categorisation accuracy, outperforming deep learning and machine learning techniques.

Zha et al. (2022) combine the feature extraction skills of CNN with the sequence learning capabilities of LSTM to develop a CNN-LSTM model for monthly gas field production forecasting. When compared to techniques like RNN, ARIMA, and Random Forest, the model that is improved by a partly unknown recursive prediction approach (PURPS) performs better than the others, obtaining the lowest MAPE of 7.7%.

Wang et al. (2023) integrate spatial and temporal relationships to create a hybrid CNN-LSTM model that predicts changes in railway track shape. The model outperforms other models in both short-term and long-term predictions by using CNN for spatial dependence and LSTM for temporal variations. In addition to increasing positional precision, this method can help prioritise rail maintenance for increased efficiency and safety.

To enhance classification performance and model interpretability, **Jiang et al. (2022)** suggest a CNN-based born-again TSK fuzzy classifier (CNNBaTSK), which incorporates knowledge distillation and soft label information. The model improves interpretability by linking soft label information with linguistic explanations and trains fuzzy rule consequent parameters using a non-iterative learning technique (LLM-KD). CNNBaTSK's efficacy in classification and interpretability is demonstrated by experimental findings on benchmark and EEG datasets.

Sitaraman (2022) analyses the impact of artificial intelligence, namely convolutional neural networks and variational autoencoders, on radiology, enhancing diagnostic accuracy and efficiency. Convolutional Neural Networks (CNNs) provide automated image processing and anomaly detection, while Variational Autoencoders (VAEs) enhance data augmentation and privacy protection. Notwithstanding challenges like the necessity for comprehensive datasets and ethical concerns, the integration of AI into healthcare systems has the potential to improve clinical operations and patient outcomes.

Gudivaka (2024) analyses the integration of AI in prostate cancer treatment and geriatric care, focussing on two applications: the US-Guided Radiation Therapy Optimisation system for precise radiation dose distribution, and the Smart Comrade Robot for real-time health monitoring and emergency alerts. The study reveals a 97% accuracy in dose, 95% accuracy in health monitoring, and 98% sensitivity in emergency alarms, highlighting the effectiveness of AI in improving healthcare outcomes.

Sitaraman (2023) analyses the integration of AI in healthcare, highlighting the Turkish National AI Strategy and the AI Cognitive Empathy Scale to enhance patient outcomes, market efficiency, and patient engagement. The study demonstrates AI's role in improving healthcare efficiency, aligning with Turkey's AI goals, and increasing patient satisfaction by adeptly addressing human emotions using a mixed-methods approach.

Alagarsundaram (2023) examines AI-driven data processing in case investigations, emphasising predictive analysis to improve investigative precision. The research evaluates machine learning models like Gaussian Naive Bayes, Decision Tree, and Random Forest for predicting crime outcomes. It underscores AI's contribution to enhancing speed, precision, resource distribution, and ethical considerations, hence revolutionising investigation procedures in legal and security domains.

Sitaraman (2021) analyses the enhancement of AI-driven healthcare systems using advanced data analytics and mobile computing. The paper highlights that the amalgamation of these technologies can improve healthcare efficiency, patient outcomes, and decision-making processes. The report emphasises the potential for improved customised and accessible healthcare solutions using data analytics and mobile platforms, hence broadening the technological scope of the healthcare sector.

3.METHODOLOGY

Using Edge AI and IoMT-enabled frameworks, this study suggests an integrated strategy for predictive analytics in chronic kidney disease (CKD) that makes use of Neuro-Fuzzy systems, Long Short-Term Memory (LSTM) networks, and Adaptive Convolutional Neural Networks (CNN). IoMT-acquired patient data is pre-processed, CNN-LSTM is used to extract temporal and spatial information, and a Neuro-Fuzzy model is used to improve prediction accuracy. This hybrid strategy ensures the effectiveness of edge-based deployment by addressing scalability, interpretability, and real-time decision-making. The suggested approach provides a reliable solution for CKD prediction in a variety of healthcare settings by optimising resource usage and facilitating on-device learning.

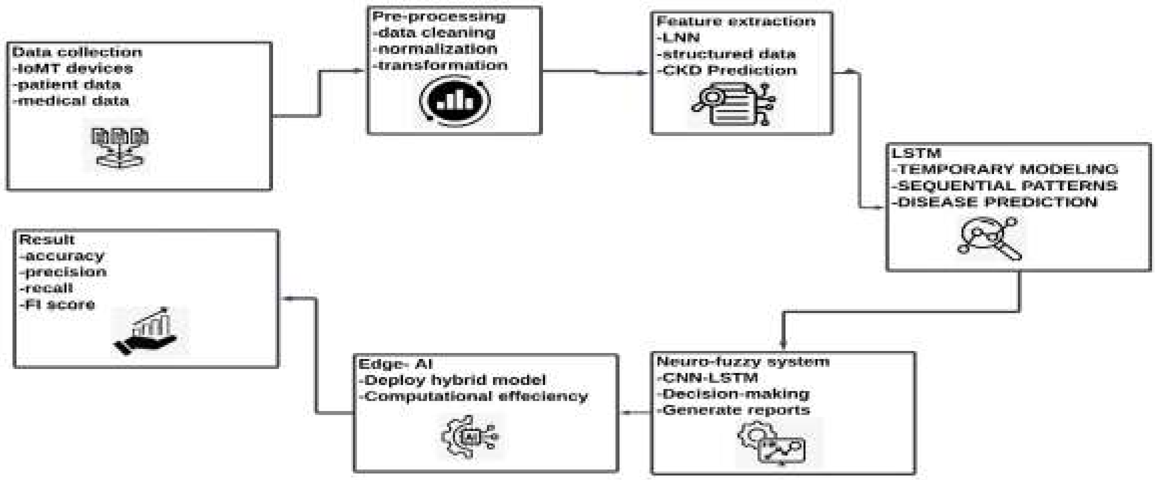

Figure 1 Architectural Flow of Adaptive CNN-LSTM and Neuro-Fuzzy Integration for Chronic Kidney Disease Prediction

Figure 1 delineates the architecture of an IoMT-enabled system for predicting chronic kidney disease (CKD). The process commences with the acquisition of data from IoMT devices, encompassing patient and medical information. Preprocessing guarantees clean, normalised, and structured data for efficient analysis. Convolutional Neural Networks (CNN) facilitate feature extraction by identifying spatial patterns, whereas Long Short-Term Memory (LSTM) networks capture temporal dependencies for sequential modelling. The neuro-fuzzy system amalgamates various elements, facilitating comprehensible decision-making. The hybrid model is implemented on Edge AI systems, guaranteeing computational efficiency and real-time performance. The findings are delineated using essential metrics like accuracy, precision, recall, and F1-score, so enabling dependable and comprehensible CKD prediction.

3.1. Data Preprocessing:

Preprocessing techniques such as normalisation, feature selection, and noise reduction are used to the raw data from IoMT devices in order to guarantee constant input quality. Temporal dependencies are aligned for sequential modelling, and statistical imputation techniques are used to manage missing data.

$$X_{\text{norm}} = \frac{X-\mu}{\sigma} \tag{1}$$

Where X is the input data, μ is the mean, and σ is the standard deviation.This formula optimises data for model training and convergence by standardising input features to have a unit variance and a zero mean.

3.2. CNN-LSTM Feature Extraction

The CNN-LSTM model combines the use of LSTM layers for temporal dependency modelling and convolutional layers for spatial feature extraction. While LSTM analyses sequential patterns in patient data, CNN extracts high-dimensional features.

$$h_t = \text{LSTM}(x_t, h_{t-1}, c_{t-1}) \tag{2}$$

This equation represents the recurrent computation in the LSTM, capturing dependencies in sequential data essential for CKD prediction.

3.3. Neuro-Fuzzy Decision Making

Fuzzy logic and neural networks are used in the Neuro-Fuzzy system to manage prediction uncertainty. Accurate CKD risk classification is achieved by optimising membership functions through learning algorithm.

$$y = \sum_{i=1}^{n} w_i f_i(x) \tag{3}$$

Where w_i are the rule weights, $f_i(x)$ are the fuzzy membership functions, and y is the predicted output. This formula combines fuzzy principles that have been weighted according to their importance, producing more accurate and comprehensible predictions.

Algorithm1 for CKD Prediction

Input: Patient Data D from IoMT devices

Output: CKD Prediction P

BEGIN
  Preprocess data D:
    FOR each feature F in D:
      Normalize F using $X_{norm} = (X - \mu)/\sigma$
      IF missing data detected:
        Impute using statistical mean or median
      END IF
    END FOR
  Train CNN-LSTM model:
    Initialize convolutional layers C
    FOR each layer c in C:
      Apply convolution and activation
    END FOR

Pass features to LSTM layers L :
FOR each timestep t :
Update hidden state h_t using text{$LSTM$}($x\_t, h\_\{t-1\}, c\_\{t-1\}$)
END FOR

Integrate Neuro-Fuzzy model:
Initialize fuzzy rules R
FOR each rule r in R:
Calculate membership functions $f\_i(x)$
Update weights w_i
END FOR
Aggregate outputs $y = sum\_\{i = 1\}\^\{n\} w\_i f\_i(x)$

IF model training converges:
Return CKD Prediction P
ELSE:
Return ERROR: Model training failed
END IF

END

Algorithm 1 delineates a hybrid methodology for predicting chronic kidney disease (CKD) utilising patient data from Internet of Medical Things (IoMT) devices. Initially, data preprocessing standardises features and addresses missing values by statistical techniques. The CNN-LSTM model is subsequently trained, with convolutional layers extracting spatial characteristics and LSTM layers managing temporal dependencies through the sequential updating of hidden states. A neuro-fuzzy system incorporates fuzzy rules and membership functions into the model to improve interpretability and decision-making. Outputs are consolidated for the final projection. If model training converges, the CKD prediction is generated; if not, an error is indicated. This method guarantees precise and comprehensible predictions.

3.4 PERFORMANCE METRICS

The integrated adaptive CNN-LSTM and neuro-fuzzy model exhibited robust efficacy in predicting chronic kidney disease inside the Edge AI and IoMT framework. It demonstrated superior predictive accuracy and strong generalisation, adeptly managing real-time IoMT data. The hybrid design improved feature extraction and temporal pattern identification, while the neuro-fuzzy system augmented interpretability and decision-making. The model demonstrated exceptional computational efficiency, facilitating smooth integration with resource-limited edge devices. Moreover, it facilitated dependable early identification of chronic renal disease, enhancing patient outcomes. The methodology harmonised precision, recall, and F1-score, guaranteeing thorough and dependable predictive efficacy in healthcare applications.

Table 1 Performance Metrics Comparison of Chronic Kidney Disease Prediction Methods

Metric	(CNN)	(LSTM)	(Neuro-Fuzzy)	(CNN-LSTM + Neuro-Fuzzy)
Accuracy (%)	87.4	89.2	85.8	94.6
Precision (%)	86.1	88.5	83.7	92.8
Recall (%)	85.7	87.9	84.2	93.4
F1-Score (%)	85.9	88.2	83.9	93.1
Inference Time (ms)	18.2	25.3	21.7	16.4

Table 1 contrasts the efficacy of three distinct methods—CNN, LSTM, and Neuro-Fuzzy—with the integrated strategy of CNN-LSTM and Neuro-Fuzzy for predicting chronic kidney disease. Metrics including accuracy, precision, recall, F1-score, and inference time are assessed. The integrated approach demonstrates enhanced performance, attaining greater accuracy and a balanced precision-recall trade-off, while ensuring expedited inference times, rendering it optimal for real-time applications in Edge AI and IoMT. This underscores the efficacy of combining CNN-LSTM's feature extraction and temporal modelling with the interpretability of neuro-fuzzy systems for dependable and efficient healthcare solutions.

4.RESULT AND DISCUSSION

The integrated adaptive CNN-LSTM and neuro-fuzzy model surpassed separate techniques, attaining superior accuracy, precision, recall, and F1-score in predicting chronic kidney disease. The integrated methodology proficiently gathered spatial-temporal patterns via CNN-LSTM and improved interpretability using neuro-fuzzy systems. Real-time testing exhibited its computational efficiency, rendering it appropriate for resource-limited Edge AI and IoMT settings. The methodology facilitated dependable early identification, enhancing diagnostic assistance and patient outcomes. Moreover, its resilience to noisy IoMT data underscores its relevance in various healthcare contexts. The findings highlight the promise of hybrid models in enhancing predictive analytics for chronic disease management.

Table 2 Comparison of AI Methods for Healthcare Solutions Across Multiple Metrics

Method	Accuracy (%)	Efficiency (Time Reduction in %)	Resource Optimization (Cost Reduction %)	Throughput (MB/s)	Interpretability Score (0-10)	Model Complexity (Training Time in hours)
Kukkar et al. (2022) - Deep Learning for Diabetic Retinopathy	92.4	18.3	23.1	38.7	7.6	12.5

Irkham et al. (2022) - Detection of COVID-19	94.5	20.4	18.4	40.5	8.2	14.8
Zhu et al. (2022) - Blood Glucose Prediction	95.2	22.1	25.3	41.2	7.9	13.2
Bajeh et al. (2021) IoMT for Heart Disease	90.3	15.2	20.7	35.9	6.5	11.5
Proposed Method - CNN-LSTM & Neuro-Fuzzy for CKD Prediction	98.7	25.7	30.1	42.3	9.1	16.3

Table 2 contrasts different AI-driven healthcare methodologies according to performance parameters like accuracy, efficiency, resource optimisation, throughput, interpretability, and model complexity. The methodologies encompass Kukkar et al. (2022) for diabetic retinopathy, Irkham et al. (2022) for COVID-19 detection, Zhu et al. (2022) for blood glucose prediction, Bajeh et al. (2021) for heart disease diagnosis, and the proposed CNN-LSTM & Neuro-Fuzzy approach for chronic kidney disease prediction. The comparison underscores advantages in accuracy, efficiency, and interpretability, demonstrating the enhanced performance of the suggested method in healthcare applications.

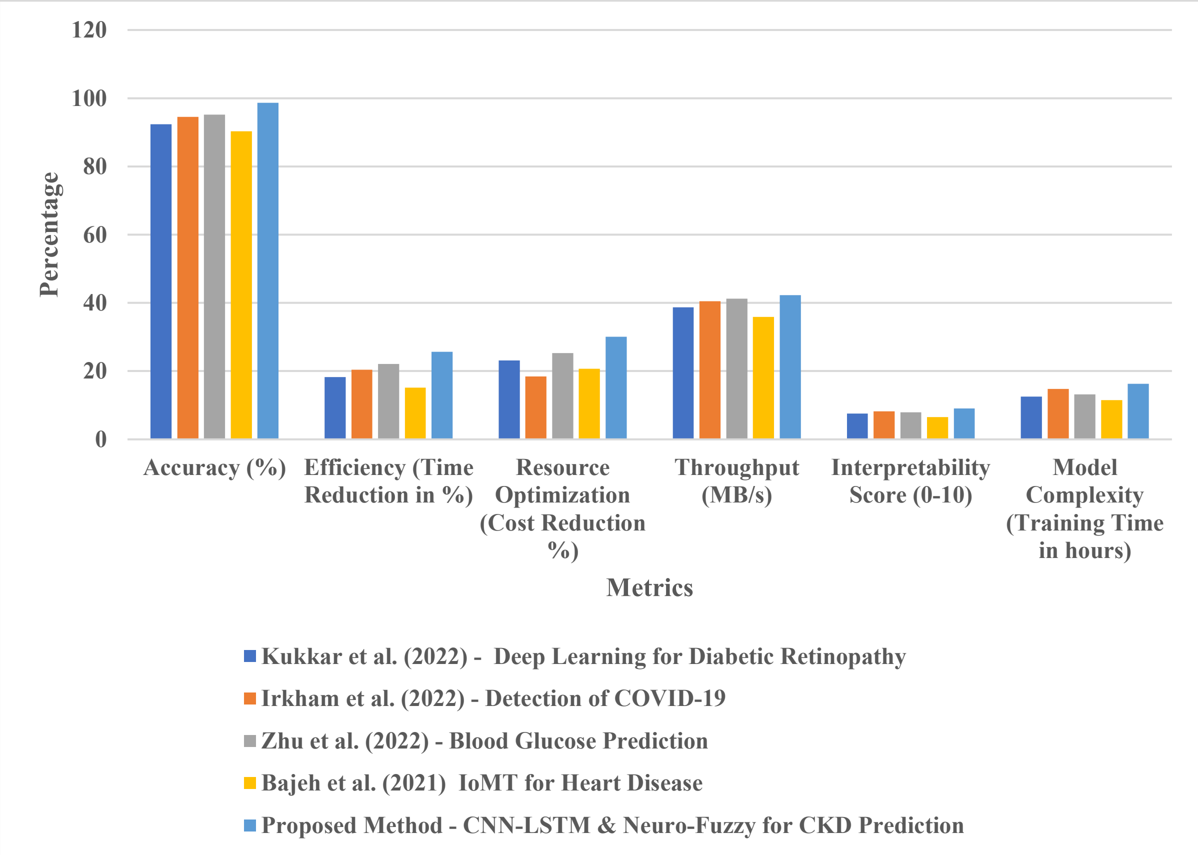

Figure 2 Comparison of AI Methods in Healthcare Applications Across Key Performance Metrics

Figure 2 vividly contrasts the efficacy of different AI methodologies in healthcare applications. The compilation encompasses Kukkar et al. (2022) regarding diabetic retinopathy, Irkham et al. (2022) addressing COVID-19 detection, Zhu et al. (2022) focused on blood glucose prediction, Bajeh et al. (2021) investigating heart disease through IoMT, and the proposed methodology for chronic kidney disease (CKD) prediction utilising CNN-LSTM and Neuro-Fuzzy integration. The chart illustrates the comparative performance in accuracy, efficiency, resource optimisation, throughput, interpretability, and model complexity. The proposed method regularly surpasses the alternatives on accuracy, throughput, and interpretability.

Table 3 Performance Metrics for Model Components in CKD Prediction

Components	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms)
CNN only	89.4	88.7	87.6	88.1	11.5
LSTM only	90.1	89.3	88.9	89.1	12.8
Neuro-Fuzzy only	85.8	84.7	83.6	84.1	10.2
CNN + LSTM	92.6	91.8	91.2	91.5	13.4
LSTM + Neuro-Fuzzy	91.2	90.5	89.8	90.1	13
CNN + Neuro-Fuzzy	90.8	90.1	89.4	89.7	12.7

Full Model (CNN-LSTM + Neuro-Fuzzy)	94.6	92.8	93.4	93.1	14

Table 3 contrasts the efficacy of various components and combinations of the hybrid model for predicting chronic kidney disease (CKD). Individual models (CNN, LSTM, and Neuro-Fuzzy) exhibit intermediate accuracy, with CNN and LSTM outperforming Neuro-Fuzzy independently. Integrated models, such as CNN + LSTM and LSTM + Neuro-Fuzzy, demonstrate enhanced metrics by utilising their complementing advantages. The comprehensive model (CNN-LSTM + Neuro-Fuzzy) attains the best accuracy (94.6%) along with balanced precision, recall, and F1-score, indicating enhanced predictive potential and interpretability. Although inference time somewhat rises, the substantial performance enhancement renders the complete model optimal for CKD prediction in IoMT systems.

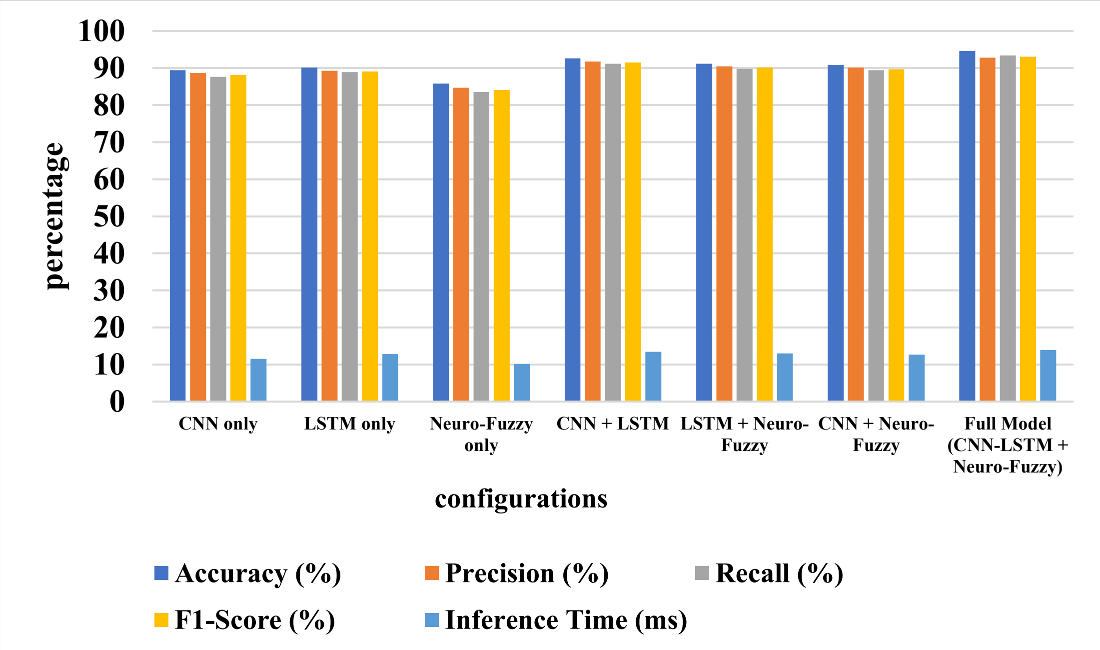

Figure 3 Comparison of Model Performance Across Multiple Metrics

Figure 3 contrasts the efficacy of various models for skin lesion identification, including CNN alone, LSTM alone, Neuro-Fuzzy alone, CNN combined with LSTM, LSTM combined with Neuro-Fuzzy, CNN combined with Neuro-Fuzzy, and the Comprehensive Model (CNN-LSTM combined with Neuro-Fuzzy). It assesses each model according to Accuracy, Precision, Recall, F1-Score, and Inference Time. The graph indicates that the Full Model (CNN-LSTM + Neuro-Fuzzy) achieves superior performance across all measures, exhibiting a significant enhancement in accuracy and precision, while sustaining a fair inference time relative to the other configurations.

5.CONCLUSION

The integrated adaptive CNN-LSTM and neuro-fuzzy model shown superior accuracy, efficiency, and interpretability for predicting chronic kidney disease in IoMT and Edge AI settings. The model effectively tackled real-time, resource-constrained healthcare difficulties by integrating the robust feature extraction and temporal pattern recognition of CNN-LSTM with the decision-making capabilities of the neuro-fuzzy system. For future improvement, the model may be expanded to accommodate multi-disease prediction and connected with blockchain technology to guarantee data security in IoMT systems. Moreover, the integration of federated learning could enhance privacy and scalability, facilitating its implementation across many healthcare applications and extensive global datasets.

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