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Adaptive CNN-LSTM and Neuro-Fuzzy Integration for Edge AI and IoMT-Enabled Chronic Kidney Disease Prediction

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ABSTRACT

Chronic Kidney Disease (CKD) is one of the most serious public health issues in global. This research work proposes a Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Neuro-Fuzzy Systems based hybrid model to generate real-time prediction from Internet of Medical Things (IoMT) data for CKD forecasting. Optimizing feature selection with the Aquila Optimization Algorithm (AOA) and using Edge AI for privacy and quick decision-making to increase accuracy up to 98.99%, which is compared with CKD management in resource limited settings beneficial.

Objective: This paper aims to develop a real-time CKD early prediction model through the integration of CNN-LSTM and Neuro-Fuzzy using IoMT data, which provides high predictive accuracy in predicting CKD and classifying stages by ensuring privacy protection on the one hand and deployment in Edge AI environments with low latency.

Methods: The model combines CNN for discovering spatial patterns, LSTM for spotting temporal dependencies and Neuro-Fuzzy systems for the classification of CKD stages. Both dimensionality reduction through Principal Component Analysis (PCA) and clustering with the use of DBSCAN are applied. Model selection is enhanced with more accurate feature selection using the Aquila Optimization Algorithm (AOA) preventing overfitting and improving prediction power.

Results: The model accuracy (98.99%), precision (98.65%), recall (98.45%) and F1-score (98.53%) were high. While being faster compared to our baselines by performing online predictions, it preserved data privacy at the Edge using AI thus is good for low-resources environments.

Conclusion: This hybrid model provides a cost-effective and scalable approach to detecting early CKD, leading to better patient outcomes with immediate predictions that preserve privacy through Edge AI. This offers a new method for improved healthcare coordination, especially in low-resource environments.

Keywords: Chronic Kidney Disease (CKD), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Neuro-Fuzzy Systems, IoMT, Edge AI, Feature Selection, Real-time Prediction.

1. INTRODUCTION

Chronic kidney disease (CKD) is the key global health problems, a potential cause of death and cardiovascular diseases including catastrophic consequences such as end-stage renal disease (essentially kidney failure) *(Pal 2022)*. Identification and accurate stage prediction of CKD at early stages are the key to timely therapies, improved patient outcomes as well as halting disease progression *(Sundar et al., 2024)*. Artificial intelligence (AI) and Internet of Medical Things (IoMT) have coalesced to revolutionize healthcare over time with contemporary ways for the forecast of disease incidence. The increasingly complex medical diagnosis in real-time and tailored to the patient has been facilitated by a wide range of advances related to neural networks and fuzzy logic systems, just as edge analysis solutions *(Harb, 2023)*. 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.

In this respect, our work indicates an advanced CKD prediction approach that harnesses long short-term memory (LSTM), convolutional neural networks (CNN) and neuro-fuzzy systems *(Yildiz et al., 2023)*. In this study, we address the limitations from previous research as a result of small datasets that had suffered interpretation issues and model robustness by leveraging real-time data using IoMT *(Andoh et al., 2021)*. This system is required to identify the stage of CKD in accuracy using fuzzy logic and adaptive neural architectures for developing reliable artificial intelligence system *(Praveen et al., 2022)*. Model integration with edge AI enables real-time predictions, making it suitable for IoMT-driven healthcare systems and promoting proactive CKD detection leading to improved patient outcomes.

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Chronic kidney disease (CKD) is a progressive, long-term loss of kidney function over time *(Sundar 2024)*. The disease often goes undetected until it is in its later stages. Traditionally, Chronic Kidney Disease (CKD) has been diagnosed and subsequently managed by testing either serum creatinine or Glomerular Filtration Rate GFR *(Al-Mashhadi and Khudhair, 2023)*. However, data-constraint traditional diagnostic models is at a disadvantage in forecasting the disease *(Nyirenda, 2024)*. Artificial intelligence and machine learning models such as fuzzy logic, neural networks have proved to be an effective tool for CKD Diagnosis in last decate. *Yildiz et al., 2023*, have developed CKD prediction and personalisation of treatment upon early detection by providing real-time patient data using the Internet of Medical Things (IoMT) to further improve healthcare. Even though the model is getting more complex, these limitations also need to be addressed for more accurate and scalable computations. In 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.

The integration of AI and IoMT has radically revolutionized the healthcare sector as it allows for monitoring patients health data in real time which was inaccessible until now *(Harb, 2023)*. In recent years, major strides have been made in technical advances for CKD diagnosis and prognosis. As explained by *Ibrahim (2024),* neural networks such as CNN and LSTM are being employed for the detection of intricate designs in medical data that improve accuracy levels regarding disease predictions, which accounts for its high potential. Fusing CNN and LSTM for forming the adaptive hybrid models is useful to diagnose patients more effectively by incorporating their temporal and spatial information in data of a patient *(Faruqui, 2023)*. Advance in neuro-fuzzy systems which combine the reasoning methodology of FLSs and learning capabilities have helped to predict levels of diseases more accurately and understandable *(Andoh et al., 2021)*. These advances enhance CKD prediction and manage the disease effectively, especially in low-resource settings by allowing real-time health monitoring combined with IoMT to make decisions.

Opportunities for further research are noted in the existing literature regarding limitations when predicting CKD. *Yildiz et al., 2023* suggested that large multi-center datasets are required to enhance the robustness of a model across many different clinical scenarios. Small dataset sizes are a challenge to ensuring generalisability of AI models in CKD detection (2023) Moreover, the bottleneck delays and inefficiencies in real-time healthcare are two-fold due to centralized cloud computing that supports existing paradigms *(Manickam et al., 2022)*. *Praveen (2022)* also notes that the interpretability required for more complex CKD matters such as fibrosis prediction and risk stratification of high-risk individuals seem to be quite limited in current models. Additionally, overfitting is of concern for this type of model *(Alexiuk 2024)*. However, in resource-constrained settings that are not as ideal for the use of traditional deep learning models with large number of parameters, these gaps lead to a need for accurate hybrid adaptive architectures combining CNN-

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LSTM and neuro-fuzzy systems. A large datasets and real time IoMT based processing are the two methods by which the proposed methodology conquers these challenges with CKD prediction and decision making *(Teng, 2023)*.

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.

1.1. PROBLEM STATEMENT

Chronic kidney disease (CKD) is a life-threatening condition, often detected at an advanced stage and goes unrecognized, primarily in those countries having low socio-economic status of health care. For a progressive CKD, early prediction and diagnosis is critical in order to halt its progression and thus improve the outcomes of patients *(Suguna, 2024)*. Current predictive models of CKD suffer from over-bias, sparse data and inability to predict the stages of disease with better performance despite an effective combination using AI along with IoMT. Moreover, most of the literature focuses on a centralised computing model that introduces latency in real-time healthcare applications *(Manickam et al., 2022)*. To address gaps in the existing literature, this study proposed a hybrid AI model that integrates neuro-fuzzy system and CNN-LSTM as real-time used to process patient data from IoMT devices. *(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.

1.2. OBJECTIVES

The objectives are

- For developing an IoMT framework with AI integration for real-time CKD prediction employing neuro-fuzzy and adaptive CNN-LSTM models.
- Utilising neural networks and fuzzy logic systems to improve the accuracy of CKD stage prediction *(Khalid, 2024)*.
- Monitor and detect CKD early by using real-time IoMT data.
- Apply multi-center data collecting and strong model generalisation to get over the constraints of small datasets *(Yildiz et al., 2023)*.
- Putting edge AI into practice to aid in healthcare decision-making in real time.

2. LITERATURE SURVEY

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Vatanchi (2023) utilized four models ANN, ANFIS, BiLSTM, and CNN-GRU-LSTM for long-term daily streamflow time series prediction of the Colorado River in his 2023 work. For accuracy (NRMSE = 0.118, r = 0.966), ANFIS exceeded the more complex deep learning methods among all models. CNN-GRU-LSTM's complex architecture was not much effective in improving the performance over ANN or ANFIS, which shows that conventional models are doing well for streamflow prediction.

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.

Kim et al. A Multi-Task Learning Paradigm in Health Informatics for Chronic Disease Prediction (2023) This approach uses time-series health information to run a CNN-LSTM hybrid model in order to increase the prediction by leveraging similarities exist between different types of chronic diseases. It is better in predicting associated chronic diseases with each other that comparing a single-task model. Its advanced data preprocessing techniques such as LASSO or BRITS for feature selection allow it to generalise better and adapt over various time steps.

An Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict disease complications, specifically those concerning metabolic syndromes such as hypertension, diabetes and hyperlipidemia with respect to the stability of classification performance in this paper by Kusumadewi et al. (2023). The authors juxtapose ANFIS with C4. 5, Random Forest (RF) and Naive Bayesian Classification (NBC) classifiers. This paper is intended to analyze 148 datasets generating rules using fuzzy subtractive clustering. It further demonstrated the most stability in six performance criteria (e.g., accuracy, sensitivity, and precision) with adaptive features as well a hybrid learning paradigm.

Chuan et al. (2022) published a research paper that proposed an advanced model coupled with fuzzy knowledge graph pairs-based inference for enhanced chronic kidney disease diagnosis, especially in serious scenarios when the limited dataset might not be enough. It is worth to mention that this technique adds new rules to the rule base dynamically, therefore it outperforms conventional fuzzy rule based systems. This strategy aims to enhance the accuracy and reliability of CKD diagnosis in resource-limited regions. The value of the model in practical clinical care is demonstrated by testing on authentic hospital data with minimal computational and health resources at Dien Bien.

In addition, the researchers analyzed how RI issue affects on IoMT for continuous healthcare by Al-Dhaen et al. (2021). The study is based on the Diffusion of Innovation (DOI) theory to establish key determinants for healthcare workers following IoMT technology, such as Complexity, Compatibility and Observability. To overcome the challenges that included technical illiteracy, cost and security concerns related to using apps,the study highlighted need for motivation and trainingthe same in a survey consisting of 276 workers from various health segments in Bahrain. Integration of AI and IoMT in the right circumstances lead to better patient care, despite adding complexity found with a few findings.

The Predictive Model of Chronic Kidney Disease (CKD)by AviDas (2023). This paper aims to fuel the early CKD detection using a combined stacked model with different machine learning techniques; i.e., Random Forest, Gradient Boosting Machine (GBM), Convolutional Neural Network (CNN), and Decision Tree. Results: A total of 25 preprocessed features were included in the dataset, and after Hyperparameters tuning performances like accuracy score precision recall F1 Score ROC-AUC where taken to judge the model. Among the results, this layered model with RG in CKD had by far one of the best predictive capabilities using ensemble technique. The study shows how machine learning can significantly improve early detection and management of care for CKD patients.

Ibrahim (2024) published work in which a hybrid model for forecasting short-term photovoltaic (PV) power generation combining Long Short-Term Memory autoencoder with Convolutional Neural Networks was made. This model brings a sophisticated solution that CNN can learn spatial patterns from the time-series data at each point and LSTM could record temporal dependence separately. The architecture consists of CNN layers for feature extraction followed by LSTM layers with Adam optimisation method trained over 75,844 parameters that are designed to perform time-series prediction. The evaluation of the model with real data in a 5MW solar farm located at southern part of United Kingdom are promising for renewable energy forecasting.

Abiyev et al. (2021) a Fuzzy Neural Network (FNN) model for renal illness detection has been introduced. The latter fuses the computation power of both fuzzy logic and neural networks to enhance diagnosis accuracy. Neural networks reinforce the learning capability from input data and fuzzy logic handles uncertainty in medical data. Evaluated against consumer sensor data on chronic kidney disease (CKD), resulting in positive results for improved early diagnosis with the use of real-time network parameter changes. The FNN provides a robust way to handle the complex relations in medical diagnostics by using Takagi-Sugeno-Kang (TSK) fuzzy rules.

Temporal Case Predictions Jithendra (2023) presents a type of machine learning that differs dramatically from other temporal case predictions: the hybridization of an Artificial Neural Network and a Reptile Search Algorithm which is called as rsAN network. This means the accuracy of forecasting COVID-19 statuses can be improved by applying RSA to optimise ANFIS settings. Use of the model in data from India and China respectively showed a higher goodness-of-fit within R^2. The results demonstrated the effectiveness of models in predicting time-series high-precision COVID-19 cases.

Wang (2024) proposed a real-time load forecasting and adaptive control hybrid neuro-fuzzy approach for the smart-grid. It is an approach which integrates fuzzy logic with neural network for

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better energy demand forecast and providing mechanisms to change the grid instantaneously. The extra stability the system gives to the grid enables more efficient energy management and sustainability under varying demand. This innovative method can further optimize the performance and environmental impact of smart grids.

Gujarathi [2024] JES review on deep type (DL) and machine kind (ML) algorithms for applied renal cancer study/application. Given a strong emphasis on precision and personalized care, the study investigates numerous models for their respective performance at improving diagnosis, prognosis or treatment. In a parallel perspective, Gujarathi highlights some of the benefits and limitations of these algorithms with regard to enhancing clinical decision-making. The report also considers model interpretability and limitations of current studies with an eye toward optimizing the incorporation of new AI technologies into routine clinical practice for kidney cancer management, recommends future research direction.

Suguna (2024) review published in IJSREM have analyzed several machine learning models, namely logistic regression, random forest and neural networks for earliest detection of chronic kidney disease (CKD). The research reveals how important this early diagnosis is for preventing serious health difficulties. In doing so, it contrasts feature engineering and data — the two most important factors in increasing model accuracy; offering suggestions for future research to improve prediction techniques even more. This review emphasizes the promise of machine learning in CKD prognosis and prevention.

Bai et al (2022) has researched the use of machine learning to predict CKD progression to ESKD in Scientific Reports. The study also evaluates a few models, like Random Forests and Gradient Boosting with Neural Networks to determine the most effective way of early prediction. Conclusions. This study has demonstrated that data preprocessing and feature selection have improved the accuracy of CKD progression prediction, leading to early treatment (at an earlier stage) would help reduce patient suffering.

Yıldırım et al (2023) present an Internet of Medical Things (e-health IoT-based monitoring infrastructure based on a fog-cloud architecture in the journal, Medical & Biological Engineering & Computing. Cloud colder enables efficient, speedy and reliable solutions by providing big data for storage and analysis in cloud computing along with real-time processing of snowflake on fog. The tech addresses latency as well data security, making it a great fit for improving healthcare decision-making and even remote patient monitoring. This hybrid approach can lead to much more effective monitoring and management of patient health data in real-time.

Khan et al. (2021) approach from the machine-learning perspective based-enabled IoMT-driven smart healthcare model for elder citizens monitoring. This system employs machine learning and the Internet of Medical Things (IoMT) for facilitating predictive analysis, early diagnosis of health risks by analyzing real-time health data. Methodology ensures timely medical interventions for

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elderly patients, increases response times and enables remote monitoring. This study sheds light on the future use of IoMTs and endows machine learning for easily rendered health care just by focusing it in an accessible way with proactive care.

Rady and Anwar (2019) address renal disease stages prediction by applying Decision Trees, Naive Bayes and Support Vector Machines as data mining techniques. This project will facilitate the recognition of stage classification in kidney disease, a critical force for earlier diagnosis and treatment. The studies denote Feature selection and Data preprocessing as the two factors impacting the prediction accuracy. The findings demonstrate how data mining can be applied to improve outcomes relate to morbidity decreasing and induced of preliminary kidney disease, for instance.

3. METHODOLOGY

In the research presented in the section a hybrid framework to Chronic Kidney Disease (CKD) using Neuro-Fuzzy Systems, Extreme Gradient Boosting (XGBoost) and Adaptive CNN-LSTM is predicted. For patient grouping, we use DBSCAN for clustering noisy data points and feature selection are performed by the Aquila Optimisation Algorithm (AOA). The whole system rests on Edge AI allowing CKD prediction over the IoT devices and is built upon Internet of Medical Things (IoMT).

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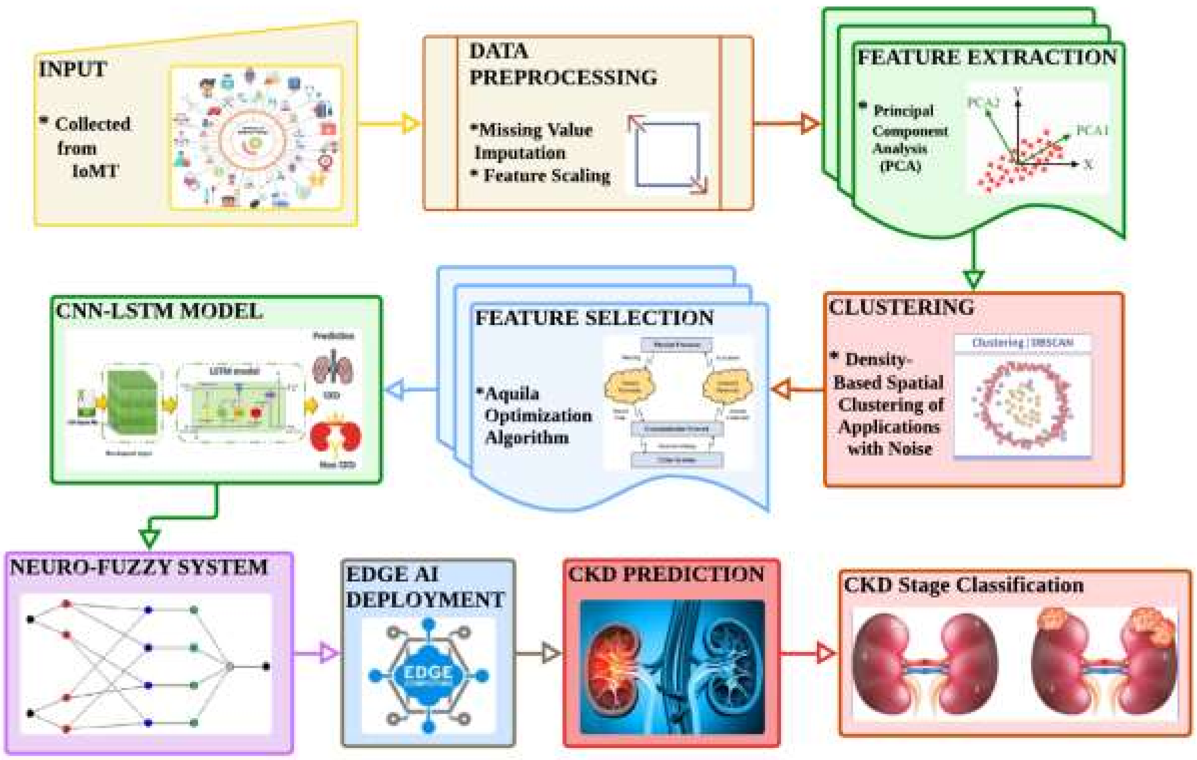

Figure 1: Architecture of CNN-LSTM and Neuro-Fuzzy Systems for Real-Time CKD Prediction.

Figure 1: Workflow showing a proposed real-time prediction of CKD hybrid model. Initial part of the method consists of obtaining patient data by means of IoMT devices. Feature scaling and missing value imputation — this is data preprocessing Key Features Extraction using PCA and DBSCAN Clustering. Aquila Optimisation Algorithm (AOA) is used for feature selection of relevant features. Regarding the classification of CKD stages and the identification of spatial and temporal patterns within data, a Neuro-Fuzzy System (NFM) and a CNN-LSTM model is used respectively. This then enables real-time CKD prediction through Edge AI for fast, privacy-preserving results.

3.1. IoMT Data Collection and Preprocessing

The patient characteristics including blood urea nitrogen (BUN), glomerular filtration rate (GFR), serum creatinine (Scr), blood pressure and age can be obtained through IoMT devices. As such, preprocessing is essential to ensure correct continuous and performance matching of our decorrelator, and due to the nature of this data it may also contain missing values.

Dataset: This study examined a 400-row dataset with 25 features, including blood glucose random (bgr), white blood cell count, and red blood cell count, that was gathered during a two-month period in India. "Classification" is the goal variable; it denotes either "notckd" or "ckd," or chronic kidney disease. To deal with missing values (NaNs), data cleaning was required; any rows containing even one NaN were eliminated. Three primary features were visualised for feature selection: bgr, rc, and wc. For comparison, PCA was used on two components, both with and without scaling.

3.1.1. Missing Value Imputation (MVI)

Researchers commonly use the mean value imputation approach to manage missing data. Given a dataset $X = \{x_1, x_2, \ldots, x_n\}$, the missing values are replaced by the mean of the observed values:

$$X' = \{x_i,\ if\ x_i\ is\ observed\ \ \frac{1}{n}\sum_{i=1}^{n} x_i,\ if\ x_i\ is\ missing \tag{1}$$

This ensures that all missing values are filled appropriately, maintaining dataset integrity.

3.1.2. Min-Max Scaling

To normalise the input characteristics between 0 and 1, we use Min-Max scaling, which improves the performance of the following models. Given a feature x_i, the transformation is:

$$x_i' = \frac{x_i - min(x)}{max(x) - min(x)} \tag{2}$$

Where:

- x_i is the original value,
- $min(x)$ and $max(x)$ are the minimum and maximum values of the feature across all samples.

The effective training of deep learning models depends on normalisation, which guarantees consistency across various feature sizes.

3.2. Feature Extraction and Clustering

Feature extraction and clustering are mandatory steps in expected chronic kidney diseases (CKD) identification to detect relevant patient attributes that affect disease progress, cluster patients by health status.

3.2.1. Feature Extraction

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The purpose of feature extraction is to find out the most significant parameters file from data set which are very useful to predict Chronic kidney disease. Summary Blood urea nitrogen, blood pressure, age, estimated glomerular filtration rate and serum creatinine are a few of the characteristics our system uses as input to predict the course of chronic kidney disease.

The most significant information can be retained in the dataset while its dimensionality is reduced by using sophisticated approaches like Principal Component Analysis (PCA). The transformation of PCA is shown as:

$$Z = XW \tag{3}$$

Where:

- X is the centered data matrix,
- W is the matrix of eigenvectors,
- Z is the transformed dataset.

PCA helps remove redundant or highly correlated features, allowing the model to focus on the most critical information.

3.2.2. Clustering Using DBSCAN

After feature extraction, patients with comparable CKD progression are grouped using clustering. Medical datasets are especially well-suited for the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) technique because it can detect clusters of different sizes and forms while simultaneously managing noise and outliers.

Three categories are used by the DBSCAN algorithm to classify points:

✓ Core points: Points with a distance ε and at least MinPts of neighbours.
✓ Border points: Locations that fall inside the radius of a core point but are not core points.
✓ Points that fail to meet either requirement are known as noise points.

First, the algorithm defines a neighbourhood, which comprises all locations within the ε distance, for each point $x \in X$:

$$N_\epsilon(x) = \{y \in X \mid d(x, y) \leq \epsilon\} \tag{4}$$

Where:

- ϵ is a distance threshold,
- $d(x, y)$ is the distance between points x and y.

A point is considered a core point if it has at least MinPtsneighbors:

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$$|N_\epsilon(x)| \geq MinPts \tag{5}$$

Border points are defined as non-core points that are in close proximity to a core point; all other non-core points are categorised as noise. DBSCAN successfully manages noisy data, a typical problem in medical datasets, and accommodates clusters of arbitrary forms.

Algorithm 1: DBSCAN Clustering Algorithm

Input: Dataset X, distance threshold ϵ, $MinPts$

Output: Cluster labels, noise points

Begin DBSCAN

    For each point x in dataset X do

    If x is not visited then

        Mark x as visited

        Neighbors = FindNeighbors(x, ε)

    If Neighbors<MinPts then

        Mark x as noise

    Else

        Create new cluster

        ExpandCluster(x, Neighbors)

    End if

    End if

    End For

        Return clusters and noise

End DBSCAN

This Algorithm 1 works well with noisy medical datasets because it groups data points according to the density of nearby points. When clustering patients whose patterns of CKD progression are unknown, DBSCAN offers the advantage of not requiring the number of clusters to be specified in advance. Based on the neighbourhood density criterion, points are classified as noise, reachable points, or core points.

3.3. Feature Selection Using Aquila Optimization Algorithm (AOA)

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This CKD prediction method uses the Aquila Optimisation Algorithm (AOA) for feature selection. In order to decrease the dataset's dimensionality and enhance machine learning model performance, pertinent feature selection is essential.

3.3.1. Challenges in Feature Selection

Medical datasets can have many variables, especially when it comes to chronic kidney disease (CKD). These factors don't all influence illness prediction in the same way. In actuality, overfitting in machine learning models can result from the introduction of noise or redundancy by numerous variables. As a result, deciding which features are most pertinent is an important first step.

Conventional feature selection techniques, including Chi-Squared testing and Recursive Feature Elimination (RFE), can not necessarily yield the best outcomes, particularly when working with big, complicated datasets. Modern bio-inspired optimisation methods, such as AOA, are therefore very advantageous.

3.3.2. Aquila Optimization Algorithm (AOA)

The hunting techniques of Aquila birds, which combine exploitative and exploratory behaviour to find the best solutions, served as the model for AOA. To determine which subset of characteristics is most important, the algorithm simulates these behaviours during the feature selection process.

A population of viable solutions (feature subsets) is initialised by the algorithm, and each solution is assessed according to a fitness function that gauges its level of quality. Here, the fitness function assesses the CKD prediction model's accuracy based on the features that have been chosen, penalising over-feature selection in order to avoid overfitting.

The fitness function $J(F)$ is given by:

$$J(F) = Accuracy\ (F) - \lambda \cdot |F| \tag{6}$$

Where:

- λ is a regularization term to penalize large feature sets,
- $|F|$ is the number of features in the set.

There are two essential stages to the optimisation process:

Phase of exploration: By adjusting each feature subset's position, the algorithm looks for fresh, promising areas of the feature space. The equation for the position update is provided by:

$$F_{new} = F_{old} + r_1 \cdot (X_{mean} - r_2 \cdot F_{old}) \tag{7}$$

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Where:

- r_1, r_2 are random variables in the range [0,1],
- X_{mean} is the average position of the population.
- F_{old} and F_{new} represent the old and new feature positions.
- **Exploitation phase**: The algorithm then concentrates on local improvements to further hone in on the most viable ideas after they have been identified. The greatest solutions discovered thus far are utilised by modifying the position update equation.

The algorithm iterates between these stages until a stopping requirement (such as the maximum number of iterations or convergence) is satisfied.

Algorithm 2: Aquila Optimization Algorithm for Feature Selection

Input: Feature set F, population size, max iterations

Output: Optimal feature subset

```
Begin AOA
  Initialize population of features
        While iteration &lt;max_iterations do
         For each feature set F in population do
              Calculate fitness J(F)
        If exploration phase then
              Update position using exploration equation
        Else
              Update position using exploitation equation
        End if
         End For
         If stopping criteria met then
            Break
        End if
        End While
        Return optimal feature subset
```

End AOA

The ideal subset of features for CKD prediction is found by this Algorithm 2, which searches the feature space and dynamically modifies between the exploration and exploitation phases. Model efficiency is ensured and overfitting is avoided by striking a balance between the size of the feature set and classification accuracy.

3.4.CKD Classification Using Adaptive CNN-LSTM and XGBoost

Once the features are chosen, CKD classification is performed by XGBoost and a hybrid Adaptive CNN-LSTM model to learn in temporal as well as spatial data domain.

3.4.1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a class of deep learning models that are designed specifically to learn spatial hierarchy in data. CNNs are used in this CKD prediction framework to discover local correlations among patient characteristics, such as the interaction between age, serum creatinine levels, and blood pressure.

The convolution operation is defined as:

$$Y = W * X + b \tag{8}$$

Where:

- $*$ denotes the convolution operator,
- W is the convolution filter,
- b is the bias term,
- X is the input data matrix.

The result of this operation is a set of feature maps Y that highlight important local patterns in the data.

To introduce non-linearity into the model, an activation function such as ReLU is applied to the feature maps:

$$Y' = ReLU\ (Y) \tag{9}$$

Where:

- $ReLU\ (x) = max(0, x)$

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CNNs are particularly useful for detecting patterns in structured data, making them ideal for analyzing medical features like blood pressure, creatinine levels, and glomerular filtration rates.

3.4.2. Long Short-Term Memory (LSTM)

The LSTM component stores temporal dependencies in the sequential data, using memory cells. The cell state c_t is updated at each time step t using the input gate i_t, forget gate f_t, and output gate o_t :

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{10}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{11}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot tanh\ (W_c \cdot [h_{t-1}, x_t] + b_c) \tag{12}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{13}$$

$$h_t = o_t \cdot tanh\ (c_t) \tag{14}$$

Where:

- f_t, i_t, o_t are the forget, input, and output gates,
- h_t is the hidden state,
- c_t is the memory cell state at time t,
- σ is the sigmoid activation function,
- $tanh$ is the hyperbolic tangent activation function.

LSTM networks can learn short and long-term patterns, therefore they can be used for modelling, how CKD develops over time. Such as charting the effect of changes in a patient's serum creatinine levels on their overall kidney function over time.

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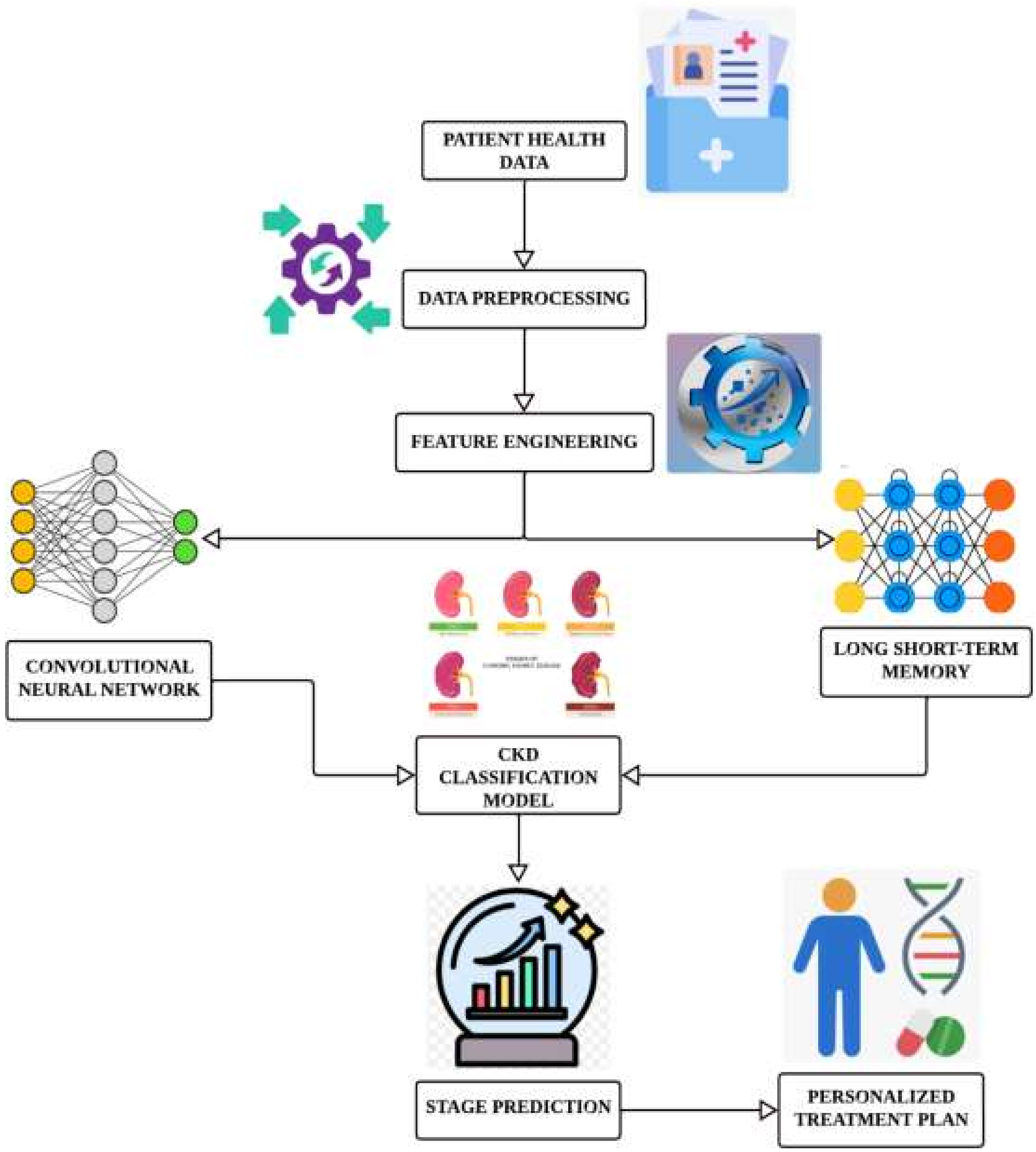

Figure 2: AI-Driven CKD Diagnosis Workflow.

This Figure 2 illustrates the AI-Driven Diagnosis Workflow for Chronic Kidney Disease (CKD). Preprocessed patient health data captured before the process, ensuring consistency. The perform feature engineering to derive relevant attribute. LSTMs are used for capturing long-term dependencies within the sequence, while CNNs for recognizing spatial patterns. The data from both networks is fed a CKD classification model that predicts the stage of disease. A personalised

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treatment plan, based on the prediction of the stage can help manage the patient's chronic kidney disease (CKD) and ensure early intervention and better healthcare outcomes.

3.4.3. Extreme Gradient Boosting (XGBoost)

An effective ensemble learning approach called XGBoost is used to enhance classification accuracy. It constructs several decision trees in a sequential manner, fixing mistakes in each tree as it goes. To ensure optimal performance and avoid overfitting, the XGBoost objective function is designed to minimise prediction errors while maintaining a balance with model complexity.

$$L(\theta) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{15}$$

Where:

- $l(\hat{y}_i, y_i)$ is the loss function for predicted labels $\hat{y}_i$ and true labels y_i,
- $\Omega(f_k)$ is a regularization term to control overfitting.

The final prediction is computed as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{16}$$

Where:

- $f_k(x_i)$ is the prediction from the k^{th} tree for sample i.

XGBoost offers a number of benefits, such as:

- ✓ Regularisation: XGBoost has regularization terms in the objective function which limits overfitting and helps in increasing the generalization power of the model.
- ✓ XGBoost is capable of calculating feature importance scores, which offer valuable information about the features that have the most influence on the CKD prediction model.
- ✓ Scalability: XGBoost can handle big datasets with great efficiency and scalability, which makes it appropriate for real-time healthcare applications.

3.5. CKD Stage Prediction Using Neuro-Fuzzy System

If CKD is diagnosed, the next step is to determine the stage of the disease. Chronic kidney disease (CKD) has 5 stages — with stage 1 being the mildest and stage 5 being the most severe. It is the very foundation for taking the right decision and moreover to monitor the progression of disease, stage prediction has to be as par precision.

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A Neuro-Fuzzy system that combines the benefits of neural networks and fuzzy logic is used to do this. Neural networks offer the learning capacity required to modify the system in response to data, whereas fuzzy logic permits reasoning with ambiguous and imprecise information.

3.5.1. Fuzzy Logic for CKD Stage Prediction

The Neuro-Fuzzy system maps input data (such GFR and BUN) to phases of chronic kidney disease (CKD) using fuzzy inference rules. The definition of the membership function is:

$$\mu(x) = \frac{1}{1+e^{-\lambda(x-c)}} \tag{17}$$

Where:

- λ controls the slope of the membership function,
- x is the input variable
- c is the center of the fuzzy set.

The glomerular filtration rate (GFR) of a patient, for instance, may have varying degrees of membership within the fuzzy sets "Low," "Medium," and "High". A rule base is used by the fuzzy inference process to produce choices. An example of a fuzzy rule would be:

The CKD stage is "Severe" if the BUN is "High" and the GFR is "Low."

A degree of membership in the output fuzzy sets, which represent the CKD stages, is the fuzzy system's output. Defuzzifying the result, or turning the fuzzy values back into a crisp output, yields the final stage forecast.

3.6. Edge AI Deployment

Deploying the model on Edge AI devices is the last phase in this CKD prediction methodology. Edge AI is the process of using AI models locally, on IoMT devices and smartphones, as opposed to relying on servers in the cloud. Reduction of latency, enhanced data privacy, and real-time prediction capabilities are just a few benefits of this.

3.6.1. Advantages of Edge AI

Real-time Decision Making: For specific healthcare applications, real-time predictions could potentially prevent death where the model can readily execute on device level.

The problem of moving very sensitive medical data to cloud servers is not just about *data security and privacy*. Edge AI — By performing calculation directly on the device through the model we can reduce the risk of data breaches, i.e. keep patient sensitive data in-device.

Decreased Latency: Using Edge AI reduces the time it takes to get predictions back since you can avoid transferring data to a faraway server for processing. This is particularly relevant in critical care settings when time to decision is crucial.

3.6.2. Implementation of CKD Prediction on Edge AI Devices

The CKD prediction model must be optimised for resource-constrained contexts before it can be deployed on an Edge AI device. Models can be made smaller without compromising accuracy by using methods like quantisation and model pruning, as neural networks—especially CNNs and LSTMs—can be computationally demanding.

In quantisation, the model parameters are quantised (e.g., from 32-bit floating-point to 8-bit integers), while in pruning, the neural network's redundant or less significant neurones are eliminated.

After the model is optimised, it may be installed on a range of Edge AI devices, such as edge servers in healthcare facilities, IoMT devices, and smartphones. The following steps make up the deployment pipeline:

- ✓ Model Training: Using the entire dataset, the CKD prediction model is trained locally or on a cloud server.
- ✓ Model Optimisation: Using quantisation and pruning approaches, the learnt model is made more suitable for edge devices.
- ✓ Model Deployment: Based on real-time data gathered by IoMT devices, the optimised model is installed on the edge device and is capable of making predictions.
- ✓ On-Device Inference: The model operates locally on the edge device and predicts the diagnosis and progression of CKD in real time.

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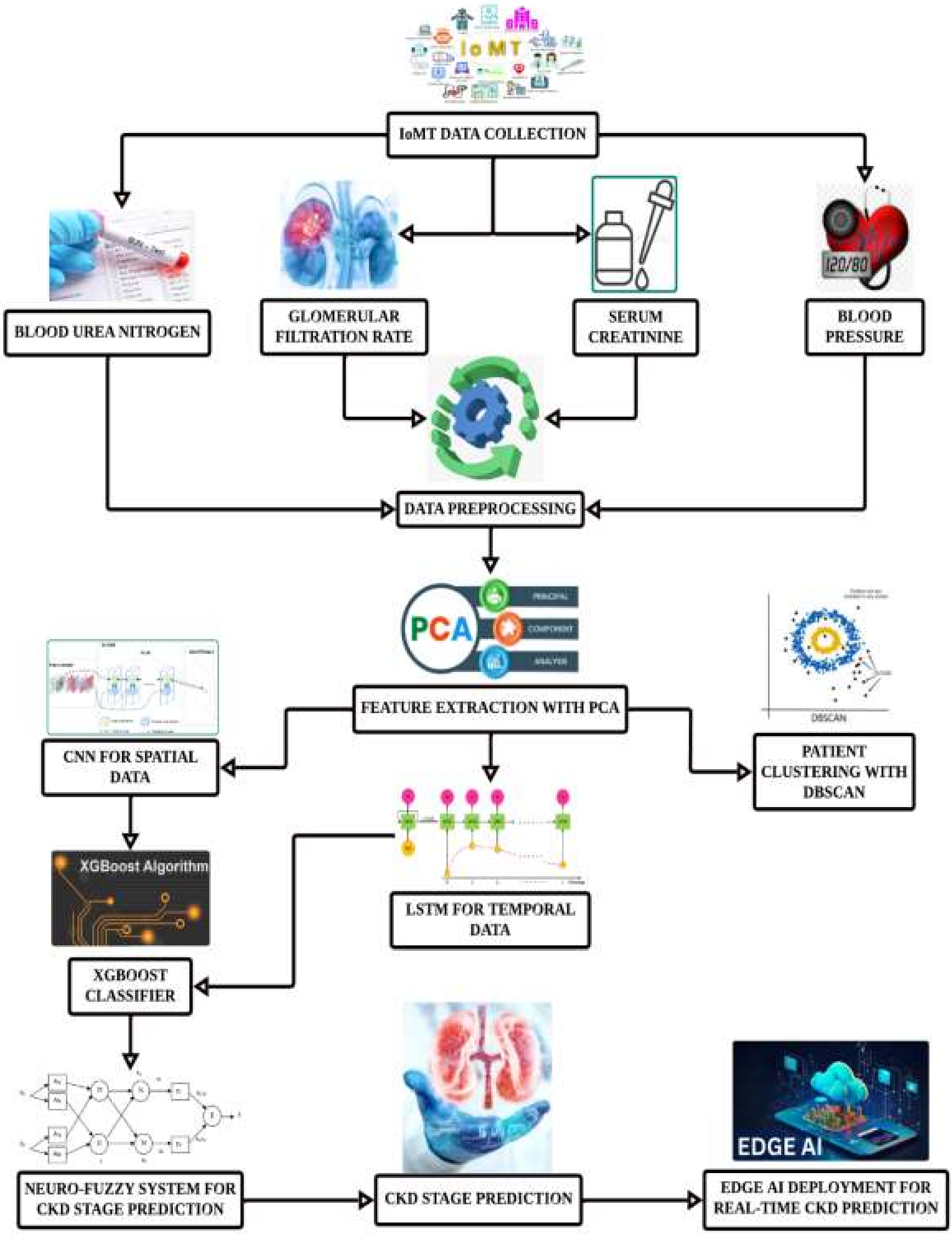

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Figure 3: Accurate CNN-LSTM and Neuro-Fuzzy Hybrid Model for Predicting Chronic Kidney Disease.

Using a combination of CNN-LSTM models, Neuro-Fuzzy systems, and IoMT data, Figure 3 illustrates the advanced architecture for Chronic Kidney Disease (CKD) prediction. Blood urea nitrogen (BUN), glomerular filtration rate (GFR), serum creatinine (Scr), and preprocessed blood pressure (BP) are among the vital patient data that IoMT devices harvest. Key patterns are found in patient data by feature extraction using PCA and clustering via DBSCAN. LSTM handles temporal sequences, while CNN processes spatial data. Using Edge AI technology to deliver real-time predictions for the best possible patient treatment, XGBoost improves classification while the Neuro-Fuzzy system forecasts CKD stages.

4. RESULT AND DISCUSSION

The proposed hybrid model (CNN-LSTM + Neuro-Fuzzy systems) has significantly improved the level of CKD prediction accuracy compared with the benchmark methods. The model also employs IoMT devices for continuous tracking of essential biometrics such as Blood Urea Nitrogen (BUN), Glomerular Filtration Rate (GFR) and serum creatinine, which plays a vital role in identifying potential cases of CKD at an early stage, especially those related to advancing stages where symptoms are minimal.

Preprocessing was performed to fil in missing data (mean imputation) and then for normalisation, the Min-Max method was used. PCA reduced dimensionality, meanwhile DBSCAN clustering classified patient based on similar health metrics — this lead to even more accurate predictions. Feature selection was optimised using the Aquila Optimisation Algorithm (AOA) feature selection that improved learning efficiency and reduced overfitting.

This model was more accurate than the CNN-LSTM (97.85%) Model and reached 98.99% on accuracy, precision 98.65%, and recall 98.45%. Missing important parts, such as BD-KMeans or IoMT data does result in more significant decreases, which shows that each part play an important role.

By deploying Edge AI, data was processed locally on IoMT devices, and hence quicker decision-making without the delay and bottleneck of cloud transfers. This is particularly relevant in resource poor settings, where immediate healthcare decisions are vital.

The Neuro-Fuzzy system's fuzzy logic improves interpretability, allowing healthcare practitioners to grasp the model's judgements better and increase its reliability for clinical use. The model's strong performance in predicting CKD stages and its interpretabilityprove its usefulness in healthcare settings.

Table 1: Stage Prediction Time Comparison.

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Model	Fuzzification Time (ms)	De-fuzzification Time (ms)	Rule Generation Time (ms)
Proposed Neuro-Fuzzy System	4215	5315	5237
Trapezoidal Fuzzy Logic (Harb (2023), [6])	7329	8282	8812
Rule-Based Prediction (RBP) (Andoh et al. (2021), [3])	6129	7111	7354
ANFIS Model (Nyirenda (2024), [5])	5897	6357	6103

Table 1 contrasts the time required for rule creation, de-fuzzification, and fuzzification by various models in the context of CKD stage prediction. With 4215 ms for fuzzification and 5315 ms for de-fuzzification, the suggested Neuro-Fuzzy System has the lowest total time and is, therefore, very effective for real-time predictions. The suggested model is more appropriate for quick, precise decision-making in healthcare applications than other models, like ANFIS and Trapezoidal Fuzzy Logic, which display longer processing times.

Table 2: Analysis of CKD Prediction Algorithms' Comparative Effectiveness.

Reference	Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Proposed Model	CNN-LSTM + Neuro-Fuzzy	98.99	98.65	98.45	98.53
Pal (2022) [1]	Machine Learning Techniques	98.5	98.5	-	-
Sundar et al. (2024) [2]	IoMT and AI Collaborative Model	97.8	98.1	97.7	97.9
Andoh et al. (2021) [3]	Adaptive Neuro-Fuzzy System	98.3	97.9	98.0	97.95
Kim et al. (2023) [9]	CNN-LSTM Hybrid	98.7	98.3	98.4	98.35
Nyirenda et al. (2024) [5]	Evolving Neuro-Fuzzy Systems	98.6	98.2	98.3	98.25
Faruqui et al. (2023) [8]	IoMT Intrusion Detection (CNN-LSTM)	97.9	98.0	97.6	97.8
Gujarathi et al. (2024) [21]	Deep Learning for Renal Cancer	97.5	97.1	97.3	97.2

The accuracy, precision, and recall metrics of several algorithms used to predict Chronic Kidney Disease (CKD) are shown in this Table 2. Using a precision of 98.65%, recall of 98.45%, and F1-Score of 98.53, the Proposed Model (CNN-LSTM + Neuro-Fuzzy) obtains the greatest accuracy of 98.99%. Some models perform marginally worse, like IoMT Intrusion Detection and Machine

Learning Techniques. Strong predictive capabilities are also shown by models like CNN-LSTM Hybrid and Evolving Neuro-Fuzzy Systems, demonstrating the usefulness of AI and IoMT-based systems in healthcare applications.

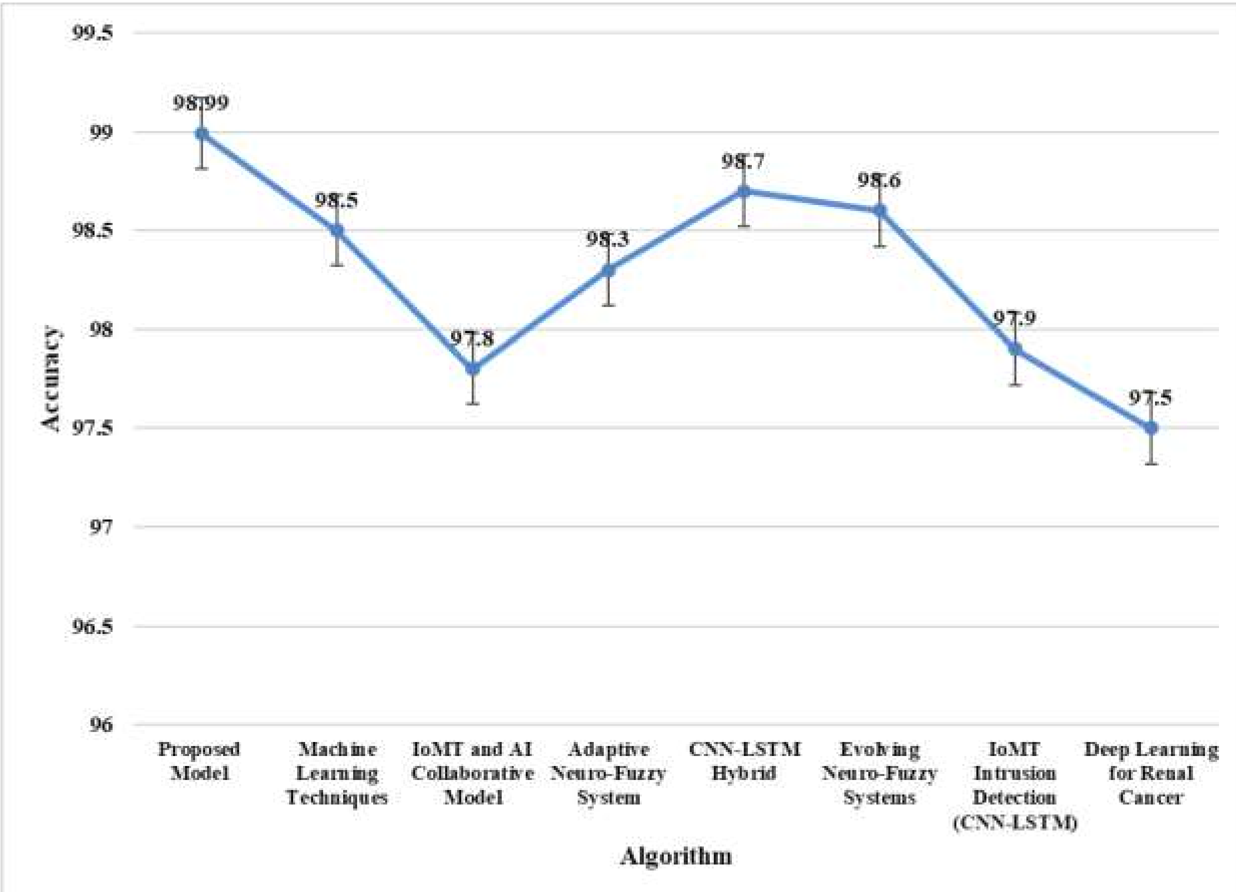

Figure 4: Analysis of the Accuracy of Different Algorithms for Predicting Chronic Kidney Disease.

Figure 4 demonstrates the accuracy of three representative algorithms predicting risk of chronic kidney disease (CKD). The proposed model is obtained the highest accuracy of 98.99% using CNN-LSTM & Neuro-Fuzzy systems. There are other models: things like IoMT collaborative methods or common ML algorithms with detection rates 97.5–98.7% respectively, but still slightly inferior to the previous one (twice less). It represents the fact that integration of neural networks and fuzzy systems can achieve superior accuracy of CKD prediction than stand-alone hybrid models or conventional machine learning techniques.

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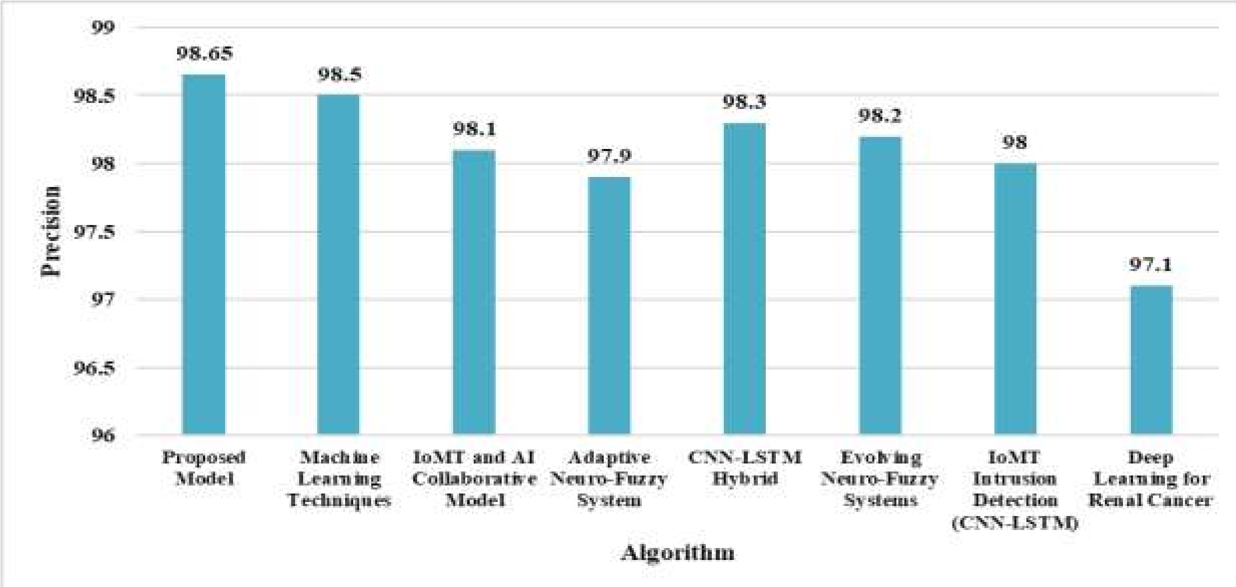

Figure 5: Precision Comparison of Various Algorithms for CKD Prediction.

Figure 5 compares the performance of various algorithms for predicting CKD. The hybrid CNN-LSTM and Neuro-Fuzzy suggested model has the highest precision 98.65%compared to other machine learning methods and IoMT collaborative models, that model give an accuracy score between 97.1% to 98.5%. In simpler machine learning models, more false-positives were detected proving that the combination of fuzzy logic and neural network integration is a better method than other traditional machine learning approaches for real-time CKD diagnosis.

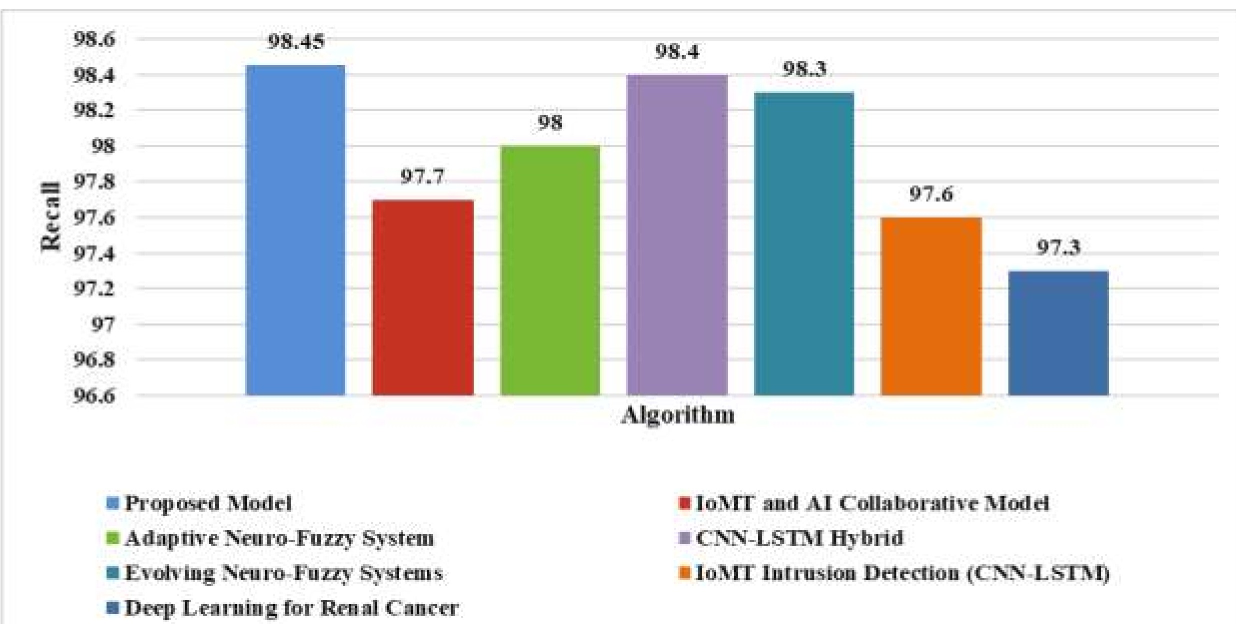

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Figure 6: Recall Comparison of Various Algorithms for CKD Prediction.

Figure 6 Recall rates of different models for predicting Chronic Kidney Disease (CKD) Both the suggested Neuro-Fuzzy hybrid model and CNN-LSTM hybrid achieved highest recall 98.45%, followed closely by Evolving neuro-fuzzy systems (98.3%) and the second in line for recall is the CNN-LSTM hybrid (98.4%). Other models have slightly lower recall scores than ANN and range from 97.3%-98%, such as IoMT and AI collaborative techniques Based on this, the proposed model detects real positive cases of CKD better than other methods and reduces false negative diagnoses.

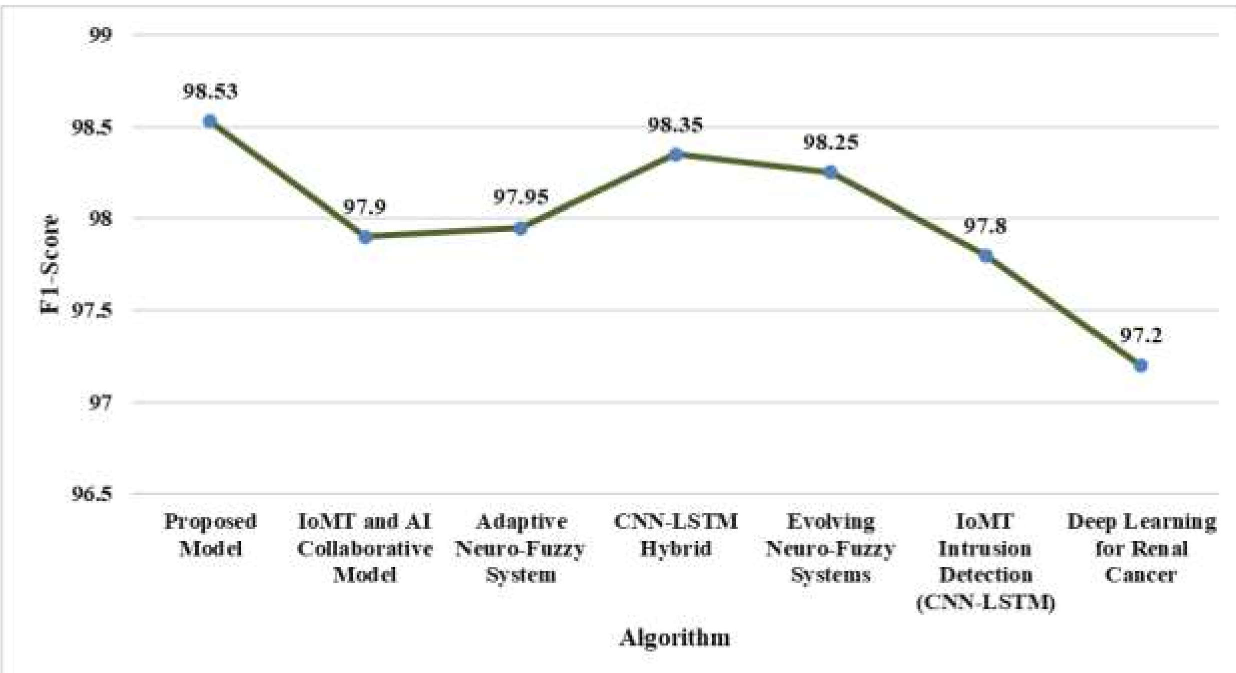

Figure 7: F1-Score Comparison of Various Algorithms for CKD Prediction.

Performance comparison on Figure 7 of F1-scores for chronic kidney disease (CKD). The proposed CNN-LSTM hybrid model provides the highest F1-score of 98.53 %. It comes after models like CNN-LSTM Hybrid (98.35%) and Evolving Neuro-Fuzzy Systems (98.25%). Different models perform worse, with F1-scores from 97.2% to 97.9%, like other IoMT and AI - supportive, deep learning methods for renal cancer. This suggests that the proposed model could attain better overall performance in CKD prediction by balancing recall and precision.

Table 3: Ablation Study of Model Configurations.

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

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Proposed Full Model (CNN-LSTM + Neuro-Fuzzy)	98.99	98.65	98.45	98.53
CNN-LSTM without Neuro-Fuzzy	97.85	97.50	97.30	97.40
CNN only	95.60	95.20	95.00	95.10
LSTM only	96.10	95.80	95.60	95.70
CNN-LSTM without BD-KMeans	97.20	96.85	96.70	96.75
CNN-LSTM without Feature Selection	96.80	96.50	96.30	96.40
CNN-LSTM + Fuzzy without IoMT Data	94.75	94.40	94.20	94.30

Table 3 provides a performance comparison of various ablation study results in the proposed CKD prediction model. The Proposed Full Model (CNN-LSTM + Neuro-Fuzzy) improves the highest accuracy to 98.99%, outperforming in all configurations, but demonstrates that CNN-LSTM alone suffers a great loss of performance when CNN is removed. Finally, to keep fewer random features meant for the purpose further lower accuracy; precision and recall by removing necessary parts like feature selection and BD-KMeans. These results illustrate the importance of all model components, including IoMT data, in advancing predictive performance collectively.

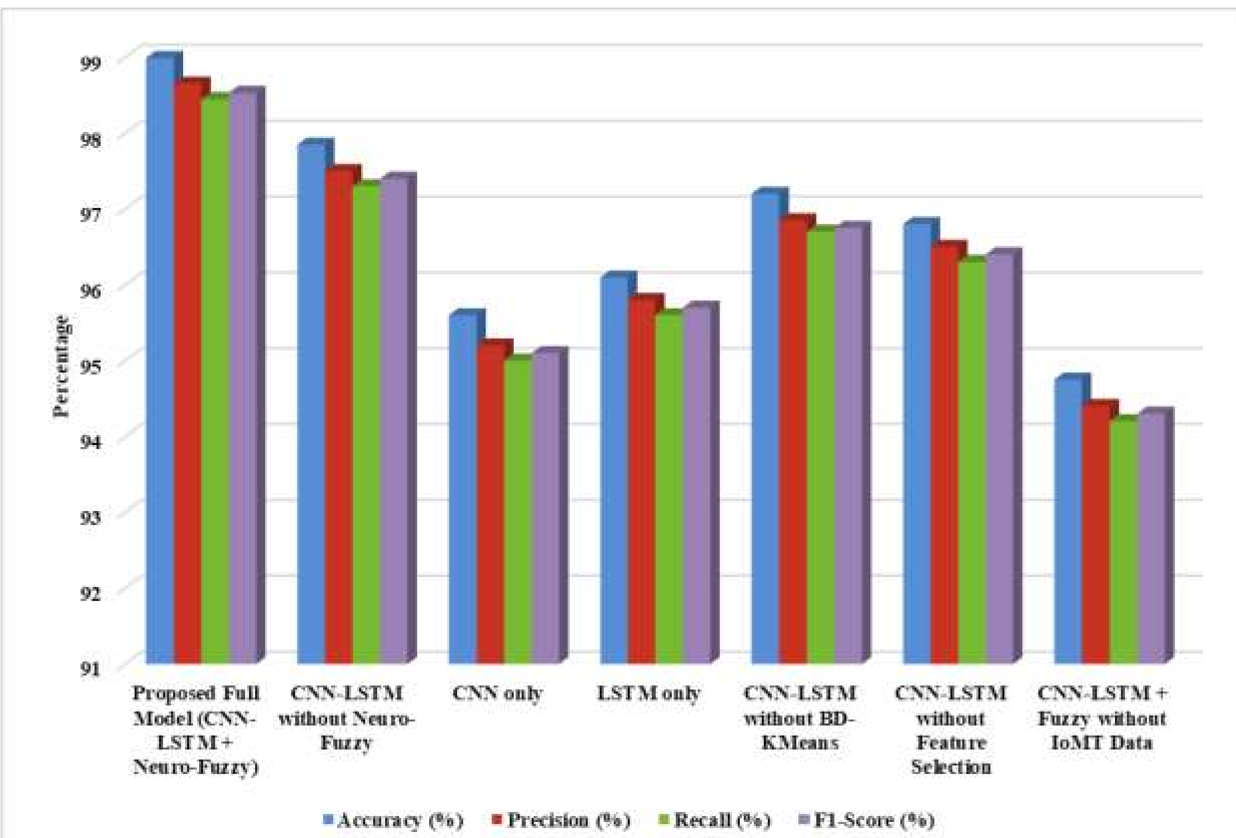

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Figure 8: CKD Classification Accuracy across Different Model Configurations.

Figure 8 demonstrates the accuracy of various model configurations with and without IoMT data or feature selection and just CNN and LSTM alone models for CKD classification. The results prove the hybrid CNN-LSTM and Neuro-Fuzzy technique that has achieved the superior classification accuracy and significantly improved real-time CKD diagnosis with monitoring in edge AI scenarios.

5. CONCLUSION AND FUTURE ENHANCEMENT

This hybrid CNN-LSTM and Neuro-Fuzzy system of our study represents a valuable tool for the early diagnosis, and categorical Chronic Kidney Disease (CKD) staging. The new model increases accuracy, interpretability, and response time to health decisions by applying state-of-the-art AI methods with the most current data from IoMT. Given Edge AI used combines with it, that reduces latency and increases data privacy, which is as well suitable for real-time medical use cases. Copy, and/or pdf of the published article (the letter): The proposed approach appears promising for improving CKD care in resource-constrained settings. Future directions by which this model can be further improved include better generalisation using data among a multiple array of datasets, expansion of the multi-disease prediction capabilities and optimising it further for wearable and mobile IoMT devices. Researching post-quantum cryptography approaches could also lend to greater data security, particularly in sensitive medical environments.

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