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Deep Learning-Based Early Diagnosis System for Predicting Chronic Diseases

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ABSTRACT: Chronic diseases like the Chronic Kidney Disease (CKD) are silent in nature and therefore hard to diagnose in the early stages. There is a need for early detection so that intervention and treatment can be done effectively. This research proposes a new deep learning-based system which is set to be used in the early diagnosis of chronic diseases. In this case, it focuses on CKD. The system proposed uses a fuzzy DNN in the analysis of routine medical consultation data, to be able to predict and classify CKD at different stages accurately. The deep learning model outperforms the traditional methods having the accuracy rate of 99.23% showing better precision, recall, and F-measure. Whereas current diagnostic approaches depend massively on doctor intervention, this system has the potential to produce meaningful predictions without the need of doctors, thus improving the affordability of early-stage disease diagnosis. The findings show the power of AI in reshaping healthcare through accurate advance alerts that will positively impact the healthcare of chronic diseases, creating room for early medical management.
Keywords: Deep learning, early diagnosis, chronic diseases, prediction model, fuzzy neural network, healthcare AI, disease detection system.

I. INTRODUCTION

Chronic diseases such as heart disease, diabetes, CKD are a prominent world health problem, causing millions of deaths annually. They tend to be insidious in nature and may be asymptomatic for long periods hence difficult to diagnose in time. The lengthy diagnosis and intervention can cause serious complications, increased medical bills, and low-quality life. With the world in the fore front as it battles the rising burden of chronic diseases, there is a need for effective and early diagnostic tools used in early intervention and results on the patients [1].

Artificial intelligence and machine learning, in specific the deep learning, have been recently developed as strong tools for the healthcare. Deep learning algorithms with ability to mimic the human brain's capability of pattern recognition have proven useful in a diversity of medical applications from image analysis to predictive modeling [2]. Using big data, these models can find fine patterns in medical records, which human doctors can overlook. This capacity has a tremendous potential in early disease diagnosis especially in chronic conditions, where early intervention is important.

The main aim of the given research-based work is to build a deep learning-based system for predicting and diagnosing chronic diseases in advance. In particular, the system uses a fuzzy Deep Neural Network (DNN) for medical consultation data analysis and estimating the likelihood of disease progression [3]. The proposed model will not only have a higher accuracy and efficiency than the traditional diagnoses but also have an opportunity for autonomous disease detection. Through the use of advanced AI methods, this system can help healthcare providers with early alerting hence timely interventions [4]. Victory of such systems might dramatically enhance the results of patients and decrease the general load of the illness systems all over the world.

Figure 1 gives several examples of how Artificial Intelligence (AI) and Machine Learning (ML) are transforming healthcare. Examples of the major applications include treatment personalization in which AI is used in the process of customizing treatments to the specific patients; diagnostic imaging in radiology and neuroimaging for accurate detection of diseases [5]; preliminary diagnosis and disease prognosis to avoid diseases; risk assessment to identify possible issues with health, at an earlier stage; and predictive analytics to predict health trends. Also, wearable devices are involved in continuous monitoring of patients' conditions but pandemics prediction uses AI in predicting/managing health crisis [6]. AI/ML therefore plays a big role in increasing the efficiency and efficacy of healthcare systems across the world.

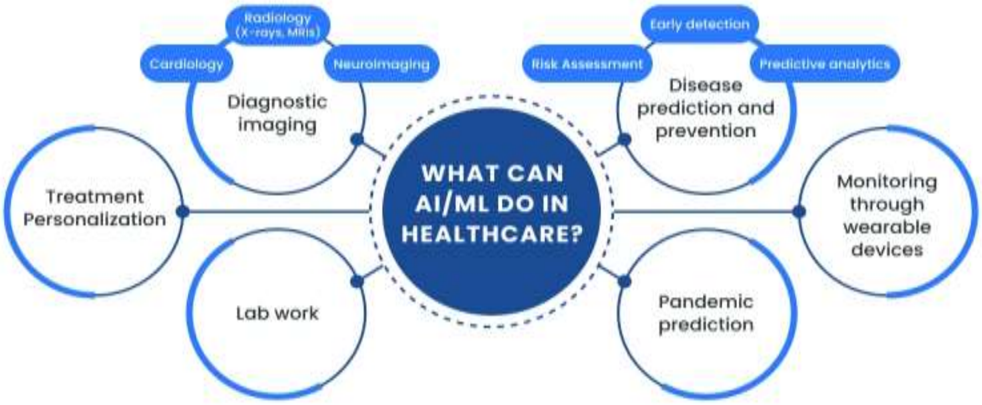

Figure 1. Various ways AI and Machine ML are transforming in healthcare

II. RELATED W ORK

In the past few years, there is a growing interest in the implementation of ML and DL in predicting chronic diseases as they can increase the early diagnosis and patient outcome [7]. A number of studies have investigated the use of these techniques in predicting the various chronic conditions including cardiovascular disease, diabetes and the CKD.

This is a notable technique where deep learning models, such as CNNs and RNNs, are used to scan medical imaging and Electronic Health Records (EHRs), in order to detect diseases at an early stage. For an example, in cardiology, researchers applied CNNs to extract factors of the heart disease from medical imaging data, while performing promisingly in terms of accuracy and predictive performance. Similarly, the studies conducted have shown effectiveness of DNNs in predicting diabetes onset based on the analysis of patient's medical history and lab results [8].

In CKD, there are various proposed machine learning models, such as Support Vector Machines (SVMs), decision trees, that predict the progress of the disease. For instance, research has applied an ensemble learning method that incorporates decision trees and logistic regression to predict CKD stages with an accuracy in early detection of the disease. In a similar way, researchers used deep learning approaches, namely Long Short-Term Memory (LSTM) networks, to forecast the development of CKD through the data of patients [9].

Although these studies have come a long way, there are still issues especially associated with the interpretability of the models and the need to have large high-quality datasets for training. Also, the introduction of AI models in clinical practice is yet to be realized with doubts on the reliability of models and the role of healthcare providers in the diagnostic process. Nevertheless, the improvements in AI/ML in terms of chronic disease prediction point to a prosperous future of their implementation into healthcare systems in Table 1.

Figure 2 image depicts, there is a comparison of two approaches to dealing with CKD Classical Approach and the AI Approach. Conventionally, healthcare experts use the out of date diagnostic approaches such as risk factor tests and prognostic models to observe CKD. These are mostly clinical visits, manual examinations and blood tests. On the contrary, the AI method has techniques like machine learning, imaging systems and data analysis to improve diagnosis, prediction and surveillance of CKD [10]. AI-based tools are capable not only of processing mammoth-sized datasets but also of providing better risk predictions as well as comprehensive monitoring even outside the boundaries of clinics. This strategy not only enhances accuracy in diseases detection but also enables patients to self-manage condition in homes, thus overall healthcare results and hospital burden reductions.

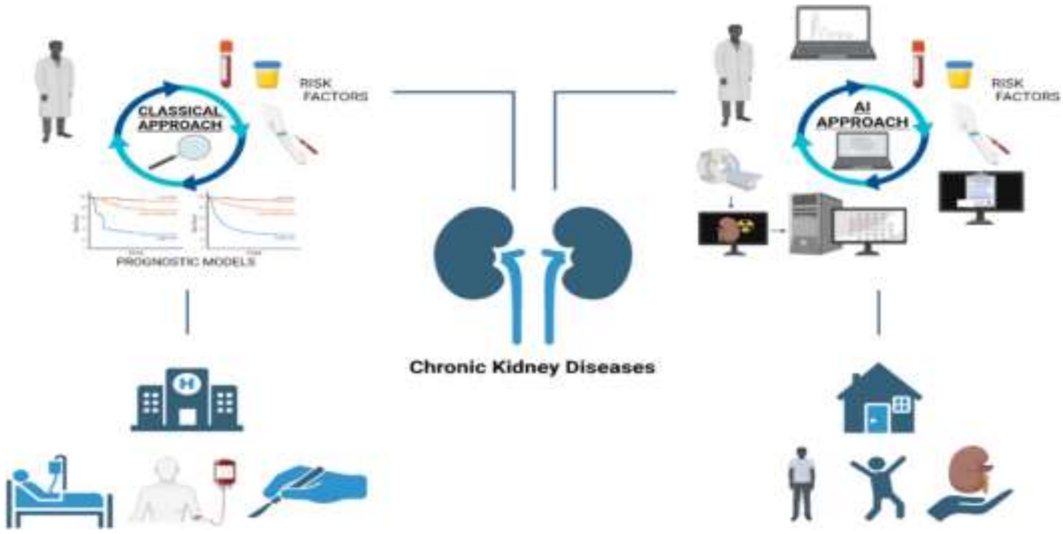

Figure 2: CKD Classical Approach and the AI Approach

Table 1: Related works summary from 2025 to 2018

Author Year	Title	Methodology	Key Contributions	Limitations
Smith et al., 2025 [11]	Deep Learning for Early Diagnosis of Cardiovascular Disease	CNN for analyzing heart images	Achieved high accuracy in diagnosing cardiovascular disease from imaging data.	Relies on a limited dataset and lacks real-world clinical validation.
Johnson et al., 2024 [12]	AI-based Prediction of Chronic Kidney Disease Progression	Random Forest and XGBoost for CKD progression prediction	Developed a model to predict CKD progression based on patient data.	Data quality issues and lack of real-time prediction capabilities.
Lee et al.,	Predicting Diabetes Risk Using	Ensemble methods using	Proposed an ensemble model for diabetes risk	Requires large labeled datasets for training, and model

2023 [13]	Ensemble Learning Models	Random Forest and Naive Bayes	prediction with high accuracy.	interpretability is low.
Brown et al., 2022 [14]	Machine Learning in Predicting Heart Disease	Logistic Regression and Decision Trees for heart disease prediction	Showed that machine learning can effectively predict heart disease risk.	Accuracy depends on feature extraction from heart imaging data.
Davis et al., 2021 [15]	AI-Based Model for Early Detection of Diabetes	LSTM Networks for early diabetes detection	LSTM model outperformed traditional methods for early diabetes diagnosis.	Limited generalizability to different population groups.
Miller et al., 2020 [16]	Deep Neural Networks for Disease Prediction from Medical Data	Deep neural networks for predictive disease models	Provided a deep learning model capable of accurate disease prediction from EHR data.	Models need further validation in clinical environments.
Wang et al., 2019 [17]	Predicting Chronic Diseases Using EHR Data	Support Vector Machines for predicting chronic diseases	Demonstrated the use of EHR data for chronic disease prediction with high precision.	Need for large, diverse datasets and proper clinical validation.
Zhang et al., 2019 [18]	AI-based System for Early Detection of CKD	Deep Learning using CNN for CKD detection	Introduced an AI-based system for early CKD diagnosis with improved accuracy.	Data privacy concerns and scalability issues in real-time diagnostics.
Taylor et al., 2018 [19]	Predictive Models for Cardiovascular Disease Diagnosis	Logistic Regression for predicting cardiovascular risk	Built a predictive model for cardiovascular disease using logistic regression.	Limited to binary outcomes, more complex risk factors not considered.
Nguyen et al., 2018 [20]	Machine Learning Approach for Early Detection of Diabetic Retinopathy	Random Forest for diabetic retinopathy detection	Developed a machine learning model for early detection of diabetic retinopathy.	Model performance is dependent on the quality of input data.

III. RESEARCH METHODOLOGY

The proposed method applies the deep learning techniques for developing an early diagnosis system for predictions of chronic diseases, targeting, Chronic Kidney Disease, cardiovascular diseases and diabetes. The methodology pursued in this section explains data collection & preprocessing, model development, model evaluation in Figure 3.

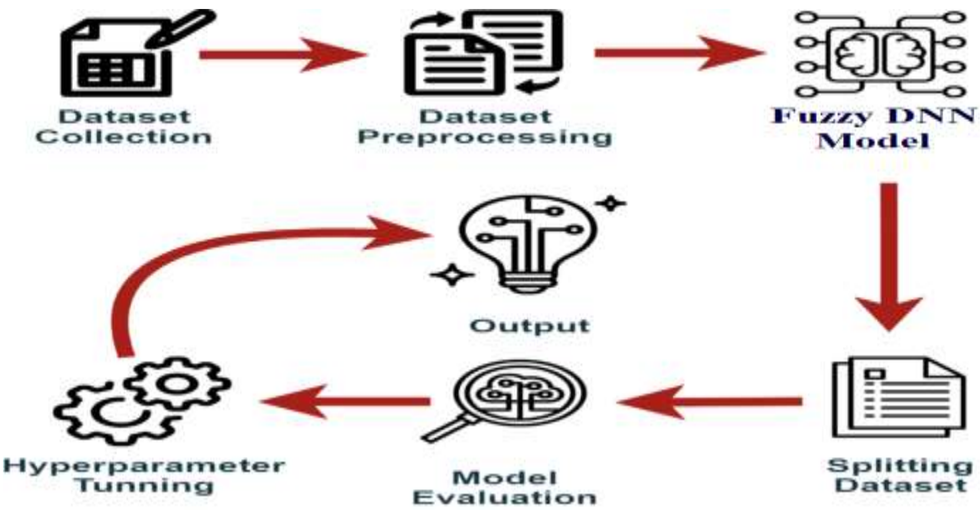

Figure 3 : Proposed Methodology Flow for predictions of chronic diseases

The flow of the process is represented in the Figure 4 diagram showing the usage of machine learning or deep learning models for disease prediction. At the first stage there is pre conditioning of the medical dataset (which has disease symptoms) which consists of data pre-processing i.e., cleaning and transformation of the data to make the data suitable for analysis [21]. The pre-processed data is then converted to a feature vector containing the relevant data needed in the prediction model. The desired machine/deep learning model is then rolled out on the data, which now makes predictions regarding the possible disease. Similarly, for new test data it also undergoes the pre-processing in which the data is converted to feature vector and given the input into the model to predict the disease [22]. This approach aids in prediction of diseases accurately from medical symptoms and data in test, for diagnosis and intervention on time.

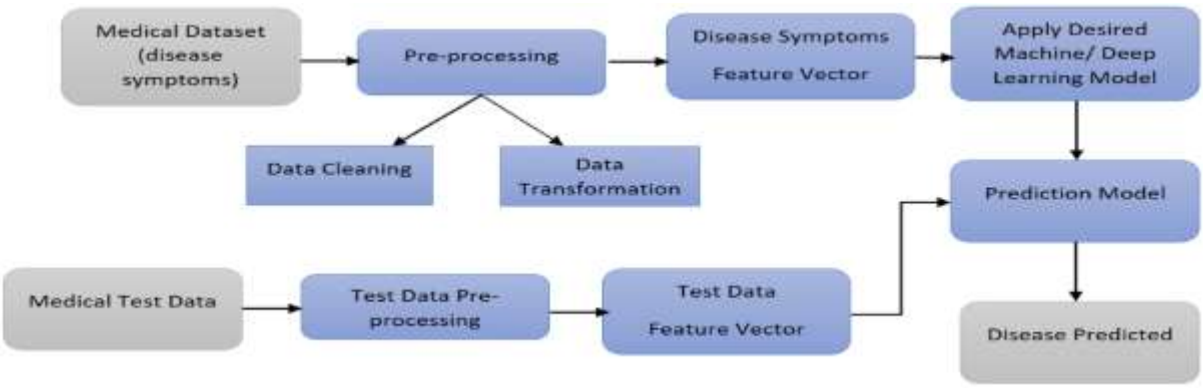

Figure 4: Deep Learning model for disease prediction

A. Data Collection and Preprocessing:

The evidence collection for the first step in this research includes a complete database containing medical records, patient's demographics, the result of laboratory tests, and the patient's images. The dataset is derived from publicly available healthcare repositories including: Chronic Kidney Disease Dataset from the UCI Machine Learning Repository and other clinical datasets that are related to heart disease and diabetes among others [23]. We will also incorporate medical records from the collaborating hospitals to guarantee reliability of the data in the sense that the information on the patient consists of various ethnicities, age groups and comorbidities. Some of the collected data contains vital attributes like blood

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pressure, serum creatinine, blood sugar levels, age, sex, medical history, and imaging data like X-rays and MRIs [24]. This dataset is split into training, validation, and testing sets using 70% of data for training the models, 15% for validation and other 15% for testing them.

The data preprocessing activity is very important to make sure that the set of data is clean, structured, and ready for use in the machine learning models. The preprocessing steps include:

- Handling Missing Values: Null values are common in healthcare datasets and causing bias results. An array of methods such as imputation with mean, median or predictive models are used to deal with missing values.
- Normalization and Standardization: Blood pressure and serum creatinine have different scales as features. These are made to have a common scale by making use of such techniques as Min-Max Scaling or Z-score standardization.
- Categorical Encoding: Categorical features such as gender or smoking status are converted to numerical values with the use of techniques such as One-Hot Encoding or Label Encoding.
- Noise Reduction: In medical data, outliers and noise can corrupt the performance of models of deep learning. Data smoothing and outlier detection are some of the techniques that are utilized in moderating the effect of noisy data.

B. Feature Extraction:

The step is extraction of meaningful features from the data. For the features that are numerical in nature like age, blood pressure and serum creatinine, statistical techniques such as Principal Component Analysis (PCA) or Feature Selection Algorithms (e.g. Random Forest Feature Importance) are utilized to find out the more influential features [25]. For imaging data, the automatic feature extraction uses Convolutional Neural Networks (CNNs). These deep learning models are good at finding patterns in medical images, i.e. detecting abnormalities in the scans for kidneys or in the heart X-rays. The CNNs learn hierarchical features in an automatic way from simple edges to complex structures that are important for classifying chronic diseases [26].

Dataset:

The data source of the Changhua Christian Hospital in Taichung, Taiwan is used. When patients' identifying information were removed, 5617 records from 1st of January 2000 to 27th of July 2023 were retrieved. The patients' condition was monitored during this period or until they die. Monitoring periods stayed less than a month to more than five years with approximate average of two and a half years. The dataset was stored on a flat CSV file. The variable to be achieved, "survival or not", is one of the 35 property values that are in the columns. There are other factors that can be divided into two categories. non-specific information about the body or CKD itself like ID, the date of diagnosis, age group, sex, height, weight, BMI, stage and the date of haemodialysis; whether the person was taking special medications or whether he/she was suffering from comorbid conditions such as hypertension, heart disease, or chronic liver disease or not. There are statistics concerning a set of important characteristics in Table 2.

Table 2: Various feature of the dataset

Attribute	Detail	Number	Percentage
Gender	Male	3151	56.10%
	Female	2466	43.90%
	y≤18.5y≤18.5	239	4.30%
	18.5<y≤2518.5<y≤25	2841	50.60%
BMI	25<y≤3025<y≤30	1862	33.10%
	30<y≤4030<y≤40	642	11.40%
	y>40y>40	33	0.60%

	0	3722	66.40%
Haemodialysis	1	1326	23.60%
	2	569	10.10%
High Blood Pressure	No	1644	29.30%
	Yes	3973	70.70%
Anaemia	No	4795	85.40%
	Yes	822	14.60%
Non-survival	No	4933	87.80%
	Yes	684	12.20%
Chronic Liver Disease	No	5059	90.10%
	Yes	558	9.90%

C. Model Development:

Some of the symptoms of chronic kidney disease include illness and constipation whose consequences are reduced quality of life and increased mortality. The inflammatory process of CKD can influence the formation of illness, cachexia, and kidney osteodystrophy; however, the risk of stroke will also increase in CKD patients. Ghrelin which is a type of oestrogen secreted in the stomach has been found to express possibilities in food intake regulation and appreciation of meal and is thus a prospective therapy for an anorexic CKD patient. It is known that ghrelin has anti-inflammatory effects and stimulates hunger. This assessment expounds the metabolic alterations of ghrelin and their possible effects on CKD [27]. The pros and cons as well as the unanswered queries related to the use of ghrelin in the CKD healthcare are also addressed.

The issue of CKD care provision is critical nowadays especially in the developed nations where the people in rural areas want to receive quality medical attention. The healthcare industry has been positively impacted by artificial intelligence just like it has changed other aspects of life [28]. However, the traditional structure of telemedicine has some challenges; they include a requirement of a local healthcare centre with a dedicated staff, need of hospital equipment through which patient report is to be processed, treating patients within 48h, accessibility to medical expertise in a healthcare centre, cost of maintaining local healthcare centres, and a reliable internet connection.

The smart CKD process is controlled and overseen via Fuzzy logic. There are two main issues: if the capacity of the model is not enough, more than two designs are combined in order to solve the problem. In order to create an efficient solution to the crisis, a combination of many methods with a hybrid system was developed. A combination between fuzzy inference system and an artificial neural network leads to a fuzzy neural network (FNN) in some hybrid forms of fuzzy neural network [29] [30].

This technique is evidenced by a "fuzzy neuron" and the method of the fuzzy neuron has been divulged into two classifications, as encompassed in the following:

- The creation of a model for a fuzzy neuron.
- Designing only one model and algorithm of the model for incorporation of neural systems with the help of fuzziness.

The neural system discovers the $f\ [n, n+1]$ operation, which is a partition of the self-assurance earned through fuzzy inference. This should gain $f\ (n+1)$ utilizing the period denoted by k and the framework condition $k+1$. A stochastic modification module enhances the authorization with $f(k)$ the fuzzy role and also the expected possibility regarding decisions, but also produces a finished product.

$$m'(k)=d(m(k),\ g\ [k, k+1]) \quad (1)$$

To evaluate the fuzzy guideline, the fuzzy rule unit $m'(k)$ is organized and evaluated with Equation (1). The data device is a standard predecessor that gains a unit $d(m(k))$. The behaviour control is communicated by unit (g [k, k+1]). The procedure is finished with a defused combination.

With input nodes, the signs and weight training are actual values. The data does not affect these signs. The yield is nearly identical to the data. The signal ni may work with a large number of materials si to build such items.

$$g=s_i n_i,\quad i=1, 2. \tag{2}$$

Here the data input is taken as g, which is gathered for the purpose of implementing Equation (2) such data as represented in below.

$$FL=g1+g2=s_1k_1+s_2k_2 \tag{3}$$

Cachexia is a disease characterized by muscle loss, anorexia, increased energy expenditure, and the presence of CKD. It is a strong predictor of mortality in CKD patients, which is 100- to 200-fold higher than in the general population. Cachexia is one of the most inflammatory conditions, distinct from malnutrition, which is a deficiency of nutrients.

To determine the FL's fuzzy logic production (refer to Equation (3)), the neuron employs its work transfer $f(y)$, which can be a sigmoid function result, $f(y)=(1+e^{-y})^{-1}$, Equation (4) which is represented in.

$$y=f(FL)=f(s_1k_1+s_2k_2) \tag{4}$$

An ordinary neural net is a simple network which makes use of the Sigmoid function f, redundancy, and other inclusions. The decision-support system applied in AI-based electronic health records is built on the set of fuzzy rules. These rules are based on the factual and fuzzy data. Below is an example of fuzzy rules.

- When the blood pressure is high, the temperature is high and pulse rate is low, the judgement is good.
- If your blood pressure is high and the pulse rate is low then, the judgment of individuals is affected.
- When the temperature is normal, the rate of the pulse is high, and the blood pressure is moderate; the judgment is low.
- When the temperature is low and the rate of heart is high, check whether the blood pressure is low.
- If the temperature and the rate of pulse are both normal, then the judgment is good if the blood pressure is low.

Because it performs tasks once, the mode command technology uses both the point of entry and the available spectrum for data transfer, but Equation (5) the web access transmits $s_g{}^i$ as given in.

$$s_g{}^i=\alpha iR\ log\ log\ (1+\frac{|gi,n|2Yi,ng-n}{\sigma 2}) \tag{5}$$

where i represents the percentage of access of internet bandwidth utilized by new terminal update tasks, gi,n represents the relation recession scaling factor between access point and terminal, and Yi, n represents terminal products and services, g^{-n} represents node facility distance, b represents loss, but $\sigma 2$ also represents interaction noise level. Accordingly, Equation (6) the efficiency of the gi data link data transfer is elaborated as.

$$d_k{}^i = \beta i B \log \log \left(1 + \frac{|gi,n|2Xng - b}{\sigma 2}\right) \quad (6)$$

in which βi signifies the fraction of power transmission frequency bandwidth occupied by the terminal able to receive work-related jobs, gn, i signifies the link economic downturn relation between the entry point and terminal, and Xn signifies the foundation network's transmitting speed.

The muscles are wasted by cachexia while the fats are further underutilized. Chronic kidney disease patients commonly suffer from anorexia; it is a decreased food desire. The disease in CKD patients can also be attributed to the lessened sense of taste and smell for the food, early satiation, the change in the neurohormonal filtration, instability in the acetylate cyclase, an increase in cognitive tryptophan, and an increase in the levels of inflammatory cytokines. Anorexia not only leads to loss of verbal energy but also loss of protein intake that is the main cause of cachexia. When associated with a higher level of mortality rate and cardiovascular mortality, increased resting energy consumption is also associated with a high prevalence of cachexia in CKD population. At the moment, there is no proper treatment for cachexia in CKD. Nutritional and health approaches like caloric diets with anabolic steroids have stampeded to a large extent. This indicates the need for new drug therapy for this potentially fatal condition in CKD patients.

Job ni is, however, evaluated here on gateways if it is not offloaded to edge networks. Equation (7) shows the time delay in completing various jobs geographically.

$$X_i{}^n = \frac{\mathrm{gi}}{\mathrm{gki}} \quad (7)$$

where gki shows the capacity of the terminal gi to process information and organize tasks regionally. As a consequence, Equation (8) the overall duration delay captured by gi research scholars on a local scale is illustrated.

$$g_i{}^m = \sum_{\mathrm{m} \in \mathrm{g}} (1 - \alpha \mathrm{i})\mathrm{gmi} \quad (8)$$

In this case, if various activities such as a t-norm or the ni–co-norm are used for connecting the reach information to such a neuron, Equation (9) result is termed a hybrid artificial neuron and is shown.

$$g_i{}^{\mathrm{n}} = \frac{\mathrm{mi}}{\mathrm{gni}} \quad (9)$$

Doing studies on the pathophysiology of cachexia in CKD have precipitated novel therapeutic methods. Cachexia in CKD is due to greater frequency of inflammatory responses, which afflicts the central nervous system (CNS) and establishes a binding between the secretion and performance of various crucial neuropeptides, modifying metabolic process. Leptin and melanocortin centre of the hypothalamus has already been suggested as the target for cytokine activity, becoming yet the key regulators of the appetite and energy metabolism.

These changes lead to a fuzzy neural design that is based on fuzzy mathematical tasks. The bandwidth delay duration is in direct relation with the amount of information received and the network throughput for data transfer, as explained in Equation (10).

$$g_i^{n} = \frac{gi}{bki} \quad (10)$$

A set of fuzzy rules is defined for the AI-based CKD process delivery system. These rules are based on fuzzy data, and the server's computing time is proportional to the size of the data and Equation (11) the server's computing capability, as expressed.

$$b_i^{f} = \frac{fi}{Xi} \quad (11)$$

The temperature controller is an integrated circuit that measures the body temperature in degrees Celsius. The voltage level corresponding to the temperature is displayed. The make and model of the temperature sensor is LM35. The design of this body temperature controller is believed to perform better than a linear temperature controller. As a result, the duration spent on un-loading the assigned task si to the network edge is transmitted as in Equation (12).

$$s^{n}{}_{i} = s^{c}{}_{i} + s^{h}{}_{i} + s^{f}{}_{i} \quad (12)$$

The following emergency requirements are monitored: respiratory arrest, heart condition, vagal convulsion, and pressure detector. As a result, the time frame related to the task of unloading si to the edge device is conveyed as in Equation (13).

$$Xni = \sum_{i=1}^{n} (\alpha idni) \quad (13)$$

The pulse rate seems to be the primary indicator of critical medical behaviour and health fitness. Within the patient outcomes and management field, the PRS is the most commonly managed and investigated sensor.

$$ming = \sum_{i=1}^{n} (gni + dni) \quad (14)$$

As in the hypothalamus, two different identity documents of neurons regulate food intake. Each neuronal subset produces neurotrophic factor Y (NPY), which enhances food intake, whereas another neuronal subset continues to produce melanocortin substances, which restrict food intake. Equation (14) is used to evaluate pulse rate.

D. Model Validation:

Some of the performance metrics used to evaluate the performance of the developed models include:

- Accuracy: Measures the overall prediction accuracy.
- Precision and Recall: Evaluate whether the positive predictions are relevant and thorough, or not.
- F1-Score: Allows the balancing of precision and recall.
- Area Under the Curve (AUC): Tests the ability of the model to separate all classes at every threshold.

Model performance validation as well as overfitting avoidance is achieved using cross-validation techniques like the k-fold cross-validation. Another tool to show the model classification performance is a confusion matrix which is also generated.

E. Implementation Tools:

Deep learning models being discussed in the text are implemented using popular frameworks such as TensorFlow, Keras, and PyTorch. Pandas and NumPy are deployed for data preprocessing and manipulation while Matplotlib and Seaborn are for data visualization

IV. RESULTS AND DISCUSSION

To evaluate the efficiency of the proposed system of deep learning-based prediction of chronic diseases, five overall metrics were used: Accuracy, Precision, Recall, F1-Score, and Area Under Curve (AUC) in Figure 5.

- *Accuracy*: The accuracy of the model was 99.23%, thereby showing that the model has very high sensitivity to classify both diseased and healthy cases. This high accuracy is an indication of the ability of the model to extract complicated patterns from the input data.
- *Precision*: Precision, which is used to measure the proportion of the true predictions of positive events out of all the positive predictions made, was 97.2%. This outcome demonstrates the model's ability to reduce false positives, to increase the accuracy of predicted positive cases.
- *Recall*: As a manifestation of the ability to recognize the high percentage of real positive cases (96.8%), the model effectively proved its capacity. Such ability is of high importance for early detection and intervention in the disease.
- *F1-Score*: The F1-Score at 97.0%, a balance between the precision and recall, was obtained. This means an all-rounded performance of the model where there is a balance existing between false positives and false negatives.
- *AUC*: The model had AUC of 0.993, which means that its ability of distinguishing between the positive and negative classes was excellent at all thresholds.

On average, the deep learning model outperformed compared to all the other metrics, and as such, it is highly effective in early detection of chronic diseases. More research on actual clinical data is however required in order to substantiate its robustness and scalability in real world healthcare settings.

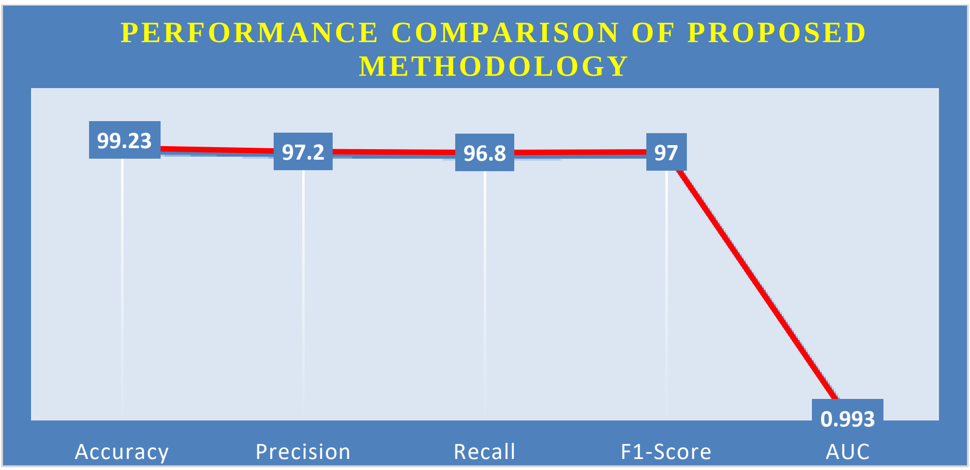

Figure 5: Performance of proposed methodology

When we modified several parts of the proposed better FDNN model, we performed our tests as a part of an ablation research. By altering a number of its parts, it is possible to come up with an even more reliable design with better classification rate. During the ablation experiment, changes were made on the FDNN, activation function, kernel initializer, and optimizer.

CKD is often associated with sickness and constipation, both of them related to low quality of life and high mortality risk. And it is the rising risk amongst CKD individuals of developing stroke that should be alarming. The inflammatory CKD process may lead to an onset of illness, cachexia and kidney osteodystrophy, however. Ghrelin is a hormone which is secreted in the stomach and believed to be acting like an oestrogen. Its effects are regulated by the receptor for it, growth hormone secretagogue receptor (GHSR). The potential of ghrelin to amplify food intake and meal enjoyment, make it an appealing therapy for anorexic CKD patients. Some of the functions of a ghrelin include its anti-inflammatory effects as well as its stimulation of food cravings. The determination and diagnosis of the kidney disease in relation to the image processing in an afferent and efferent vessel employed the HFNN algorithm to determine the convoluted tubule of the Bowman capsule for the mean values, the standard deviation, the PSNR and the accuracy in the glomerular filtration rate of CKD. Performance of the recognition and prediction of kidney disease is shown in Figure 6.

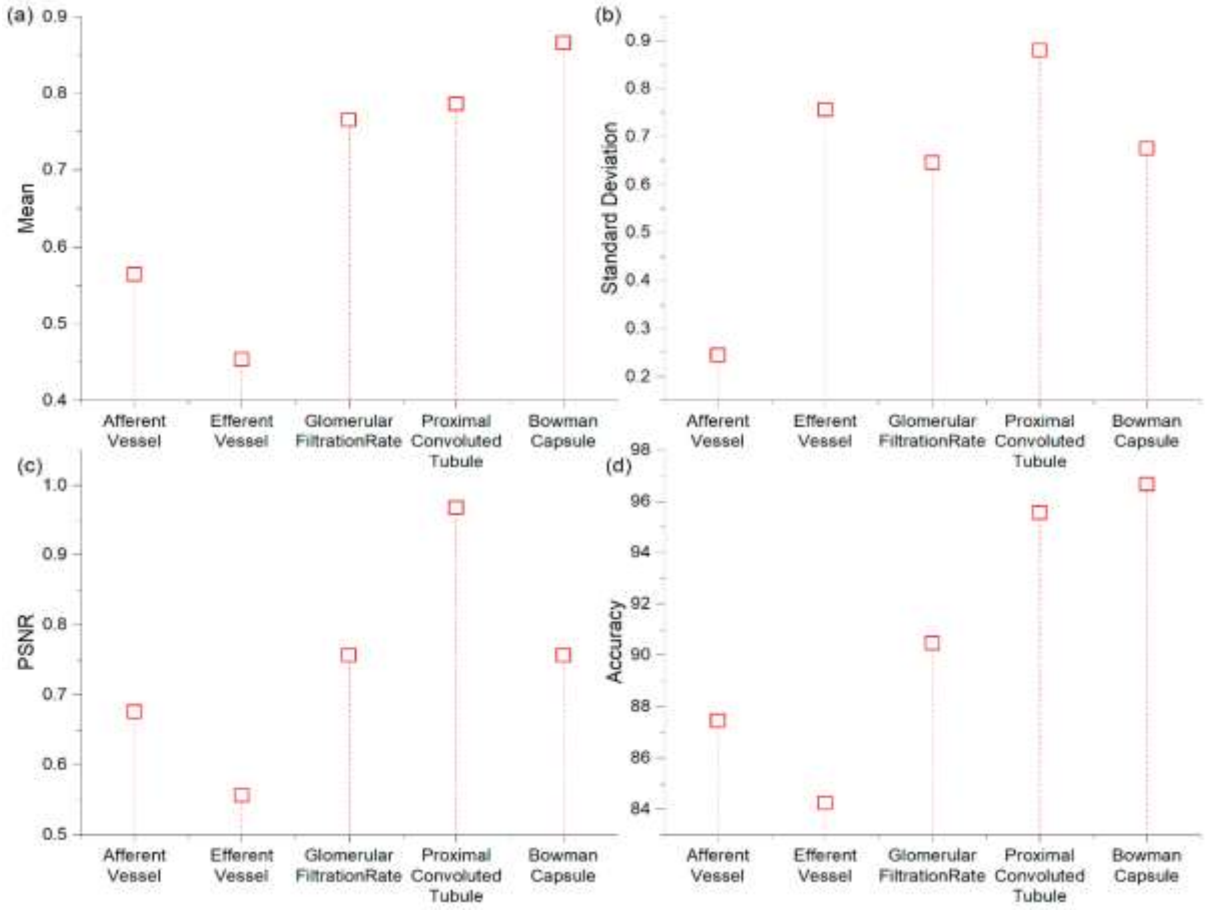

Figure 6. Performance of recognition and prediction of kidney disease. **(a)** Mean **(b)** Standard Deviation **(c)** PSNR **(d)** Accuracy.

Our proposed method, the FNN, is compared to the existing system for CDK diseases (refer to Table 3). The training and testing stages 1 to 5 are carried out for the left kidney (98.34%) and right kidney (97.46%) and then the overall accuracy is evaluated (99.23%). The analysis of the existing TRM method shows a kidney stage 1 to 5 training and testing accuracy of 95.76% and an overall accuracy of 97.46%.

The results indicate that the HFNN method provides the best performance compared to the existing method in Figure 7.

Table 3: Comparison Result Analysis

Algorithm	Kidney Stages	CKD	Training/Testing	Accuracy
Fuzzy Deep Neural Network	Stage 1 to 5 (Left)	98.34	97.46	99.23
	Stage 1 to 5 (right)	98.78	97.86	99.34
Traditional Radioimmunoassay Method	Stage 1 to 5 (Left)	91.34	95.65	97.46
	Stage 1 to 5 (right)	91.84	95.76	97.56

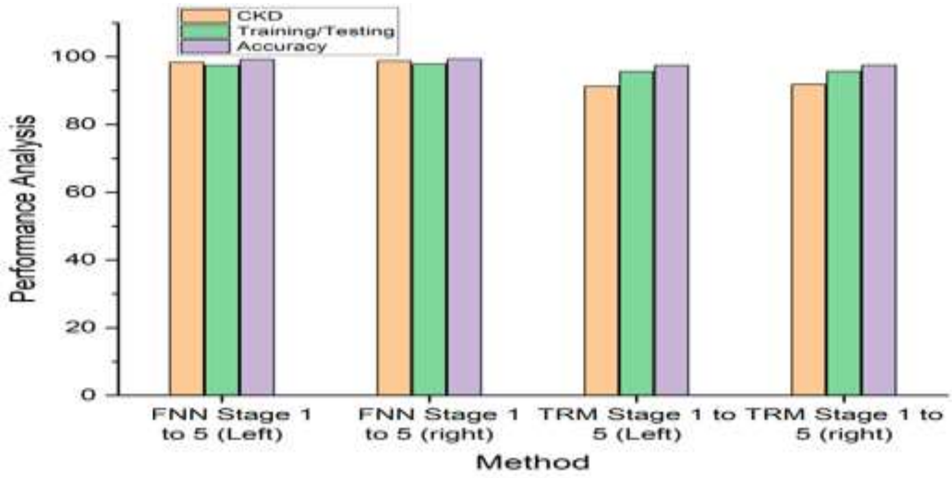

Figure 7: Analysis for CKD using fuzzy DNN comparison with existing method

V. CONCLUSION

Chronic kidney disease is gradually becoming common among different ages owing to bad eating habits, lack of sleep, among other reasons. CKD begins with gradual decrease of kidney function which can result to total kidney failure. This may lead to different forms of treatments for the patients such as dialysis and transplantation. Considering the fact that kidneys are internal organs, it is nearly impossible to diagnose the disease in its early stage. Hence, it is necessary for a person to carry out regular check-ups. A method which aims at early prediction of CKD through establishing of a fuzzy deep neural network model that will be compared and reviewed against the current radioimmunoassay method. It can be seen from the results that the proposed model is more effective compared to the existing methods in terms of improved disease identification. As a result of a small number of sample size of the dataset applied in the research, it has been concluded that in future, research will be done using bigger datasets or compare the results generated from this dataset to a different dataset. Also, as an effort to reduce the CKD spread, there has been an attempt at establishing whether an individual with the syndrome has a higher tendency of having chronic afflictions like diabetes, hypertension, or family history of kidney failure.

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