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# A Deep Learning Approach for Kidney Disease Recognition and Prediction through Image Processing

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**Abstract:** Chronic kidney disease (CKD) is a gradual decline in renal function that can lead to kidney damage or failure. As the disease progresses, it becomes harder to diagnose. Using routine doctor consultation data to evaluate various stages of CKD could aid in early detection and prompt intervention. To this end, researchers propose a strategy for categorizing CKD using an optimization technique inspired by the learning process. Artificial intelligence has the potential to make many things in the world seem possible, even causing surprise with its capabilities. Some doctors are looking forward to advancements in technology that can scan a patient's body and analyse their diseases. In this regard, advanced machine learning algorithms have been developed to detect the presence of kidney disease. This research presents a novel deep learning model, which combines a fuzzy deep neural network, for the recognition and prediction of kidney disease. The results show that the proposed model has an accuracy of 99.23%, which is better than existing methods. Furthermore, the accuracy of detecting chronic disease can be confirmed without doctor involvement as future work. Compared to existing information mining classifications, the proposed approach shows improved accuracy in classification, precision, F-measure, and sensitivity metrics.

**Keywords:** kidney disease; image processing; fuzzy logic; deep neural network; hybrid of fuzzy and deep neural network

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**Citation:** Kumar, K.; Pradeepa, M.; Mahdal, M.; Verma, S.; RajaRao, M.V.L.N.; Ramesh, J.V.N. A Deep Learning Approach for Kidney Disease Recognition and Prediction through Image Processing. *Appl. Sci.* **2023**, *13*, 3621. https://doi.org/10.3390/app13063621

Academic Editor: Jan Egger

Received: 8 February 2023
Revised: 8 March 2023
Accepted: 9 March 2023
Published: 12 March 2023



## 1. Introduction

Computer vision techniques that resemble video surveillance, such as image segmentation, fall under the category of image saliency detection. The low-resolution image issue is addressed using a convolutional neural network (CNN) and deep learning CNN to enhance the image quality and clarity of identification [1]. In this paper [2], the author explains the issue-solving methods in three different aspects faced when using CNNs. Facial expression recognition is a form of progress, but it does not provide accurate results in live detection. By combining a first examination report (FER) with the CNN method, the quality of the content becomes better and more understandable. Typically, machine vision is used to create a laser spot energy that operates in a superposition area. The models used in this area involve a convolutional network with a deep learning (DL) concept [3]. If a possibility exists to detect the presence of acute kidney disease in a human body through machine learning (ML) concepts, it would be beneficial for both doctors and patients to solve this issue. The accuracy of the results shows that non-renal sequential organ failure assessment (SOFA) prediction can occur even in the presence of acute kidney disease (AKD) [4].

The term health information categorization refers to the use of a classifier model with datasets to improve the definition of healthcare. Clinical records are organized to identify and predict objectives. This has a significant impact on how extraction outcomes are predicted. These techniques assist medical professionals in making accurate analytical conclusions during specific diagnoses. Although tree topologies in classifications can be easily coupled [5], the decision tree is still widely used in decision-making as a classification technique. To be more specific, information retrieval tools can be designed to uncover valid, beneficial, and logical frameworks, instances, themes, or decision-making elements hidden within health information [6]. Both children and adults can suffer from chronic kidney disease (CKD), where the kidney's ability to function consistently deteriorates [7].

CKD is widely studied due to the high risk of renal problems in certain groups of individuals, including those with hypertension, obesity, or with a parent diagnosed with CKD [8]. The decline in renal function is gradual and occurs over a long period, which distinguishes it from severe renal disease [9]. Based on information from previous patients, individuals with the same health conditions can be grouped and effective treatment options can be provided [10]. Regular occurrence identification techniques extract important features and functions that describe the entire sample [11,12]. Chronic kidney disease is a major clinical emergency that is often ignored. End-stage renal disease occurs when the kidneys are damaged and unable to remove harmful substances from the blood [13]. Some recent works aim to identify life-threatening illnesses, including renal disease, by using sequence models such as naive Bayes and artificial neural network (ANN) models such as C4.5 to predict the occurrence of CKD [14]. Kidney ultrasound imaging for the prediction of kidney function and chronic kidney disease (CKD) has long been regarded desirable in clinical practise due to its safety, simplicity, and cost-effectiveness. It used kidney length annotations to cut off the kidneys' periphery and other data augmentation techniques to provide more data with variances in order to further extract information from ultrasound pictures. Moreover, bootstrap aggregation was used to reduce overfitting and enhance the generalizability of the model [15].

The main contribution of the paper is:

- To begin, we gather CKD scan pictures and use a normalization technique to preprocess the images.
- To identify the existence of renal illness, cutting-edge machine learning algorithms have been created.
- To demonstrate a fuzzy deep neural network (FDNN) for the detection and prognosis of renal illness.

The rest of the article is structured as follows: Section 2 presents a literature review; Section 3 presents a suggested method; Section 4 presents the result and discussion; and the last section presents a conclusion.

## 2. Literature Review

In order to effectively treat and control chronic kidney disease, early identification and characterisation are believed to be essential components. In the study, effective data mining methods are used to uncover and extract hidden information from clinical and laboratory patient data. This information may help doctors identify disease severity stages with the greatest accuracy [16]. Aljaaf et al. investigate the potential of several machine-learning techniques for the early diagnosis of chronic kidney disease. While this topic has been extensively investigated, we are using predictive analytics to assist our technique as it looks at the link between the data parameters and the characteristic of the target class [17]. Using the Internet of Medical Things (IoMT), images captured by cameras are analyzed to detect the presence of disease in the human body, as explained in this paper [18], which reports a 96.88% verification rate for histopathological images. Deep learning (DL) and machine learning (ML) occupy the fourth position among industrial revolutions, with

DL being based on artificial neural networks. This paper [19] provides a comprehensive overview of deep learning techniques and their applications. Due to the large amount of data, data-parallel processing methods have been introduced, bringing many benefits to the processing system through resource allocation. This paper [20] introduces a deep learning interfacing model. Both ML and DL concepts rely on algorithms to function. This paper [21] explains the proper use of algorithms in the machine learning concept and the ability to automatically detect algorithms if necessary. Recently, web corruption has occurred, caused by either the host or hackers. Bi-LSTM (bi-directional long short-term memory) is one tool used to protect web-based applications. The output is checked in two modes, with the first mode passing at 93.1% and the second mode reaching 93.91% [22].

When a person is affected by a disease, such as kidney disease, the risk of spreading other diseases increases. For example, kidney disease can lead to cardiovascular or kidney failure. Doctors or machines need to estimate the time frame for this to occur [23]. Mobile phones, which use machine learning algorithms, may also allow users to unlock their phone using facial recognition. Traditionally, facial recognition was accomplished through a separate mechanism using neural concepts, as demonstrated in [24], where the author used electrocardiography for testing. Both ML and DL concepts also aid in classifying and analysing Indore identification, similar to crime and robbery, with an accuracy rate of up to 75% using hotspot connections and city information [25]. It can be challenging for machines to differentiate images on a black and white surface, but if there is colour differentiation, the results are clearer. The authors of [26] explore the possibility of identifying the presence of stones in the human kidney through machine analysis.

It is anticipated that alternative or comprehensive treatments will focus on therapies that aim to enhance quality of life, prevent illness, and address diseases that conventional medicine has limited success in treating. The manufacturer demonstrated a preference for using iridology to distinguish between different forms of kidney disease, either normal or exceptional [27]. A total of 192 individuals with chronic kidney disease and 169 healthy individuals were evaluated. A method for acquiring, processing, and characterizing iris images using wavelet transformation and a flexible neuro-fuzzy inference system was developed to reduce dependence on iridologists. The results showed, for both individuals with kidney problems and healthy individuals, an accuracy rate of 81% and 92%, respectively [28]. A CNN was constructed to identify 10 major crop diseases using a database of 500 photos of healthy and diseased grain stems and leaves collected from agricultural fields. The proposed convolution neural algorithm achieved an accuracy of 95.48% using a 10-fold cross-validation architecture. This accuracy is significantly greater than a traditional classification model [29].

## 3. Proposed System

### 3.1. Problem Statement

The limitations of DL systems are another crucial factor to remember. These techniques are often regarded as “black boxes”, making it challenging to “understand” them without additional diverse data. The discussion in this paper is limited to the FDNN classification issue and segmentation characteristics. To better educate and explain the DL findings to doctors, clinical co-variables are also crucial. Moreover, it is critical to comprehend the most effective communication tactics for conveying to doctors the significance of each co-variable in the ultimate DL outcome.

Recent research allows for direct observation or imaging of the entire vascular system, which is an easier task when performed on external body parts, but takes longer when it comes to internal parts. Large-scale retinal studies have shown that concepts such as these could be related to or combined with artificial intelligence and deep learning methodologies. The main reason for using artificial intelligence in healthcare is the availability of medical data, and the rise of complex algorithms that form the backbone of AI and ML. Images are the only input for machines, and they function based on the questions asked by the user by understanding errors and comparison concepts (Figure 1).

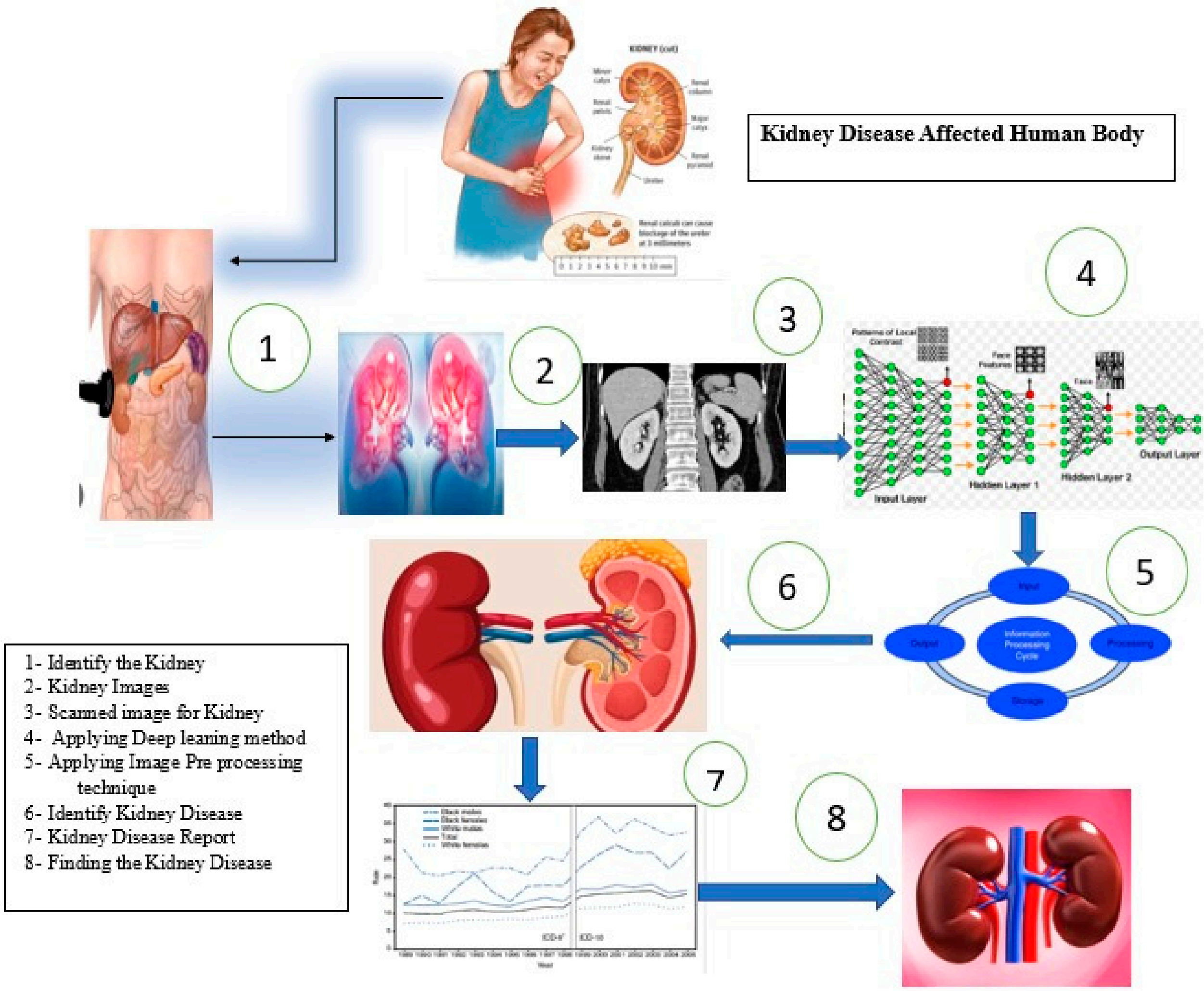


**Figure 1.** Proposed Model for Kidney Disease Prediction.

Figure 2 shows the five stages of chronic kidney disease in a human, which progresses from Stage 1 to Stage 5, and affects both the right and left kidneys equally. In this research, the aim is to predict and analyze these stages, and numerical features are extracted from kidney images to make the predictions.

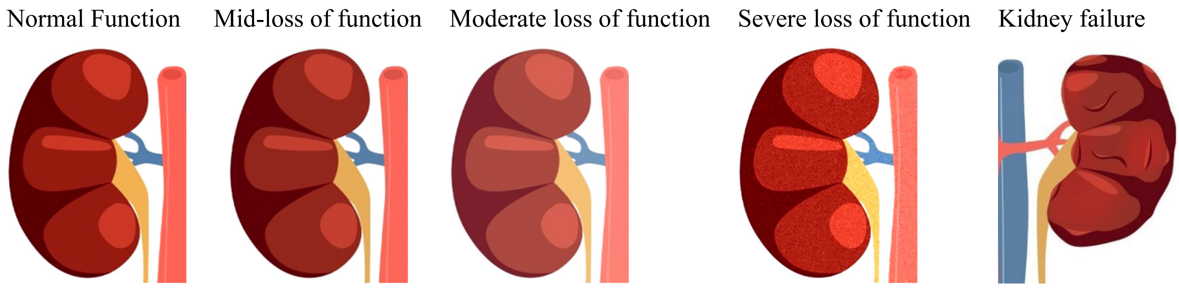


**Figure 2.** Stages of Renal Kidney Disease.

*3.2. Dataset*

The Changhua Christian Hospital in Taichung, Taiwan, is the source of the dataset. With patients' identifying information deleted, a total of 5617 records from 1 January 2000 to 27 July 2017 were obtained. Patients' conditions were monitored throughout this time or until they pass away. Patients' monitoring times varied from less than a month to over five years, with an average of about two and a half years. A flat CSV file was used to hold the dataset. The intended variable, "survival or not", is among the 35 properties that are listed in columns. Other factors can be broken down into two categories: general information about the body or the CKD itself, such as the ID, diagnosis date, age, gender, height, weight, BMI, stage, haemodialysis and its date; and whether or not the person was taking special medications or had comorbid conditions, such as high blood pressure, heart disease, chronic liver disease, or other conditions. Table 1 contains statistics regarding a number of significant characteristics [30].

**Table 1.** Various feature of the dataset.

| Attribute | Detail | Number | Percentage |
|---|---|---|---|
| Gender | Male | 3151 | 56.1% |
| | Female | 2466 | 43.9% |
| | $y \leq 18.5$ | 239 | 4.3% |
| | $18.5 < y \leq 25$ | 2841 | 50.6% |
| BMI | $25 < y \leq 30$ | 1862 | 33.1% |
| | $30 < y \leq 40$ | 642 | 11.4% |
| | $y > 40$ | 33 | 0.6% |
| | 0 | 3722 | 66.4% |
| Hemodialysis | 1 | 1326 | 23.6% |
| | 2 | 569 | 10.1% |
| High Blood Pressure | No | 1644 | 29.3% |
| | Yes | 3973 | 70.7% |
| Anemia | No | 4795 | 85.4% |
| | Yes | 822 | 14.6% |
| Non-survival | No | 4933 | 87.8% |
| | Yes | 684 | 12.2% |
| Chronic Liver Disease | No | 5059 | 90.1% |
| | Yes | 558 | 9.9% |

As the dataset is mostly clean and comprehensive, minimal preparation was required. The ID element and two date attributes were simply dropped, since the former was not important and the latter were not full. Moreover, the absence of a haemodialysis date might reflect one of two very different things: either the patient was receiving haemodialysis but the date was not recorded, or the patient did not yet need it. As there is no easy method to discern between the two diametrically opposed circumstances, we decide to combine them all so that the remaining data would better fit the prediction algorithm. Moreover, we tested our models using 5-fold cross-validation on the dataset.

The MJ Health Research Foundation gave permission for and provided all of the datasets that were utilised. The MJ Health Research Foundation and the Far Eastern Memorial Hospital's Research Ethics Review Committee assessed and approved the study's strategy with regard to ethical concerns about the use of database data (FEMH-IRB-107126-E, Protocol Version 7, 18 June 2020). (Approval No.: MJHRF-2016005A).

The dataset was then preprocessed using the normalising technique known as min–max normalisation. One of the most popular methods for normalising data is the min–max method. For each feature, the lowest value is converted to a 0, the highest value is converted to a 1, and all other values are converted to a decimal between 0 and 1.

## 4. Proposed Work

Chronic kidney disease (CKD) often causes symptoms such as illness and constipation, leading to a decrease in quality of life and increased risk of death. The inflammatory process of CKD can impact the development of illness, cachexia, and kidney osteodystrophy, but also increases the risk of stroke in CKD patients. Ghrelin, a form of oestrogen produced in the stomach, has been found to have potential benefits in regulating food intake and meal appreciation, making it a potential therapy for anorexic CKD patients. Ghrelin has been shown to have anti-inflammatory properties and to stimulate food cravings. This evaluation discusses the metabolic changes in ghrelin and its potential implications for CKD. The benefits, drawbacks, and unanswered questions about using ghrelin in CKD healthcare is also discussed.

The provision of CKD care is a major challenge in modern times, particularly in developed countries where people in remote locations want access to high-quality medical care. Artificial intelligence has greatly benefited the healthcare industry, just as it has transformed other aspects of life. However, the conventional telemedicine setup faces certain challenges, such as the need for a local healthcare centre with a dedicated team, the need for hospital equipment to process patient reports, treating patients within 48 h, access to medical expertise within a healthcare centre, the cost of local healthcare centres, and the requirement for a reliable Wi-Fi connection.

The smart CKD process is managed and monitored using fuzzy logic. There are two main issues: when the model's capacity is insufficient, more than two designs are merged to resolve the issue. To provide an efficient solution to the crisis, a hybrid system was created by combining multiple methods. In some forms of hybrid fuzzy neural network, a fuzzy inference system is combined with an artificial neural network, resulting in a fuzzy neural network (FNN).

This method involves a "fuzzy neuron", and the fuzzy neuron method has been separated into two classifications, as described in the following:

- The development of a fuzzy neuron model.
- Creation of a single model and algorithm of the model for incorporating neural systems through 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.

$$m'(k) = d(m(k), g[k, k+1]) \tag{1}$$

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 $n_i$ may work with a large number of materials $s_i$ to build such items.

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

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

$$FL = g_1 + g_2 = s_1 k_1 + s_2 k_2, \tag{3}$$

Cachexia is a disease characterized by muscle loss, anorexia, increased energy expenditure, and the presence of chronic disease (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, $f(y) = (1 + e^{-y})^{-1}$, which is represented in Equation (4).

$$y = f(FL) = f(s_1 k_1 + s_2 k_2) \tag{4}$$

An ordinary neural net is a basic network that employs Sigmoid function $f$, redundancy, and other inclusions.

The decision support system used in AI-based electronic health records is based on a set of fuzzy rules. These rules are derived from both factual and fuzzy data. The following are examples of fuzzy rules.

- If the blood pressure is high, the temperature is high, and the pulse rate is low, judgment is good.
- If your blood pressure is high and your pulse rate is low, your judgment is likely to be impaired.
- If the temperature is normal, the pulse is rapid, and the blood pressure is moderate, then the judgment is low.
- If the temperature is low and the heart rate is high, then determine whether the blood pressure is low.
- If the temperature and pulse rate 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 the web access transmits $s_i^g$ as given in Equation (5).

$$s_i^g = \alpha_i R \, log \, log \left(1 + \frac{|g_{i,n}|^2 Y_{i,n} g^{-n}}{\sigma^2}\right) \tag{5}$$

where $i$ represents the percentage of access of internet bandwidth utilized by new terminal update tasks, $g_{i,n}$ represents the relation recession scaling factor between access point and terminal, and $Y_{i,n}$ represents terminal products and services, $g^{-n}$ represents node facility distance, $b$ represents loss, but $\sigma^2$ also represents interaction noise level.

Accordingly, the efficiency of the $g_i$ data link data transfer is elaborated as in Equation (6).

$$d_i^k = \beta_i B \, log \, log \left(1 + \frac{|g_{n,i}|^2 X_n g^{-b}}{\sigma^2}\right) \tag{6}$$

in which $\beta_i$ signifies the fraction of power transmission frequency bandwidth occupied by the terminal able to receive work-related jobs, $g_{n,\, i}$ signifies the link economic downturn relation between the entry point and terminal, and $X_n$ signifies the foundation network's transmitting speed.

Muscles waste away due to cachexia, while fats are also underutilized. Patients with chronic kidney disease (CKD) often experience anorexia, which is defined as a loss of appetite. The disease in CKD patients can also be linked to reducing the sense of taste and smell for food, early satiation, changes in neurohormonal filtration, instability in acetylate cyclase, increased cognitive tryptophan, and increased levels of inflammatory cytokines. Anorexia not only decreases verbal energy, but also protein intake, which is a major contributor to cachexia. Increased resting energy consumption has been linked to higher mortality rates and cardiovascular mortality in CKD patients, and it is also tied to the prevalence of cachexia in these patients. Currently, there is no effective treatment for cachexia in CKD. Nutritional and health strategies, such as caloric diets with anabolic steroids, have largely proven ineffective. This highlights the urgency for the development of new drug treatments for this potentially fatal condition in CKD patients.

Job $n_i$ 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.

$$X_i^n = \frac{g_i}{g_i^k} \tag{7}$$

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

$$g_i^m = \sum_{m \in g} (1 - \alpha_i) g_i^m \tag{8}$$

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

$$g_i^n = \frac{m_i}{g_i^n} \tag{9}$$

Discoveries about the pathophysiology of cachexia in CKD have led to innovative therapeutic approaches. Cachexia in CKD is caused by an increase in the frequency of inflammatory responses, which affects the central nervous system (CNS) and creates a relationship between the release and function of several key neuropeptides, affecting metabolic activity. Leptin and the melanocortin centre in the hypothalamus have already been proposed as targets for cytokine activity, and they remain crucial regulators of appetite and energy metabolism.

These changes result in a fuzzy neural design that relies on fuzzy mathematical tasks. The bandwidth delay duration is proportional to the amount of information received and the network throughput for data transfer, as stated in Equation (10).

$$g_i^n = \frac{g_i}{b_i^k} \tag{10}$$

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 the server's computing capability, as expressed in Equation (11).

$$b_i^f = \frac{f_i}{X_i} \tag{11}$$

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 $s_i$ to the network edge is transmitted as in Equation (12).

$$s_i^n = s_i^c + s_i^h + s_i^f \tag{12}$$

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 $s_i$ to the edge device is conveyed as in Equation (13).

$$X_i^n = \sum_{i=1}^{n} (\alpha_i d_i^n) \tag{13}$$

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.

$$ming = \sum_{i=1}^{n} (g_i^n + d_i^n) \tag{14}$$

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 and complicated diseases such as heart attack. When a subject $f1$ places its finger on the data panel, the sensor activates. The result is identified on the input panel. The sensor provides a 5-volt direct power source as in Equation (15).

$$s.t.\ f1 : \sum_{h_i \in d} m_i \leq m_y \tag{15}$$

The smart CKD process of client management and monitoring framework is required. The framework suggested $f2$ in Equation (16) is a framework profiting from a fuzzy logic system that is simple to use and enforced for creating decisions.

$$f2 : \sum_{g_i \in d} \alpha_i \leq 1 \tag{16}$$

Circulating levels of leptin and insulin suppress appetite by inhibiting the production of neuropeptide Y (NPY) and increasing the production of monoaminergic protein, while also suppressing the manufacturing of agouti-related peptide (AgRP) in the hypothalamus. Inflammatory mediators cause anorexia through their central actions. Cytokines reduce gastrointestinal activity, as metabolic changes affect the hormonal system and modulate the neuropeptide identity in the hypothalamus, both of which can impact eating behaviour.

The $f3$ in Equation (17) suggests a novel method for organization, as it makes use of both detectable information and a fuzzy decision-making process.

$$f3 : \sum_{g_i \in d} \beta_i \leq 1 \tag{17}$$

Desirability is explained in terms of lag time, seeing as $f4$ in Equation (18) aims to reduce the lag time of such a power sector, where less time delay was correlated with greater strength.

$$f4 : m_i^n \geq 0, \forall i \in d \tag{18}$$

The strength and endurance values are calculated as in Equation (19).

$$d_i = \frac{1}{g_i} \tag{19}$$

Effective and accommodating treatment options for CKD patients are highly needed. Ghrelin is more effective than most other orexigenic hormones, as it increases food intake in both small mammals and humans. Recent findings support the potential use of ghrelin and its analogues as food craving stimulants and anabolic treatments for cachexia associated with uraemia and other diseases. Ghrelin may impair energy metabolism, but it can also exacerbate cachexia through IGF-dependent and insulin-like growth factor processes.

## 5. Experimental Result

By changing various components of the proposed better FDNN model, we carried out our tests as part of an ablation research. By changing various components, it is possible to create a more dependable design with improved classification accuracy. Throughout the ablation experiment, modifications were made to the FDNN, activation function, kernel initializer, and optimizer.

The suggested approach was tested using the Origin pro simulation software. CKD often causes illness and constipation, both of which are linked to reduced quality of life and increased mortality risk. The inflammatory CKD process may contribute to the development of illness, cachexia, and kidney osteodystrophy, but it is the increased risk of stroke in people with CKD that is concerning. Ghrelin is a hormone produced in the stomach and is thought to act as an oestrogen. Its effects are mediated by the growth hormone secretagogue receptor (GHSR). Ghrelin's potential to increase food consumption and meal enjoyment make it a promising therapy for anorexic CKD patients. Ghrelin has been shown to have anti-inflammatory properties and stimulate food cravings. The recognition and prediction of kidney disease in the context of image processing in an afferent and efferent vessel used the HFNN algorithm to identify the convoluted tubule of the Bowman capsule for the mean and standard deviation, PSNR, and accuracy in the glomerular filtration rate of CKD (Table 2). Performance of the recognition and prediction of kidney disease is shown in Figure 3.

**Table 2.** Renal Function Tests Analysis for Kidney Disease Identify using Hybrid Fuzzy Neural Network Algorithm.

| Parameters | Afferent Vessel | Efferent Vessel | Glomerular Filtration Rate | Proximal Convoluted Tubule | Bowman Capsule |
|---|---|---|---|---|---|
| Mean | 0.5643 | 0.4534 | 0.7654 | 0.7864 | 0.8658 |
| Standard Deviation | 0.2445 | 0.7563 | 0.6453 | 0.8796 | 0.6756 |
| PSNR | 0.6756 | 0.5564 | 0.7564 | 0.9675 | 0.7564 |
| Accuracy | 87.45 | 84.24 | 90.46 | 95.55 | 96.67 |

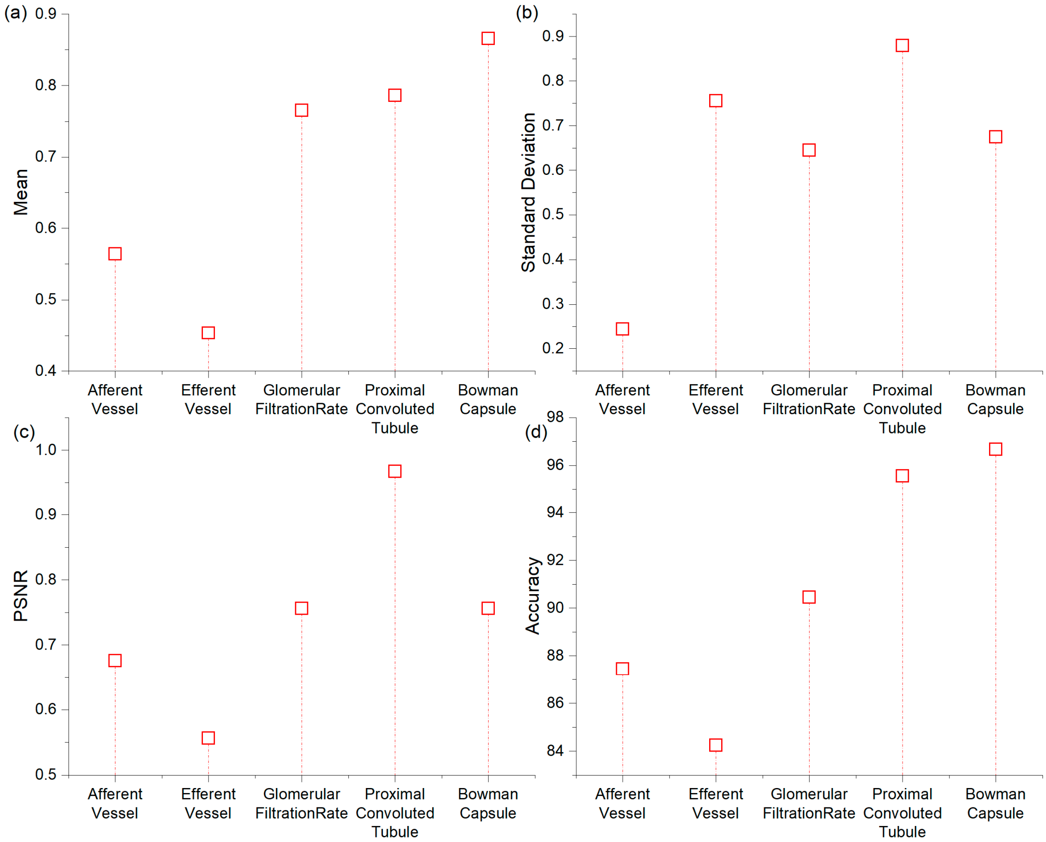


**Figure 3.** Performance of recognition and prediction of kidney disease. (**a**) Mean (**b**) Standard Deviation (**c**) PSNR (**d**) Accuracy.

In today's world, providing care for patients with chronic kidney disease (CKD) is a major challenge, especially in countries with limited access to quality medical care. The advancement of artificial intelligence (AI) has greatly impacted healthcare, just as it has transformed other fields. However, the conventional telemedicine approach has certain limitations, such as the need for a local health centre with dedicated personnel and hospital equipment, the time it takes for patients to receive treatment and medical information from experts, the cost of local clinics, and the requirement for stable Wi-Fi connectivity. The percentage of wireless internet channel capacity used by the port to inform users of new activities is represented by I. The connection downtime transformation function between the entry point and the stations is represented by $g_i^n$, while $y_i^n$ represents the terminal's products or services. The node's building location is represented by $g^{-n}$, b represents the news team's loss, and $\sigma^2$ represents the quality of communication sound used within the network, as shown in Figure 4. Table 3 presents the analysis of CKD severity in five stages using the hybrid fuzzy neural network algorithm to evaluate the overall accuracy of the training and testing for CKD severity.

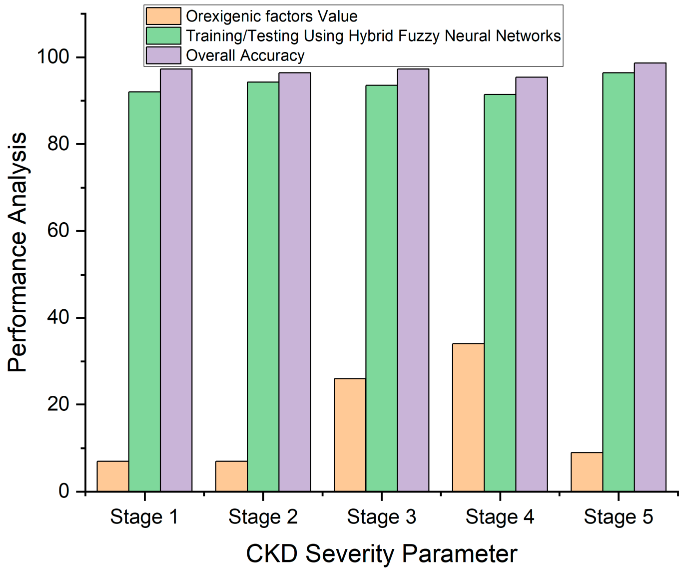


**Figure 4.** Analysis of CKD severity using a hybrid fuzzy neural network algorithm.

**Table 3.** Performance result analysis for the CKD severity using hybrid fuzzy neural network algorithm.

| CKD Severity Parameter | Value | Training/Testing Using Hybrid Fuzzy Neural Networks (%) | Overall Accuracy (%) |
|---|---|---|---|
| Stage 1 | 7 (8.4) | 92.12 | 97.34 |
| Stage 2 | 7 (8.4) | 94.34 | 96.45 |
| Stage 3 | 26 (31.3) | 93.56 | 97.35 |
| Stage 4 | 34 (41) | 91.45 | 95.46 |
| Stage 5 | 9 (10.8) | 96.45 | 98.67 |

Stage 1: Normal renal function despite kidney damage. Stage 2: Mild kidney function loss. Stage 3: Moderate to severe renal dysfunction and mild to moderate kidney dysfunction. Stage 4: Serious kidney function loss. Stage 5: Failure of the kidney.

The fuzzy logic for smart CKD process management and monitoring is characterized by the command line $g_i$ information processing ability to complete tasks locally. As an outcome, the whole latency is recognized by $g_i$ researchers only at the local scale, as in Equation (8), represented in Figure 5. There are several issues to consider: when a single model is insufficient to solve a problem, more than two designs are collaborated to overcome the problem. When two or more models are joined to offer an effective answer to a challenging issue, a hybrid system is developed. In a hybrid model of fuzzy neural networks, fuzzy logic systems analyze CDK in comorbidities using the HFNN algorithm to evaluate hypertension values based on training and testing (Table 4) in diabetes cerebrovascular disease to evaluate accuracy.

**Table 4.** Performance analysis for CDK in co-morbidities using hybrid fuzzy neural network algorithm.

| Co-Morbidities | Value | Training/Testing Using Hybrid Fuzzy Neural Networks (%) | Accuracy (%) |
|---|---|---|---|
| Hypertension | 78 (94) | 89.34 | 92.34 |
| Diabetes | 59 (71.1) | 85.53 | 90.21 |
| Dyslipidemia | 73 (88) | 82.23 | 88.34 |
| Ischemic heart disease | 24 (28.9) | 94.56 | 96.42 |
| Cerebrovascular disease | 5 (6) | 93.13 | 95.34 |

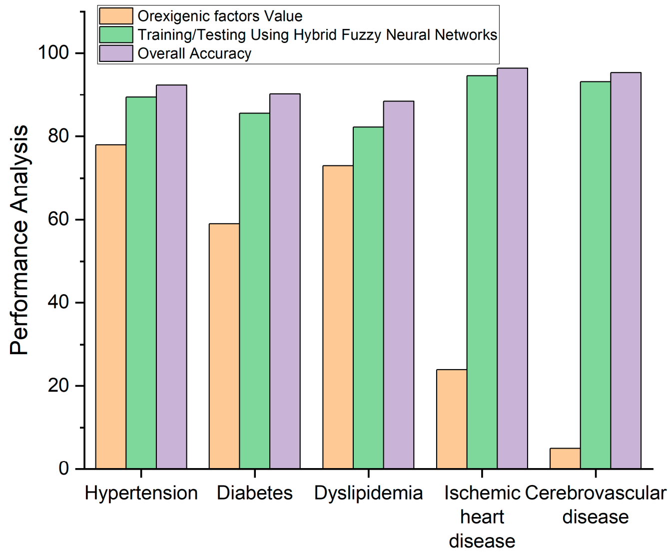


**Figure 5.** Analysis for CDK in Co-morbidities using hybrid fuzzy neural network algorithm.

If different operations, such as a t-norm or $n_i$-conorm, are used to provide information to a neuron, it is referred to as a hybrid artificial neuron, as shown in Equation (9). Figure 6 shows that ghrelin stimulates pre-adipocyte differentiation while inhibiting adipogenesis, suggesting that it works with adipocytes to promote adipogenesis. In conclusion, small-scale clinical studies in CKD patients have provided valuable evidence to support the short-term orexigenic effects of subcutaneous ghrelin administration. However, the clinical utility of ghrelin in CKD will be determined by long-term improvements in appetite, muscle mass, and function, as well as poor outcomes compared to our proposed method. Our proposed method, the HFNN, is compared to the existing system for CDK diseases (refer to Table 5). 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.

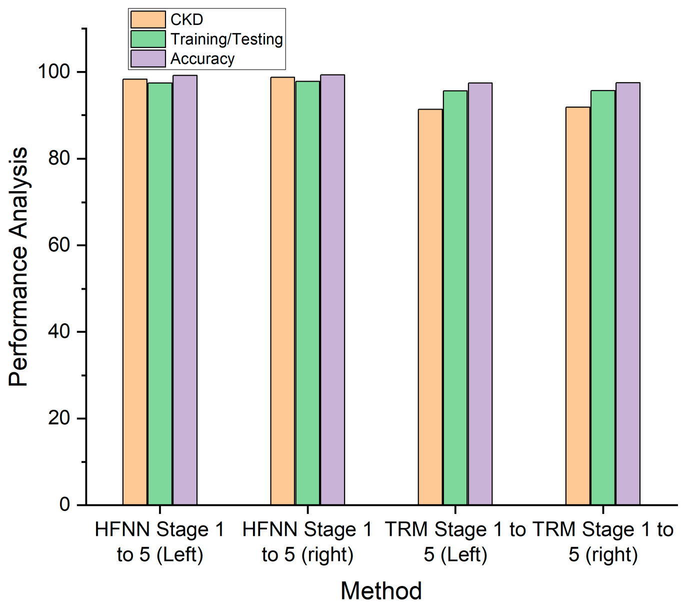


**Figure 6.** Analysis for CKD using hybrid on fuzzy neural network comparison with existing method.

**Table 5.** Comparison Result Analysis.

| Algorithm | Kidney Stages | CKD | Training/Testing | Accuracy |
|---|---|---|---|---|
| Hybrid on 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 |

## 6. Conclusions

Chronic kidney disease (CKD) is becoming more widespread across various age groups due to poor diet, lack of sleep, and other factors. CKD starts with the slow decline of kidney function and can lead to total kidney failure. This can result in various treatments for patients, including dialysis and transplantation. As the kidneys are internal organs, it is difficult to diagnose the disease in its early stages. Therefore, it is important for individuals to have regular check-ups. This research focuses on early-stage prediction of CKD by developing a hybrid fuzzy deep neural network model, which is compared and evaluated against the current radioimmunoassay method. The results show that the proposed model outperforms the existing method in more accurate disease identification. Due to the small sample size of the dataset used in the research, it has been decided that future work will be carried out with bigger datasets or by comparing the outcomes of this dataset with those of another dataset. Also, in an effort to reduce the prevalence of CKD, an effort has been made to determine whether an individual with this syndrome is more likely to have chronic risk factors such diabetes, hypertension, or a family history of kidney failure.

**Author Contributions:** Conceptualization, K.K., M.P., M.M., S.V., M.V.L.N.R. and J.V.N.R.; Methodology, K.K., M.P., M.M. and S.V.; Validation, K.K., M.P., S.V., M.V.L.N.R. and J.V.N.R.; Formal analysis, K.K., M.P., S.V., M.M. and M.V.L.N.R.; Investigation, K.K., M.P., M.V.L.N.R. and J.V.N.R.; Resources, K.K., M.P., S.V., M.V.L.N.R. and J.V.N.R.; Writing—original draft, K.K., M.P., M.M., S.V., M.V.L.N.R. and J.V.N.R.; Writing—review and editing, K.K., M.M. and M.P. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the project SP2023/074 Application of Machine and Process Control Advanced Methods supported by the Ministry of Education, Youth and Sports, Czech Republic.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available through email upon request to the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.

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