Integrating Fuzzy Logic and Medical Parameters for Reliable Chronic Kidney Disease Risk Prediction

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ABSTRACT
This study explores the integration of fuzzy logic with critical medical parameters-Creatinine, Blood Urea Nitrogen (BUN), and Protein in Urine—to enhance the accuracy and reliability of Chronic Kidney Disease (CKD) risk prediction. Traditional diagnostic methods often struggle with the inherent uncertainty and variability in medical data, leading to potential misclassifications. By employing a fuzzy logic-based model, this research systematically incorporates varying levels of the three biomarkers to infer CKD risk levels as Low, Moderate, or High. The fuzzy rule base allows for nuanced decision-making that aligns more closely with clinical observations, providing a more flexible and adaptive approach to risk assessment. This model aims to support healthcare professionals in early diagnosis and improved patient management by offering a transparent, interpretable framework for CKD risk evaluation amidst uncertain data conditions.

Keywords: Fuzzy logic models, chronic kidney disease (CKD), risk prediction, creatinine levels, blood urea nitrogen (BUN), protein in urine, kidney health, fuzzy inference system,

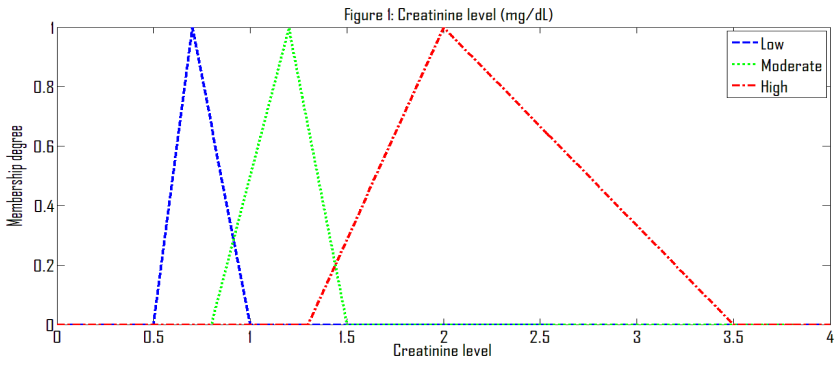
1. INTRODUCTION

Chronic kidney disease is a progressive condition influenced by numerous factors, including creatinine levels, blood urea nitrogen (BUN), and protein in urine—all of which can vary significantly among individuals and do not always conform to strict diagnostic thresholds. Traditional methods often rely on fixed cutoffs to assess CKD risk, potentially overlooking subtle variations that could indicate early stages of the disease. Fuzzy logic systems, however, interpret these clinical indicators within a range, allowing for more nuanced analysis by handling imprecision and uncertainty in data. In a fuzzy logic-based CKD prediction model, each medical parameter is assigned a membership function (often triangular or trapezoidal), reflecting its degree of relevance to CKD risk. These membership values are then processed in a fuzzy inference system, which combines the information from multiple indicators to yield an overall risk level. Finally, defuzzification methods, such as the centroid method, are used to convert the fuzzy output into a crisp, actionable risk score, allowing clinicians to make informed decisions. This approach provides continuous, adaptable risk assessment, enhancing early detection and facilitating personalized patient monitoring. By using fuzzy logic, CKD risk prediction becomes more accurate and reliable, offering a valuable tool that aligns with the complexities of real-world patient data and supports proactive kidney disease management.

Kubota et al. (2004) proposed an innovative approach for automated kidney region extraction using a technique known as "q-learning." This method was one of the early attempts to automate kidney imaging processes, aiming to improve the accuracy and efficiency of kidney-related diagnostics. The study laid foundational work for using intelligent signal processing in medical imaging, particularly for kidney disease, by focusing on reliable region extraction which is crucial for accurate diagnosis. Sobrinho et al. (2016) took a step further by developing a formal specification tool intended to support early diagnosis of chronic kidney disease (CKD). The study emphasized the need for early detection, providing a structured approach to improve the reliability of diagnosis through formal specifications. This work was significant

in that it incorporated standardized guidelines for CKD diagnostics, making it possible to develop more systematic and replicable tools that enhance diagnostic reliability and decision-making. Wickramasinghe et al. (2017) focused on dietary prediction for CKD patients by analyzing blood potassium levels using machine learning algorithms. This approach showcased the potential of using predictive algorithms in managing CKD, particularly in providing personalized dietary recommendations. By considering individual blood potassium levels, this study contributed to the growing trend of integrating machine learning with healthcare data, promoting tailored treatment plans for patients with chronic kidney disease. Iqbal et al. (2018) investigated the use of texture analysis on ultrasound images to detect CKD. This study applied advanced texture analysis techniques to enhance the precision of ultrasound diagnostics. By analyzing specific textures that may correlate with CKD, the authors provided a non-invasive method to assist radiologists in identifying early stages of kidney disease. Their work demonstrated the importance of image-based feature extraction in CKD diagnosis, aligning with the trend of using advanced imaging techniques to improve diagnostic accuracy. Varughese and Abraham (2018) highlighted the urgent need for CKD awareness and treatment improvement in India. The authors called for a systemic change in CKD management due to the high prevalence and late diagnosis of CKD in the Indian population. This study drew attention to the socioeconomic factors and healthcare system limitations affecting CKD outcomes, advocating for improved screening and early intervention strategies as critical steps toward reducing CKD morbidity and mortality. Kumar et al. (2021) explored the optimization of wire EDM process parameters for D2 steel. Although the study is outside the field of CKD, it demonstrates the broader application of optimization techniques, which are also relevant in medical contexts, particularly in fine-tuning diagnostic processes and predictive models to improve efficiency and accuracy. Kumar et al. (2021) also presented an optimization model for designing the powertrain of a formula student race car, which, while focused on engineering, contributes to understanding optimization methods that could be applied in healthcare, particularly for designing efficient diagnostic frameworks and computational models to enhance CKD prediction and monitoring. Mezan et al. (2021) synthesized silica nanoparticles (SiO2) from rice husk ash, highlighting advancements in material science with potential applications in medical imaging and drug delivery. Nanotechnology can improve the sensitivity and specificity of imaging techniques, potentially enhancing the detection of CKD markers at a molecular level. Rachana et al. (2021) developed a follicle recognition technique for detecting polycystic ovarian syndrome (PCOS), showcasing the application of image recognition and segmentation techniques in healthcare diagnostics. Such methods have parallels in CKD diagnostics, where feature extraction and pattern recognition are essential for accurate detection and monitoring of kidney abnormalities. More and Singla (2021) made significant contributions with two studies: one on a generalized deep learning framework for grading rheumatoid arthritis severity and another on a segmentation and feature extraction model for knee MR images. Both studies demonstrated the power of deep learning and multi-resolution networks in medical image analysis, providing a foundation for similar applications in CKD. Using deep learning for automated severity grading could streamline CKD diagnosis, allowing clinicians to focus on more personalized treatment decisions. These studies collectively illustrate the evolving landscape of CKD diagnosis, with innovations spanning from image analysis and machine learning to nanotechnology and optimization techniques. By integrating such methodologies, researchers are advancing toward reliable, early detection systems for CKD, which hold promise for improving patient outcomes through timely intervention and personalized care.

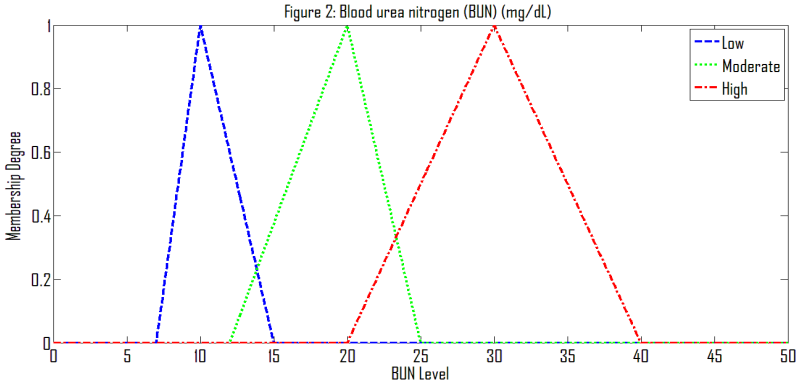
2. Definition of input and output variables



$$\mu_{\text{Creatinine ,Low}}(x) = \begin{cases} 0 & x < 0.5 \\ \frac{x-0.5}{1.0-0.5} & 0.5 \le x \le 1.0 \\ \frac{1.5-x}{1.5-1.0} & 1.0 < x \le 1.5 \\ 0 & x > 1.5 \end{cases} \quad (1)$$

$$\mu_{\text{Creatinine ,Moderate}}(x) = \begin{cases} 0 & x < 0.8 \\ \frac{x-0.8}{1.2-0.8} & 0.8 \le x \le 1.2 \\ \frac{1.5-x}{1.5-1.2} & 1.2 < x \le 1.5 \\ 0 & x > 1.5 \end{cases} \quad (2)$$

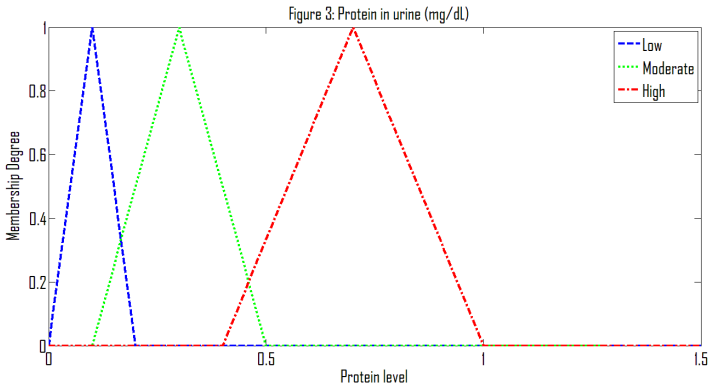
$$\mu_{\text{Creatinine ,High}}(x) = \begin{cases} 0 & x < 1.3 \\ \frac{x-1.3}{2.0-1.3} & 1.3 \le x \le 2.0 \\ \frac{3.5-x}{3.5-2.0} & 2.0 < x \le 3.5 \\ 0 & x > 3.5 \end{cases} \quad (3)$$



$$\mu_{\text{BUN ,Low}}(y) = \begin{cases} 0 & y < 7 \\ \frac{y-7}{10-7} & 7 \le y \le 10 \\ \frac{15-y}{15-10} & 10 < y \le 15 \\ 0 & y > 15 \end{cases} \quad (4)$$

$$\mu_{\text{BUN ,Moderate}}(y) = \begin{cases} 0 & y < 12 \\ \frac{y-12}{20-12} & 12 \le y \le 20 \\ \frac{25-y}{25-20} & 20 < y \le 25 \\ 0 & y > 25 \end{cases} \quad (5)$$

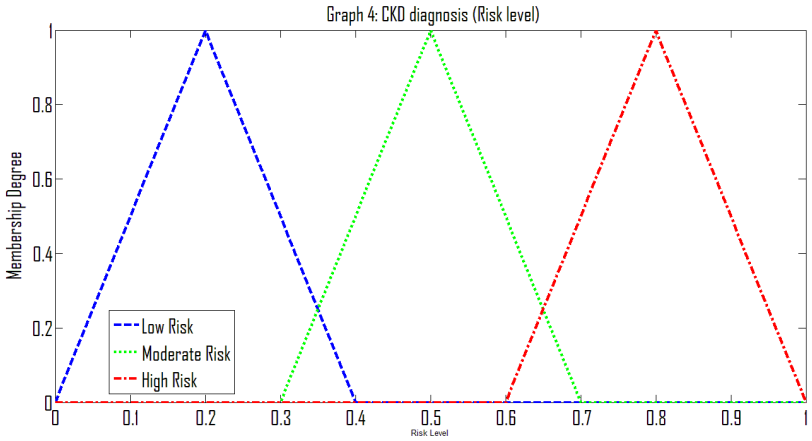
$$\mu_{\text{BUN ,High}}(y) = \begin{cases} 0 & y < 20 \\ \frac{y-20}{30-20} & 20 \le y \le 30 \\ \frac{40-y}{40-30} & 30 < y \le 40 \\ 0 & y > 40 \end{cases} \quad (6)$$



$$\mu_{\text{Protein ,Low}}(z) = \begin{cases} 0 & z < 0 \\ \frac{z-0}{0.1-0} & 0 \le z \le 0.1 \\ \frac{0.2-z}{0.2-0.1} & 0.1 < z \le 0.2 \\ 0 & z > 0.2 \end{cases} \quad (7)$$

$$\mu_{\text{Protein ,Moderate}}(z) = \begin{cases} 0 & z < 0.1 \\ \frac{z-0.1}{0.3-0.1} & 0.1 \le z \le 0.3 \\ \frac{0.5-z}{0.5-0.3} & 0.3 < z \le 0.5 \\ 0 & z > 0.5 \end{cases} \quad (8)$$

$$\mu_{\text{Protein ,High}}(z) = \begin{cases} 0 & z < 0.4 \\ \frac{z-0.4}{0.7-0.4} & 0.4 \le z \le 0.7 \\ \frac{1.0-z}{1.0-0.7} & 0.7 < z \le 1.0 \\ 0 & z > 1.0 \end{cases} \quad (9)$$



$$\mu_{\text{Risk ,Low}}(u) = \begin{cases} 0 & u < 0 \\ \frac{u-0}{0.2-0} & 0 \le u \le 0.2 \\ \frac{0.4-u}{0.4-0.2} & 0.2 < u \le 0.4 \\ 0 & u > 0.4 \end{cases} \quad (10)$$

$$\mu_{\text{Risk ,Moderate}}(u) = \begin{cases} 0 & u < 0.3 \\ \frac{u-0.3}{0.5-0.3} & 0.3 \le u \le 0.5 \\ \frac{0.7-z}{0.7-0.5} & 0.5 < u \le 0.7 \\ 0 & u > 0.7 \end{cases} \quad (11)$$

$$\mu_{\text{Risk ,High}}(u) = \begin{cases} 0 & u < 0.6 \\ \frac{u-0.6}{0.8-0.6} & 0.6 \le u \le 0.8 \\ \frac{1.0-u}{1.0-0.8} & 0.8 < u \le 1.0 \\ 0 & u > 1.0 \end{cases} \quad (12)$$

3. Membership plot functions

4. Rule base

The following rules enables a systematic approach to categorizing CKD risk based on observed biomarker levels. Each rule considers combinations of levels and provides a corresponding risk level for better diagnosis and monitoring.

Table 1:Rule Base for Chronic Kidney Disease (CKD) Risk Assessment Based on Creatinine, BUN and Protein in Urine Levels

Rule No.	Creatinine Level	BUN Level	Protein in Urine Level	Inferred Risk Level
1	Low	Low	Low	Low
2	Low	Low	Moderate	Moderate
3	Low	Low	High	Moderate
4	Low	Moderate	Low	Moderate
5	Low	Moderate	Moderate	Moderate
6	Low	Moderate	High	High
7	Low	High	Low	High
8	Low	High	Moderate	High
9	Low	High	High	High
10	Moderate	Low	Low	Moderate
11	Moderate	Low	Moderate	Moderate
12	Moderate	Low	High	High
13	Moderate	Moderate	Low	Moderate
14	Moderate	Moderate	Moderate	High
15	Moderate	Moderate	High	High
16	Moderate	High	Low	High
17	Moderate	High	Moderate	High
18	Moderate	High	High	High
19	High	Low	Low	Moderate
20	High	Low	Moderate	High
21	High	Low	High	High
22	High	Moderate	Low	High
23	High	Moderate	Moderate	High
24	High	Moderate	High	High
25	High	High	Low	High
26	High	High	Moderate	High
27	High	High	High	High

5. Defuzzification

To calculate the defuzzified CKD risk level based on the input values $(x = 0.6, y = 35, z = 0.45)$

$\mu_{\text{Creatinine ,Low}}(0.6) = \frac{0.6-0.5}{1.0-0.5} = \frac{0.1}{0.5} = 0.2$

$\mu_{\text{BUN ,High}}(35) = \frac{40-35}{40-30} = 0.5$

$\mu_{\text{Protein ,Moderate}}(0.45) = \frac{0.5-0.45}{0.5-0.3} = 0.25, \mu_{\text{Protein ,High}}(0.45) = \frac{0.45-0.4}{0.7-0.4} = 0.167$

$min\{\mu_{\text{Creatinine ,Low}}, \mu_{\text{BUN ,High}}, \mu_{\text{Protein ,Moderate}}\} = min\{0.2,0.5,0.25\} = 0.2$ Strength of Rule 8

$min\{\mu_{\text{Creatinine ,Low}}, \mu_{\text{BUN ,High}}, \mu_{\text{Protein ,High}}\} = min\{0.2,0.5,0.167\} = 0.167$ Strength of Rule 9

$max\{0.2,0.167\} = 0.2$ (Strength of Rule 8)

Output of this rule is high

$\frac{u-0.6}{0.8-0.6} = 0.2 \Longrightarrow u = 0.64$

$\frac{1.0-u}{1.0-0.8} = 0.2 \Longrightarrow u = 0.96$

Using Mean of Maximum (MOM) method

$u^* = \frac{0.96+0.64}{2} = 0.8$

Table 2: Risk Assessment Table for Chronic Kidney Disease Based on Creatinine, BUN, and Protein Levels

S.No.	Creatinine Level (mg/dL)	BUN (mg/dL)	Protein in Urine (mg/dL)	Risk Level	Risk Grade
1	1.31	18.8	0.4	0.01	Low
2	3.25	17.51	0.93	0.23	Low
3	2.32	33.06	0.31	0.79	High
4	1.79	22.6	0.73	0.90	High
5	2.32	33.15	0.64	0.80	High
6	1.52	48.31	0.99	0.31	Moderate
7	1.73	48.64	0.83	0.61	Moderate
8	3.46	40.33	0.72	0.93	High
9	2.06	47.39	0.86	0.96	High
10	2.69	44.51	0.68	0.93	High
11	2.92	17.77	0.27	0.39	Moderate
12	1.62	36.76	0.73	0.90	High
13	2.96	40.72	0.72	0.93	High
14	3.21	23.61	0.82	0.60	Moderate
15	2.69	48.88	0.45	0.54	Moderate
16	1.7	31.13	0.35	0.89	High
17	1.32	42.59	0.75	0.83	High
18	1.21	30.2	0.69	0.98	High
19	1.26	47.53	0.96	0.13	Low
20	2.93	26.98	0.7	1.00	High

The table (2) presents a risk assessment for Chronic Kidney Disease (CKD) based on three biochemical indicators: Creatinine Level, Blood Urea Nitrogen (BUN), and Protein in Urine. For each entry, the levels of these indicators are listed, followed by a calculated "Risk Level" and an associated "Risk Grade" (Low, Moderate, or High). The "Risk Level" represents a numerical score, likely derived from a fuzzy logic-based assessment, ranging from 0 to 1, where higher values indicate a higher CKD risk. The "Risk Grade" categorizes the risk into qualitative levels, helping to interpret the numerical score. This table helps clinicians quickly evaluate CKD risk by providing a snapshot of risk level based on standard biomarker values, offering an effective tool for decision-making in patient monitoring and intervention planning.

6. RESULTS AND DISCUSSION

Figure 5: 3D surface of CKD risk level based on creatinine and BUN

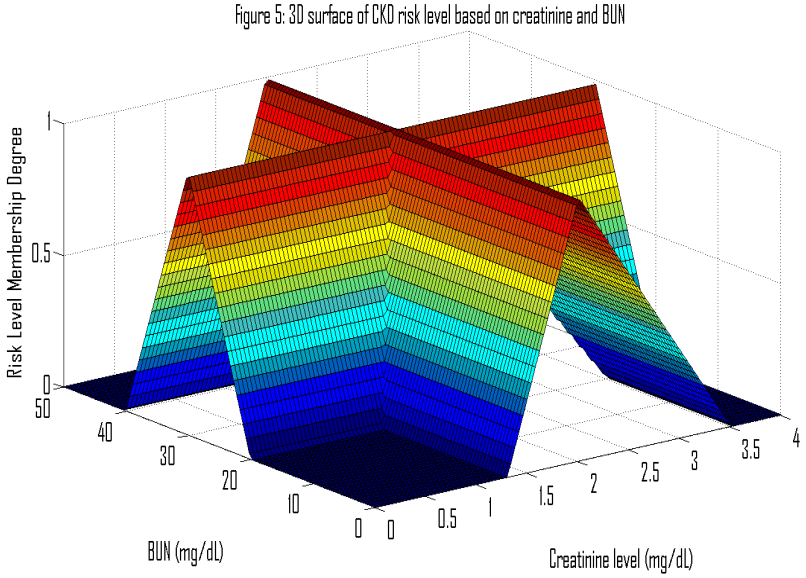


Figure 6: 3D surface of CKD Rrsk level based on creatinine and BUN

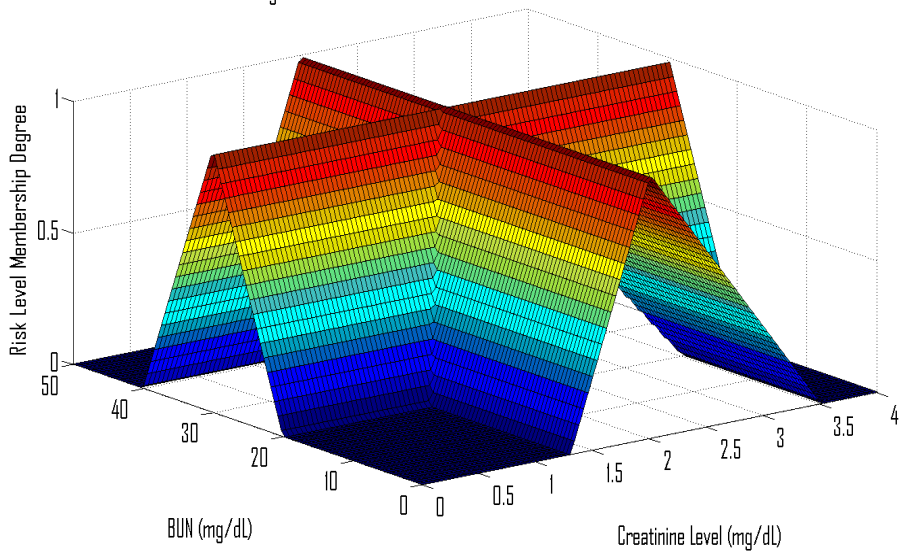
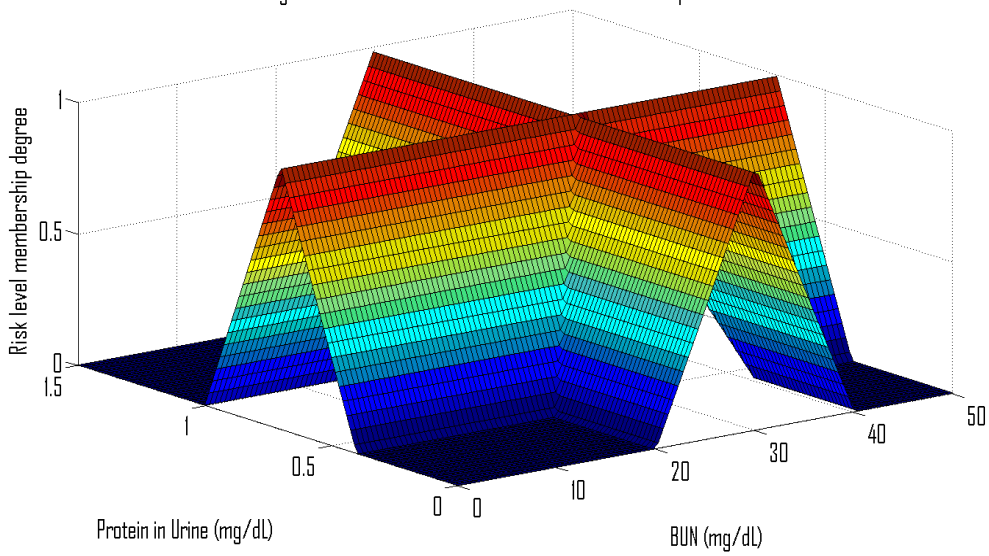


Figure 7: 3D Surface of CKD risk level based on BUN and protein in urine



The 3D surface plot in figure (5) represents the CKD risk level membership degree based on varying values of Creatinine Level (mg/dL) and Blood Urea Nitrogen (BUN) (mg/dL). The plot visualizes how the risk level membership changes with different levels of these two parameters, where the x-axis shows the creatinine levels, the y-axis represents BUN levels, and the z-axis (vertical axis) depicts the membership degree of CKD risk. Higher regions in the plot (closer to a membership degree of 1) indicate a higher likelihood of elevated CKD risk. The surface illustrates how increased values of either creatinine or BUN contribute to a higher CKD risk level, emphasizing the combined effect of these variables on CKD diagnosis. This type of plot helps to visualize the fuzzy relationship between clinical parameters and CKD risk in a way that accommodates gradual changes in risk levels rather than rigid thresholds.

This 3D surface plot in figure (6) illustrates the CKD risk level membership degree as it varies with changes in Creatinine Level and Blood Urea Nitrogen (BUN), two important indicators in assessing kidney function. The x-axis represents creatinine levels in mg/dL, while the y-axis shows BUN levels in mg/dL. The z-axis (vertical) shows the CKD risk level, with values ranging from 0 to 1, indicating the degree of membership in the high-risk category. Areas where both creatinine and BUN levels are high correspond to elevated risk levels (closer to 1), as shown by the peak regions on the surface. This plot demonstrates how a fuzzy logic-based model can capture the combined influence of creatinine and BUN levels on CKD risk, allowing for a more nuanced assessment that does not rely on strict cut-off values. The gradual

changes in risk levels across the surface highlight how risk is assessed progressively, making this model useful for early diagnosis and continuous monitoring.

The 3D surface plot in graph (7) represents the risk level for Chronic Kidney Disease (CKD) based on Blood Urea Nitrogen (BUN) and Protein in Urine concentrations. The x-axis shows Protein in Urine (in mg/dL), ranging from 0 to 50, while the y-axis represents BUN levels (in mg/dL), also ranging from 0 to 50. The z-axis indicates the membership degree of the CKD risk level, from 0 to 1, where higher values denote a higher risk. The surface demonstrates a varying degree of risk as both BUN and Protein in Urine levels change, with peaks indicating elevated CKD risk at specific BUN and protein levels. This visualization helps in understanding how different combinations of these indicators contribute to the risk assessment for CKD, providing insight into critical levels where intervention may be necessary.

7. Concluding Remarks

Integrating fuzzy logic with medical parameters for chronic kidney disease (CKD) risk prediction provides a powerful approach for managing the complexities and uncertainties inherent in medical diagnostics. By leveraging fuzzy logic, clinicians can interpret varying levels of critical indicators—such as creatinine, BUN, and protein in urine-in a nuanced way that traditional binary classifications cannot achieve. This approach allows for continuous risk assessment, which improves early detection, supports more personalized patient monitoring, and aids in timely decision-making. Ultimately, fuzzy logic-based CKD risk prediction offers a reliable, adaptable, and clinically relevant tool, enhancing the accuracy and flexibility of diagnosis while enabling a proactive approach to patient care.

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