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A MAMDANI FUZZY INFERENCE SYSTEM ENHANCED WITH MIN-MAX NORMALIZATION FOR UROLOGICAL DISEASE DIAGNOSIS

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ABSTRACT

This research examines how an Adaptive Neuro-Fuzzy Inference System (ANFIS) can be used to classify medical conditions by analysing different symptoms and clinical characteristics. Utilizing advanced computational techniques is crucial in enhancing accuracy and efficiency in clinical decision-making due to the growing complexity of medical diagnoses. The ANFIS model underwent thorough assessment using various performance measures such as Accuracy, Precision, Recall, and F1-score. Furthermore, the utilization of visual evaluation tools like the ROC curve and confusion matrix aided in gaining a thorough insight into the model's effectiveness. Findings showed outstanding effectiveness, displaying a 99.80 area under the ROC curve (AUC), indicating the model's high capacity to distinguish between positive and negative instances. The confusion matrix showed a high level of accuracy in correctly identifying conditions like "BPH Prostate enlargement" and "Kidney stone." Nevertheless, it also pointed out specific categories that posed difficulties for the model, suggesting areas for possible improvement. The research highlights the significance of incorporating advanced machine learning methods such as ANFIS in healthcare environments, providing a powerful tool for improving diagnostic abilities. ANFIS can make a substantial impact on healthcare environments by enhancing the precision of medical categorizations, leading to improved patient results and more knowledgeable decision- making. In general, the results indicate that ANFIS shows great potential as a dependable approach for medical diagnosis, enabling prompt actions and enhanced patient treatment.

Keywords: *Adaptive Neuro-Fuzzy Inference System, healthcare, diagnostic classification, true positive rate, false positive rate, F1-score, patient outcomes, symptom analysis, clinical features, artificial intelligence.*

1 INTRODUCTION

Sometimes, conditions such as kidney stones, urinary tract infections, and benign prostatic hyperplasia (BPH) may manifest with overlapping symptoms in the complex medical field of urology. [1] Consequently, the treatment of these conditions is contingent upon the early and accurate diagnosis. [2] Delaying a patient's diagnosis may result in more severe issues and increased medical costs, while early intervention can substantially improve patient outcomes. Artificial intelligence (AI) has considerably advanced diagnostic techniques and provided new methods for improving the accuracy of medical diagnosis as a result of the complexity of these conditions.

The healthcare sector is rapidly recognizing the importance of Fuzzy Set Theory, created by as a tool for properly handling the uncertainty and ambiguity inherent in medical data. Unlike traditional binary systems, which classify symptoms as present or absent, fuzzy logic allows for degrees of truth, allowing for a more sophisticated interpretation of symptoms that often defy obvious diagnostic classifications. This versatility is particularly useful for diagnosing urological disorders, since several overlapping symptoms might signal a range of problems[3].

To provide a reliable framework for urological illness diagnosis, we especially use the Min- Max approach with the Mamdani Fuzzy Inference System (MFIS) in this study. Mamdani's technique, which uses fuzzy rules to organize expert information, successfully evaluates intricate correlations between symptoms and illnesses [4]. The Min-Max technique improves this framework and allows for probabilistic results depending on symptom severity by calculating the degree of membership for each symptom and the associated illness[5].

By combining the Min-Max method, optimization techniques, and the Mamdani fuzzy inference system, this study aims to provide a comprehensive solution for the diagnosis of urological illnesses. Apart from reducing diagnostic errors, the proposed approach aids physicians in making informed decisions for timely and effective patient care. This innovative approach advances the application of artificial intelligence and fuzzy logic in medical diagnostics, promising improved patient outcomes in urology and other domains.

2. LITERATURE REVIEW

[6] by this author Caprini scale study highlighted urological inpatient VTE disease factors. The Boruta methodology selected 37 Caprini scale factors for VTE disease data, and the rough set (RS) method created decision rules. The investigation identified age, planned minor surgery, obesity, and malignancy as disease factors. With 97.2% accuracy, BPANN predicted VTE disease best. The average accuracy of RS, RF, SVM, and BPANN was 79.5%, 87.9%, 92.6%, and 97.2%. where as [7] utilised fuzzy set theory to predict high-disease colon cancer symptoms in Malaysia because it can handle imprecise data. An analysis of 180 colorectal cancer patients treated at a general hospital included 17 independent characteristics of various types. Symmetric fuzzy linear regression showed ovarian symptoms enhance colorectal cancer disease. The lowest mean square error weightage is 25.73. MSE = 98.212, RMSE = 9.910. [LR-3] This research used machine learning to predict BPH disease in Chinese men. In 1,099 urological ultrasonography patients, Pearson correlation analysis identified predicted variables. A gradient boosting classifier (GBC) model predicted high-disease BPH with 97.3% accuracy using age, smoking status, and blood data, identifying males who needed ultrasounds[8].

[9] This research used a mathematical model including PSA levels, age, and prostate volume (PV) to improve prostate cancer diagnosis. To help doctors assess disease state, the scientists used fuzzy logic to estimate disease and created a staging system based on PSA and Gleason scores. The introduction of a neuro-fuzzy classification system for pattern recognition aids prostate cancer therapy planning.[10] This research created a computer-aided early cancer detection prototype to promote diet modifications and avoid tumours. Analysing renal CT images included acquisition, preliminary processing, segmentation, feature extraction, as well as classification. Fuzzy membership functions detected renal cysts, carcinoma, and earlier kidney tumours better than SVMs. [11] Fuzzy modelling analyses bladder cancer survival data and identifies disease groups. Patients are classified as high or low disease by mortality disease scores and interval type-2 fuzzy logic and Cox modelling. The method outperformed previous models in fake and real datasets while maintaining disease assessment interpretability and openness. By managing ambiguity in clinical data, this research sought to improve prostate cancer detection by the use of the Fuzzy Tsukamoto approach. The approach included feeding the Fuzzy Tsukamoto system with clinical symptom data, such as patient age, digital rectal examination (DRE) findings, and prostate-specific antigen (PSA) levels. The findings demonstrated an 85% accuracy rate in the diagnosis of prostate cancer, offering medical professionals dependable and understandable results. It is anticipated that this strategy will efficiently aid in the diagnostic process and lessen ambiguity in clinical judgement[12].

[13] For the classification of illnesses, research has suggested the Fruit Fly Optimization Algorithm (FFOA) and Multi-Kernel Support Vector Machine (MKSVM). While MKSVM classifies medical data according to predetermined criteria, FFOA is used to find the best features from a collection. However, data differences impact the accuracy of MKSVM, resulting in a higher number of wrong classifications. The Enhanced Adaptive Neuro Fuzzy Inference System (EANFIS) is used to classify CKD as normal or abnormal after a preprocessing step based on min-max normalization, Improved FFOA (IFFOA) for feature selection, and Weighted Fuzzy C Means clustering (WFCM) for clustering. Recall, accuracy, precision, and f-measure data show how effective the

method.

[14] Recent studies have attempted to link the amounts of protein biomarkers in urine samples to pancreatic cancer in order to provide non-invasive, low-cost, and potentially early cancer detection. In the physical sciences, artificial neural networks are utilized to solve extremely complicated issues. They can effectively aid in the identification of cancer. The four urine biomarkers creatinine, LYVE1, REGB1, and TFF1 are used in this study's neural network model for pancreatic cancer diagnosis. Radial basis function neural network (RBFNN) is the model used to distinguish between urine sample data from cancer patients and healthy individuals. It was developed using MATLAB software. With 76.5% accuracy, 77% recall, and 76% specificity, it may be able to diagnose PDAC patients.

[15] There is growing evidence that bodily fluids like blood, urine, and saliva may contain possible biomarkers linked to the development of tumours, thanks to advancements in liquid biopsy technology. The high-resolution complicated correlations between biomarkers and cancer subtype heterogeneity can no longer be captured by traditional correlation analysis approaches. To solve the difficulty, researchers presented machine learning approaches with liquid biopsy data to examine the essence of tumor origin jointly. We examine the machine learning protocols in this survey and offer code demonstrations for the methods discussed. We go over the frameworks and algorithmic principles that have been widely developed to uncover cancer mechanisms, as well as the potential for biomarker discovery and cancer diagnostics in the future.

[16] Artificial Intelligence has significantly improved the medical field, particularly in diagnosing and treating diseases like cancer. However, many cancer expert systems struggle to assist doctors and urologists. A Fuzzy Expert Prostate Cancer System (FEPCS) was proposed to address this issue. FEPCS uses fuzzy rules and expert opinions to calculate the risk of prostate cancer based on input parameters like Prostate Specific Antigen (PSA), Gleason Score, Metastasis, Age, and Ethnicity. The system was designed using MATLAB and, after 225 patient records were used, the accuracy of FEPCS was 81% according to the confusion matrix.

[17] Our goal in this study was to continuously and longitudinally analyze senior citizens' behaviour in order to identify any changes. In order to identify anomalies, we examined the overall behaviour evolution over extended periods of time rather than focusing on individual behaviour snapshots. As a result, we suggested a teaching strategy and established a typical pattern of behaviour for senior citizens that is connected to their Activities of Daily Living (ADL). In order to identify changes in behaviour over time, we also established a temporal similarity score between activities. We then concentrated on each task to find any irregularities at the times when behaviour changes took place. Lastly, in order for family members and/or caregivers to respond appropriately to a behaviour change, it was also required to educate them about the potential pathology found. Consequently, a fuzzy logic- based decision support system that offers details regarding the suspected disease and its severity is part of the framework described in this article.

[18] This study examined how stone types, patient variables, and upper tract anatomical parameters affect residual fragments (RFs) after flexible ureteroscopic (fURS) renal stone therapy. Between Apr 2022 and Mar 2023, 104 cases received fURS for minimally invasive therapy of medium-sized renal stones. 28 cases with RFs 3 months after operations were evaluated. All cases were assessed with non-contrast computed tomography (NCCT) to determine stone features and upper tract anatomical parameters during the 3-month follow- up. Higher hydronephrosis, larger stones, and many stones greatly affected RFs. Backward logistic regression showed no significant effect from these factors. Logistic analysis showed that Grade 2 hydronephrosis, larger stones, and many stones increased residual fragments after fURS. Endourologists should investigate RFs after fURS stone disintegration, according to the study. In sensible RF management, reliable prediction metrics may help choose effective stone removal procedures and schedule following operations.

[19] This work will use the Mamdani approach to construct a fuzzy inference system for classifying the high risk of kidney stones based on urine conditions. Urine's pH, urea, and calcium contents are employed as input

variables, while the likelihood of kidney stones developing is used as an output variable. Combinations of each variable with its corresponding linguistic phrase create the variables that are part of the fuzzy set. Matlab software is used to analyze these fuzzy sets and get a classification result that indicates whether the sets have modest or great potential. With a 94% accuracy level, the classification results from the created fuzzy inference system provide users accurate classifications. As a result, this fuzzy technique may generally help with kidney stone classification, which will help reduce the number of people who have kidney stones.

[20] This paper examines the viability of using the broad learning system (BLS) to implement a new Takagi–Sugeno–Kang (TSK) neuro-fuzzy model, specifically a dynamic fuzzy inference system based on broad learning (BL-DFIS). In addition to enhancing the precision and comprehensibility of neuro-fuzzy models, it resolves the difficult issue that models cannot independently identify the best design. A TSK fuzzy system is first achieved by BL- DFIS within the framework of BLS. To ensure high interpretability of the system, an interpretable linguistic fuzzy rule is integrated into the enhancement node, and an extreme learning machine auto-encoder is used to obtain feature representation quickly and analytically. The extended-enhancement unit, on the other hand, is made to accomplish the first-order TSK fuzzy system. For the learning of BL-DFIS, a dynamic incremental learning algorithm is also designed with an internal pruning and updating mechanism. This allows the system to automatically construct the ideal structure to achieve a compact rule base and a good classification performance. Using the most efficient model structure, experiments on benchmark datasets show that the suggested BL-DFIS can outperform various state-of-the-art nonfuzzy and neuro-fuzzy techniques in classification.

[21] The objective of this research is to determine the depth of anesthesia (DOA) at a suitable and safe level while accounting for the patient's characteristics during the induction phase. In the first phase of induction, the Bi-spectral Index signal (BIS), a popular method of managing DOA, causes delays and noise. This might result in inaccurate information throughout the control process. Moreover, the BIS index requires a lengthy procedure, expensive equipment, and limited access to device accessories. In order to address these issues, we provide a novel approach to DOA management that does not need the usage of such an index. As a result, an adaptive neuro-fuzzy inference estimation model and a feedforward neural network are used to build an estimate approach for DOA. The ideal medication dosage and stable anesthesia depth are achieved by this model, which calculates the IV anaesthetic drug dosage based on the patient's demands. Sensitivity analysis comparing the suggested calculations with actual data from the BIS method and the improved classical model (PK-PD) on 13 surgical patients is used to test them. The accuracy of 0.999 in the findings indicates that the model is well verified. Our suggested approach outperforms BIS in terms of precisely controlling DOA and effectively achieving results in practice. There are also some recommended practical ramifications for future studies and clinical procedures.

[22] Our study's objective was to create a fuzzy logic method that uses regular blood test parameters (creatinine and erythrocyte sedimentation rate) as well as NGAL (urinary and plasmatic) as input data to evaluate the likelihood of juvenile CKD development. The setup of a fuzzy model that can replicate the relationships between the input variables ESR, NGAL- P, NGAL-U, creatinine, and the output variable Prob with respect to the patient's evolution prognosis is well explained in our paper. A detailed explanation is given of the model's simulation findings, or the correlations between the input and output variables (3D graphic presentations). We suggest this model as a tool to help doctors make better choices about diagnosis, follow-up, and interventions based on the stage of chronic kidney disease. This novel method, in our opinion, might be a very useful tool for clinicians and confirms that a fuzzy logic approach is feasible for evaluating NGAL biomarker data for the development of CKD.

[23] The goal of this study is to use chemical and microscopic urine analysis to develop a fuzzy model that predicts the risk of UTIs. A Mamdani-type inference system with five inputs (nitrite, leukocyte esterase, bacteria, white blood cells, and red blood cells) and one output (infection prediction) was utilized to build a fuzzy model from a dataset of 595 samples. Following the removal of the tainted samples, the model's accuracy was 86%. The maximum recall value, 89%, was obtained while predicting the absence of UTI samples, whereas 71% was

obtained when predicting the presence of UTI samples. With a recall of 29.6%, the samples that could show both the presence and absence of a UTI had the lowest recall. The model worked well and showed sufficient accuracy, however additional parameters should be included in further studies.

[24] Our work provides a comprehensive contribution in this regard. In order to determine the severity of an illness, we first suggest a hybrid framework that combines a fuzzy system with a convolutional neural network (CNN). Two stacked layers of CNN models make up the CNN-based model, which is intended to differentiate between different forms of pneumonia and typical instances. To ascertain the level of infection severity, the fuzzy system simultaneously analyzes numerical laboratory test data and the classification results from the CNN model. Experiments on a well selected dataset using several CNN models demonstrate that the VGG16 model distinguished between bacterial and viral pneumonia with an astounding 88% accuracy and 92% specificity. Additionally, twelve real-world medical cases were used to test our fuzzy model, demonstrating its ability to accurately predict patients' required severity levels. This method improves the diagnosis procedure by enabling medical professionals to use a score system to measure the severity of viral pneumonia.

[25] In order to create unsupervised and automated intelligent systems for the prediction of prostate cancer, this study used machine learning prediction models in conjunction with the Kaggle prostate cancer dataset, which included information from 100 patients with a mixture of cancer and non-cancer. Fuzzy c-means and agglomerative hierarchical clustering are two intelligent systems that were developed and supported by unsupervised learning algorithms. These systems were able to predict an associated stage of prostate cancer and make predictions about prostate cancer with accuracies of over 80% for the different classification metrics. The study discusses the relative qualities of the two intelligent systems that were built to complement one another.

[26] This study aimed to develop a novel fuzzy logic evaluation model for pre-operative risk classification of patients undergoing laparoscopic cholecystectomy operations. The model consisted of 270 rules, with five major criteria (pulmonary, cardiac, diabetes mellitus, renal or liver disease) and three minor criteria (age, cigarette smoking, and body mass index) used for high-risk group determination. The main goal was to verify the success of risk value decisions using the fuzzy logic algorithm. Statistical analysis revealed a strong positive relationship between the 0-30%, 30-60%, and 60-90% risk ranges with complication occurrence. The study found that 172 patients were in the 0-30% risk range, 3/31 in the 30- 60% range, and 2/15 in the 60-90% range. The fuzzy-based risk classification model was successfully used to predict medical results for patients undergoing laparoscopic cholecystectomy operations, with reliable deductions achieved.

[27] The purpose of this research was to assess how well citrate and pyridoxine treatment worked to stop lithiasis from returning. We looked at kidney stone patients who had received endourological therapy. 182 patients with kidney stones up to 2 cm in diameter who had digital flexible ureteroscopy with Holmium laser lithotripsy were the subjects of our prospective, randomized trial investigation. Following that, the general therapy included a diet high in low-protein foods and two to three litres of water daily, or around 400 millilitres every four hours. They were split up into two groups. While Group A (92 patients) got a combination of 2703 mg potassium citrate, 376 mg magnesium citrate, and 25 mg pyridoxine each sachet, Group B simply received general care. Group A had a greater stone-free rate (84.78%) at 90 days than Group B (70.2%) ($p < 0.05$). Additionally, it was shown that Group A had a superior decrease in mean residual stone size (2.36 mm compared 1.66 mm, $p < 0.05$) and a higher expulsion rate than Group B (34.78% versus 20%, $p < 0.05$).

Following digital flexible ureteroscopy with Holmium laser lithotripsy, the administration of potassium citrate, magnesium citrate, and pyridoxine produced favourable outcomes for achieving stone-free status.

[28] The research aims to develop a model that accurately predicts the benign or malignant nature of a tumor using a fuzzy inference system. This system is suitable for diagnosing breast cancer based on tumor physical characteristics. However, its performance is limited due to a lack of understanding of the tumor data. The paper introduces an advanced fuzzy inference system, optimized using statistical analysis methods, and uses a

normalized breast cancer dataset to predict benign or malignant states. The system shows higher accuracy in cancer prediction.

[29] This paper's goal is to use a fuzzy inference system to forecast the phases of thalassemia. The Mamdani type Fuzzy Inference System tool in MATLAB 8.4 was used in this investigation. We have created a mathematical model of Thalassemia illness using the aforementioned tool, and we show that the existence of a Thalassemia stage in a person can be determined by applying certain fuzzy rules to the inputs. We have concluded that Thalassemia is one of the most prevalent hereditary diseases based on the phases that have been seen. This paper's goal is to use a fuzzy inference system to forecast the phases of thalassemia. In this paper, we created a mathematical model of Thalassemia illness using the Mamdani type Fuzzy Inference System tool in Ool. We show that the existence of a Thalassemia stage in a person may be determined by applying certain fuzzy rules to the inputs taken into consideration. We have forecasted the severity of Thalassemia based on the disease's observed phases. The model will be useful for medical areas and play a special role in predicting the category of Thalassemia.

[30] This chapter examines Lebesgue measures and probability in the context of classical measure theory. To comprehend the integration of Lebesgue, Choquet, and Sugeno, fuzzy measures, Sugeno measures, and possibilistic measures are presented after this talk. The creation of fuzzy expected value makes use of these ideas. The notions of fuzzy events, their probability, their dependency, and their independence are discussed at the conclusion of the chapter, along with the ideas of random linguistic variables and random fuzzy variables.

RESEARCH GAP

According to the above existing literature reviews, there are significant research gaps in urological disease assessment and prediction models. Many studies use fuzzy logic and machine learning techniques to predict diseases associated with conditions like venous thromboembolism and prostate cancer; however, they frequently lack comprehensive frameworks that incorporate multiple disease factors while providing transparent decision-making processes. Furthermore, these approaches usually target particular populations or datasets, restricting their application across demographics and clinical situations. Although prior research has successfully used different algorithms, there is still a need for models that combine interpretability and high predicted accuracy, particularly for complicated illnesses such as bladder and prostate cancer.

To fill these shortcomings, this paper provides a diagnostic system that combines the Mamdani Fuzzy Inference System with the Min-Max approach for disease evaluation. The proposed approach aims to improve predictive performance for urological diseases by incorporating multiple disease factors and improving the accuracy and transparency of disease predictions, while also ensuring that the resulting models are interpretable, allowing for timely interventions and better patient outcomes.

3. METHODOLOGY

The technique presents the methodical process used to evaluate urological illness disease and improve diagnosis accuracy. Patient data were gathered with an eye towards important disease variables for disorders like bladder cancer and benign prostatic hyperplasia. The paper used the Min-Max approach in conjunction with the Mamdani Fuzzy Inference System to provide efficient disease evaluation. Various machine learning approaches were used to verify the performance of the model; feature selection methods found important variables. This combined strategy seeks to improve prediction powers while guaranteeing interpretability, therefore supporting healthcare practitioners in efficient patient management.

3.1 Data Collection

500 individuals with symptoms including discomfort during urination, frequent urination, trouble passing pee, and more had their data gathered. 17 urological disorders, including as BPH, kidney stones, UTIs, and prostate cancer, have been connected to these symptoms. We used this information to categorise illnesses according to the frequency and severity of certain symptoms. All conditions were assessed for disease and probability using the

Mamdani Fuzzy Inference System (FIS). With improved diagnostic accuracy, medical personnel will be able to diagnose and treat urological disorders more successfully.

3.2 Fuzzification

The assessment of the disease of urological illness discovered a number of more symptoms that characterize a urological disease: These include Pain While Urinating (PWU), Fever (F), Blood in Urine (BU), Frequent Urination (FU), Persistent Need to Urinate (PNU), Difficulty

Passing Urine (DPU), Cloudy or Foul-Smelling Urine (CFU), Fever and Chills (FC), Nausea and Vomiting (NV), Back, Belly, or Side Pain (BBP), Itching (I), Blood in Semen (BS), Increased Frequency of Urination (IFU), Straining While Urinating (SU), Dribbling at the End of Urination (DEU), Pain in Lower Abdomen (PLA), Pain in Upper Abdomen (PUA), Burning Sensation (BS), Pain During Sexual Intercourse (PSI), Male Impotence (MI), Abdominal Cramps (AC), Reduced Appetite (RA), Weight Loss (WL), Night Sweats (NS), Swelling in Ankles or Feet (SAF), Feeling Tired or Fatigued (FTF), Confusion (C), Skin Rash (SR), and Skin Irritation (SI). This output is called Fuzzy Disease (FDisease). The use of the Min-Max method has been used to normalize inputs in normalizing the different scales used in patient data.

These input variables **PWU, F, BU, FU, PNU, DPU, CFU, FC, NV, BBP, I, BS, IFU, SU, DEU, PLA, PUA, BS, PSI, MI, AC, RA, WL, NS, SAF, FTF, C, SR, and SI** are

normalized to their respective domains. Symptoms like Pain While Urinating, Frequent Urination, Persistent Need to Urinate, Pain in Lower Abdomen, and Pain in Upper Abdomen, the range of the symptoms is [0, 10]. Binary symptoms of type Fever and Blood in Urine, in the range is [0, 1]. Each input is assigned membership functions that describe the linguistic labels such as low L and medium M for age, PSA levels, and high H. For lifestyle factors, poor, average, and good describes the assigned membership functions. Membership degrees (???? μ) represent the degree of truth of each crisp input variable: **pw, f, bu, fu, pnu, dpu, cf, fc, nv, bb, i, bs, ifu, su, deu, pla, pua, bs, psi, mi, ac, ra, wl, ns, saf, ft, c, sr, si,** within interval [0, 1].

3.2.1 Normalization of Input Variables

Using Min-Max normalization, each symptom input variable is transformed to a standardized range. The formula is given by:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where:

- X_{norm} = normalized input value for each symptom
- X = original input value of the symptom
- $X_{\min}$ = minimum observed value of the symptom in the dataset
- $X_{\max}$ = maximum observed value of the symptom in the dataset

3.2.2 Membership Function Calculation

The degree of membership for each input symptom can be defined using a triangular membership function. For a symptom xxx, the degree of membership μ\muμ for categories like Low (L), Medium (M), and High (H) can be represented as:

For **Low Disease** (L):

$$\mu_L(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } a \le x < b \\ 1 & \text{if } b \le x < c \\ \dfrac{c-x}{c-b} & \text{if } b < x \le c \\ 0 & \text{otherwise} \end{cases}$$

Where a, b, and c define the parameters of the membership function FDisease is the output variable of fuzzy approximation and stands for the total disease of urological disease. A larger value means the patient will likely receive a severe condition that either conveys bladder cancer or benign prostatic hyperplasia. Membership function for the output is defined in terms of clinical disease categories: Low Disease, Moderate Disease, High Disease, and Critical Disease. These categories are in step with the boundaries required by healthcare and clearly provide medical practitioners with guidelines to assess whether treatment intervention is needed.

3.3 Fuzzy Output Design for Urological Disease Assessment Scenarios.

In our research, the fuzzy output indicates the disease of acquiring urological disorders, which are classified into four clinical disease levels: low, moderate, high, and critical disease. Each of these disease categories is modelled using particular membership functions (MFs), and the fuzzy output vector is defined as follows:

$$FDisease_{Vector} = \{FDisease_{\in}[0,100], \{Low, Moderate, High, Critical\}, \{\mu_{Low}(Disease), \mu_{Moderate}(Disease), \mu_{High}(Disease), \mu_{critical}(Disease)\} \quad (4)$$

}

Where FDisease is the total disease score, which ranges from 0 to 100. The MFs determine the degree to which the patient's condition falls into one of the four disease categories:

- **LowDisease** $(\mu_{Low}(Disease))$ **:**

$$\mu_{Low}(Disease) \begin{cases} 1 & \text{if } 0 \le Disease \le 25 \\ \dfrac{50-Disease}{25} & \text{if } 25 < Disease \le 50 \\ 0 & \text{if } Disease > 50 \end{cases} \quad \textbf{(5)}$$

This trapezoidal function gives full membership to disease ratings less than 25, and reduces linearly between 25 and 50.

- **ModerateDisease** $(\mu_{Moderate}(Disease))$**:**

$$\mu_{Moderate}(Disease) = \begin{cases} 0 & \text{if } Disease \le 25 \text{ or } Disease > 75 \\ Disease - 25 & \text{if } 25 < Disease \le 50 \\ 25 & \\ \dfrac{75-Disease}{25} & \text{if } 50 < Disease \le 75 \end{cases} \quad \textbf{(6)}$$

This triangle function reaches its apex at a disease score of 50, which represents moderate danger.

- **HighDisease** $(\mu_{High}(Disease))$ **:**

$$\mu_{High}(Disease) \begin{cases} 0 & if\ Disease \leq 50 \\ \dfrac{Disease - 50}{25} & if\ 50 < Disease \leq 75 \\ 1 & if\ Disease > 75 \end{cases} \quad (7)$$

High disease begins with a score of 50 and progresses to full membership at 75 and above.

- **CriticalDisease** $(\mu_{Critical}(Disease))$ **:**

$$\mu_{Critical}(Disease) = \begin{cases} 0 & if\ Disease \leq 75 \\ \dfrac{Disease - 74}{25} & if\ 75 < Disease \leq 100 \\ 1 & if\ Disease = 100 \end{cases} \quad (8)$$

This feature activates at increasing disease levels, guaranteeing that patients approaching a disease score of 100 are identified as essential.

3.4 Aggregation of membership functions

The final disease score is obtained by merging these membership functions via the use of fuzzy aggregation. For the purpose of calculating the output disease membership, the maximum membership degree among the following four categories is taken into consideration:

$$\mu_{FDisease}(Disease) = \max\{\mu_{Low}(Disease), \mu_{Moderate}(Disease), \mu_{High}(Disease), \mu_{Critical}(Disease)\} \quad (9)$$

3.5 Defuzzification

We use the Centroid Method of defuzzification, which determines the centre of gravity of the aggregated membership functions, to convert the fuzzy output into a crisp disease score. The diseasecrisp, is calculated as follows:

$$Disease_{crisp} = \frac{\int_0^{100} Disease \cdot \mu_{FDisease}(Disease) dDisease}{\int_0^{100} \mu_{FDisease}(Disease) dDisease} \quad (10)$$

Healthcare professionals may easily understand and use the disease score, which is a meaningful output that represents the weighted average of the fuzzy memberships.

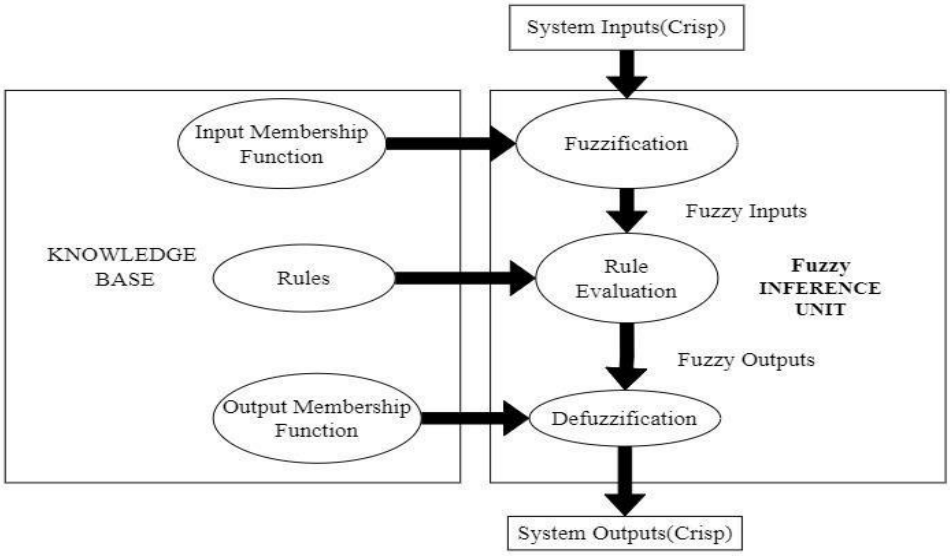


Figure 1 Block diagram of a fuzzy inference system

3.6 Evaluation metrics

Accuracy: The simplest way to measure how often the classifier makes correct predictions is by using accuracy. This could also be seen as the ratio of all true positives predictions got divided by the total number prediction made.

$$Accuracy = \frac{TP + TN}{S}$$

Precision: In contrast to this ratio in addition to one minus from it, i.e., (1 – precision), which presents the percentage false negatives; 1/Precision yields recall.

$$\Pr ecision = \frac{TP}{TP + FP}$$

Recall: On other hand there are called false negatives in relation with True Negatives.

$$\text{Re}\, call = \frac{TP}{TP + FN}$$

F1-Score: It is obtained through taking the harmonic mean between recall and precision scores.

$$F1 = \frac{2 * \Pr ecision * \text{Re}\, call}{\Pr ecision + \text{Re}\, call}$$

4. Tools and Software utilized

The main software platform used for this work was MATLAB Version 2023a, and the Mamdani Fuzzy Inference System was designed and simulated using the Fuzzy Logic Toolbox. In order to construct input and output variables, configure membership functions, and manage data processing for the study of urological disease disease, this environment offered the necessary features.

Algorithm1 UrologicalDiseaseClassificationAlgorithm

1:**BEGIN**

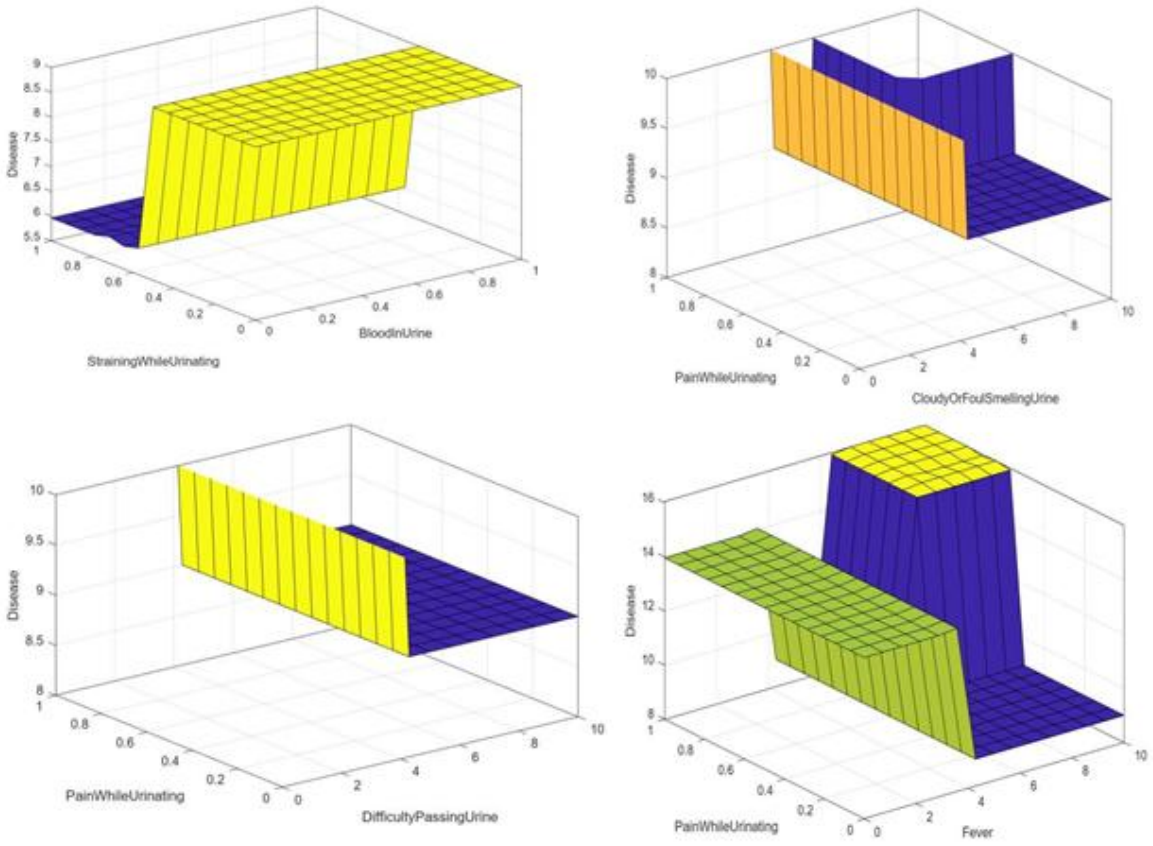
*{*Step1:Initialize the Fuzzy Inference System*}*
2:CREATE FIS named"Disease Classification"
3:SET Defuzzification Method to"Mean of Maximum"
*{*Step2:Define Inpu tVariables (Symptoms)*}*
4:ADD Input"Pain While Urinating" with range[0,10] 5:ADD Membership Functions:
6:-Low: trapezoidal[0,0,2,4]
7:-Medium: triangular [3,5,7]
8:-High: trapezoidal [6,8,10,10]
9:ADD Input "Fever"with range[0,1]
10:ADD Membership Functions:
11:-No: trapezoidal [0,0,0.2,0.5]
12:-Yes: trapezoidal [0.5,0.8,1,1]
13:ADD Input "Blood In Urine" with range[0,1]
14:ADD Membership Functions:
15:-No: trapezoidal [0,0,0.2,0.5]
16:-Yes: trapezoidal [0.5,0.8,1,1]
17:ADD Input "Frequent Urination"wit hrange[0,10]
18:ADD Membership Functions:
19:-Low: trapezoidal [0,0,2,4]
20:-Medium: triangular [3,5,7]
21:-High: trapezoidal 6,8,10,10]
*{*Step 3:Define Output Variable (Diseases)*}* 22:ADD Output "Disease"with range[1,17] 23:ADD Membership Functions for each disease: 24:-Kidney Cancer: trapezoidal [0,1,1,2]
25:-Bladder Stone: trapezoidal [1,2,2,3]
26:-Pyelonephritis:trapezoidal [2,3,3,4]
27:-Metalnesis Stenosis: trapezoidal [3,4,4,5]
28:-Ureteric Stone: trapezoidal [4,5,5,6]
29:-Urethral Stricture: trapezoidal [5,6,6,7]
30:-BPH: trapezoidal [6,7,7,8]
31:-Epididymitis:trapezoidal [7,8,8,9]
32:-PID:trapezoidal [8,9,9,10]
33:-Prostate Cancer: trapezoidal [9,10,10,11]
34:-Kidney Stone:trapezoidal [10,11,11,12]
35:-Phimosis: trapezoidal [11,12,12,13]
36:-Testicular Cancer:trapezoidal [12,13,13,14]
37:-Interstitial Cystitis:trapezoidal [13,14, 14,15]
38:-Urethritis: trapezoidal 14,15,15,16]
39:-UTI:trapezoidal [15,16,16,17]
40:-GUTB:trapezoidal [16,17,17,18]
*{*Step4:Define Fuzzy Rules*}*
41:DEFIN Efuzzy rules based on symptoms and disease associations
42:**for** each rule **do**
43: **if**(symptoms match)**then** 2
44: Assign disease
45: **endif**
46:**endfor**
*{*Step5:Add All Rules to the FIS*}*
47:ADD all defined rules to the FIS
*{*Step6:Test the FIS with Patient Data*}*
48:INPUT patient symptoms into the FIS
*{*Step7:Output the Results*}*
49:OUTPUT classified disease based on fuzzy inference

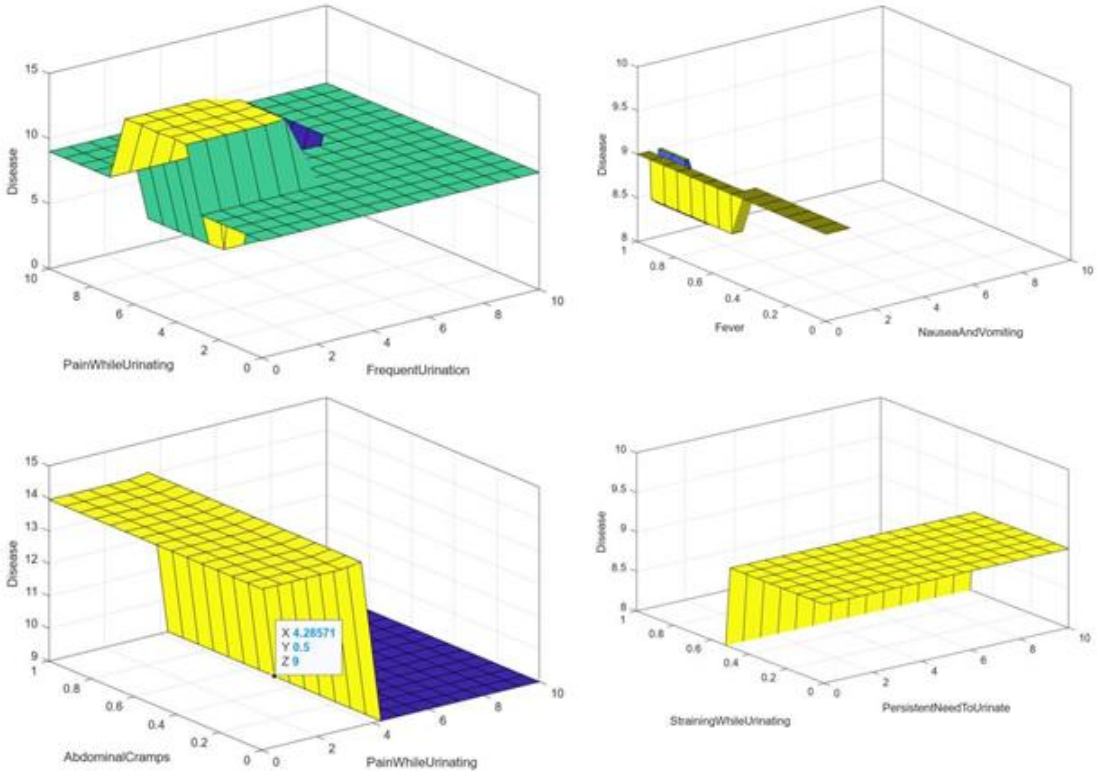
50:**END**

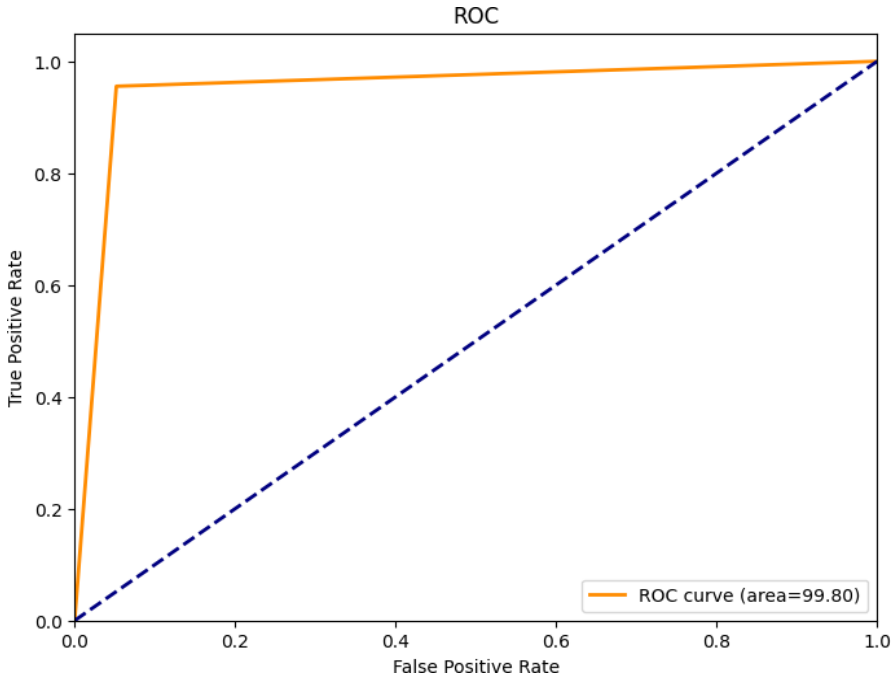
5 RESULTS AND DISCUSSION

The Mamdani Fuzzy Inference System's classification of urological illnesses based on patient symptoms is presented in this section. The Receiver Operating Characteristic (ROC) curve, confusion matrix, and important metrics including accuracy, precision, recall, and F1-score are used to assess the model's performance. These results demonstrate the model's ability to correctly diagnose urological problems.

5.1 Results





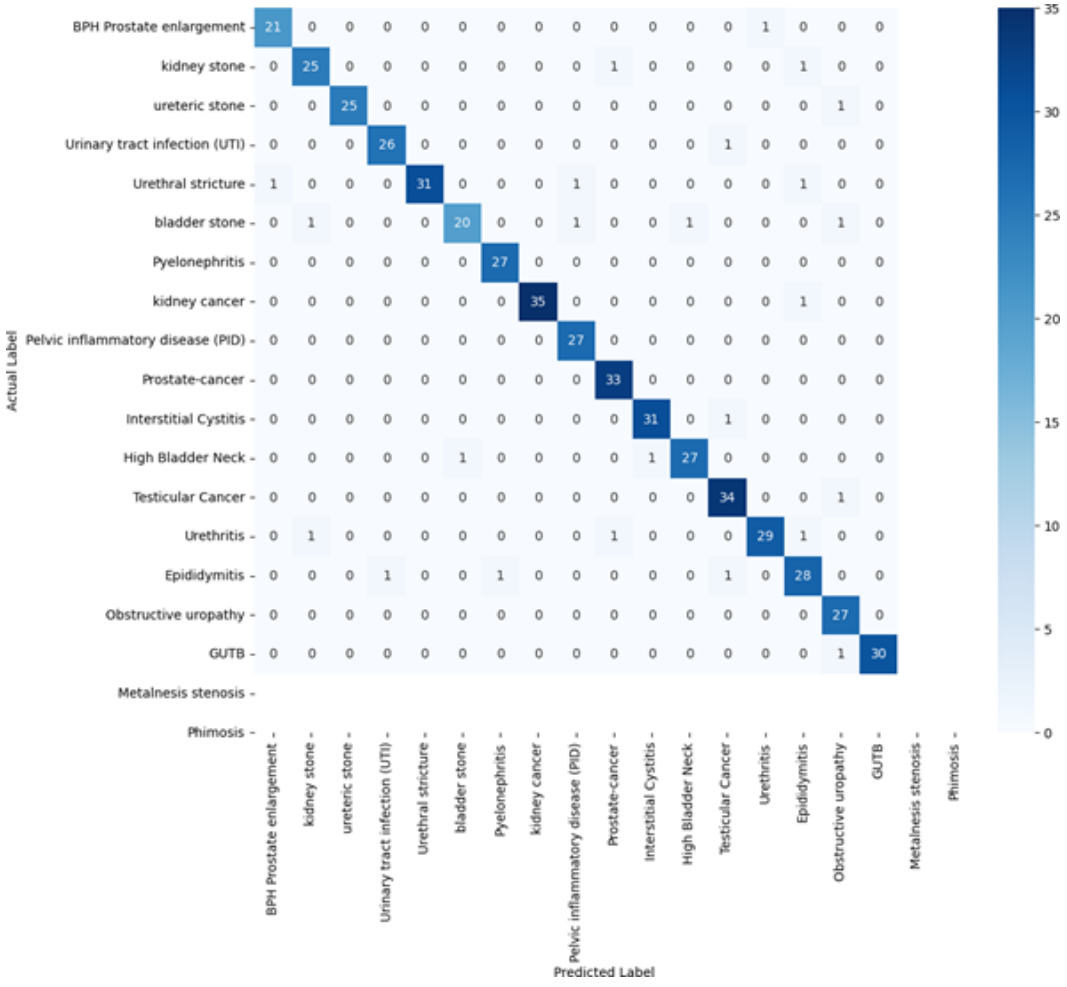


The image shows a Receiver Operating Characteristic (ROC) curve, a visual tool used to evaluate the effectiveness of a binary classification model. In this particular scenario, the ROC curve shows the balance between a model's True Positive Rate (TPR) and False Positive Rate (FPR). The ROC curve's x-axis corresponds

to the False Positive Rate, depicting the ratio of negative instances erroneously identified as positive. The True Positive Rate is depicted on the y-axis and shows the percentage of positive cases correctly identified as positive. An ideal model would display an ROC curve closely following the upper-left corner of the graph, achieving a TPR of 1 and an FPR of 0. Nevertheless, in actuality, the majority of models show some level of compromise between these two measures.

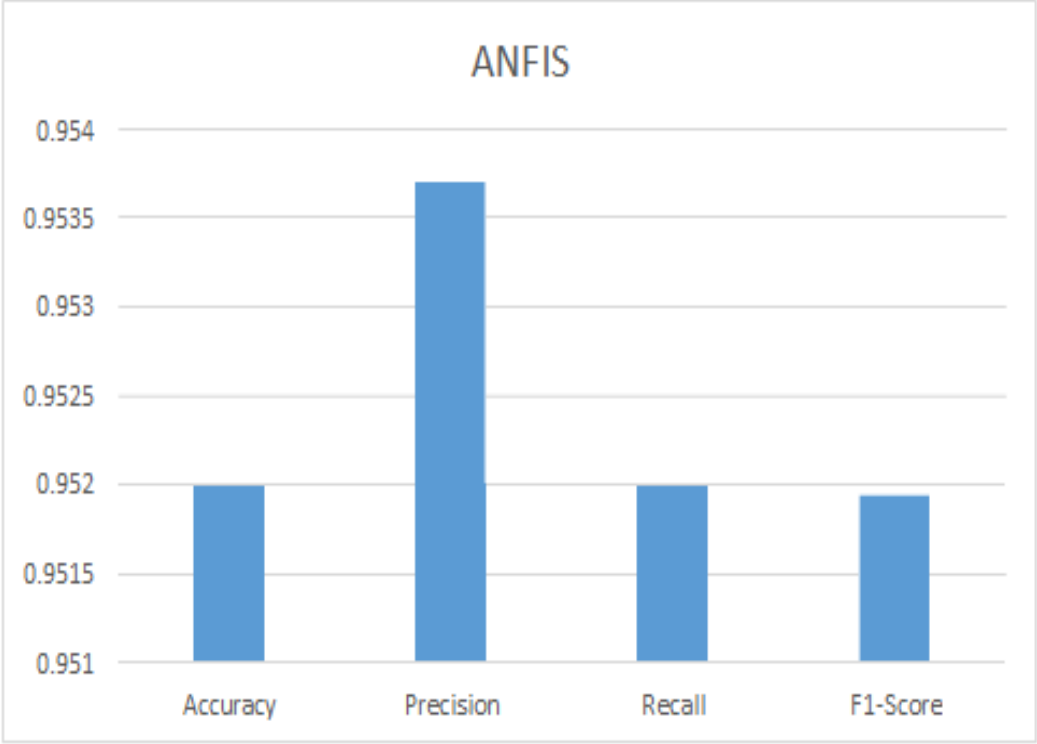
The ROC curve of the model being assessed is depicted by the orange line on the plot. The AUC, which stands for area under the curve, is a popular measure for evaluating the overall

effectiveness of the model. In this instance, an AUC of 99.80 is computed, showing outstanding performance. A greater AUC value indicates that the model is more adept at differentiating between positive and negative instances. The ROC curve of a random classifier is represented by a diagonal line, indicating an AUC of 0.5. Hence, if the AUC value is considerably higher than 0.5, it suggests that the model is outperforming random chance. The ROC curve shape gives information about how well the model can differentiate between positive and negative instances at various thresholds. A more pronounced incline of the curve shows improved differentiation, as the model can raise the TPR without a substantial rise in the FPR. On the other hand, a gentler incline indicates a lower capability of the model to differentiate between the two categories.



The image displayed shows a confusion matrix, which is used to assess the effectiveness of a classification model. In this particular instance, the confusion matrix shows the count of instances that were classified correctly and incorrectly by the model for each class. The instances' actual labels are shown in the rows of the

confusion matrix, while the columns display the model's predicted labels. The diagonal values in the matrix represent the count of accurately classified instances (true positives or true negatives). The values in the off-diagonal elements show how many times mistakes were made in classifying instances (either false positives or false negatives). The confusion matrix values offer an understanding of how well the model performs for every class. For instance, the value at row 1, column 1 (21) represents 21 cases of "BPH Prostate enlargement" being accurately identified. The entry in the first row and second column (0) shows that there were no misclassifications of "BPH Prostate enlargement" as "Kidney stone. “Through the analysis of the confusion matrix, we can pinpoint the classes where the model excels and the classes that present more difficulties for classification. In this instance, the model seems to be doing a good job for categories like "BPH Prostate enlargement," "Kidney stone," and "Ureteric stone," as shown by the high values on the diagonal elements for these categories. Nevertheless, the model might face challenges in distinguishing between specific categories like "Urethral stricture" and "Bladder stone" due to the presence of elevated off-diagonal values between them. Moreover, the confusion matrix enables the calculation of different performance measures like accuracy, precision, recall, and F1-score. These measurements offer a more numerical evaluation of the model's complete performance.



The Mamdani Fuzzy Inference System model's performance metrics are shown in a bar graph in the picture. The metrics of Accuracy, Precision, Recall, and F1-Score are shown in the graph. The ratio of correctly identified cases to all occurrences is used to determine accuracy,

which assesses how accurate the model's predictions are. The accuracy of the model in this instance is 0.952. By dividing the number of true positives by the sum of true positives and false positives, one may calculate precision, which is the ratio of correct positive predictions to all positive predictions. A high precision of 0.9535 indicates that the Mamdani Fuzzy Inference System is a model that makes very few inaccurate positive predictions. By dividing the total number of true positives by the sum of true positives and false negatives, recall is a quantitative measure of the proportion of real positive cases that the model correctly detects. With a recall rate of 0.952, a high recall number means that the model detects most positive cases. The F1-Score offers an equal evaluation of both

metrics as it is computed as the harmonic average of recall and accuracy. With an F1-score of 0.952, the model has a high F1 score, indicating that it well balances accuracy and recall. The Mamdani Fuzzy Inference System is doing very well overall, as shown by the bar graph, which shows excellent accuracy, precision, recall, and F1-score values that suggest its capacity to identify examples effectively with little mistakes across all four evaluation criteria.

5.2 Discussion

A comprehensive understanding of the categorisation model's performance may be obtained by evaluating it using several measures. The Receiver Operating Characteristic (ROC) curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) of the model, is shown by the orange line in the figure. The model is quite good at differentiating between positive and negative examples; its excellent Area Under the Curve (AUC) score of 99.80 is higher than the average AUC of 0.5 seen in random classifiers. The model's consistency across various thresholds is shown by the ROC curve's fast ascent, which suggests that a high True Positive Rate (TPR) may be attained without a discernible increase in False Positive Rate (FPR). Moreover, the model's classification accuracy for different classes is shown in the confusion matrix. numbers off the diagonal represent wrong classifications, whereas numbers on the diagonal represent the number of accurate classifications. By properly identifying 21 instances of "BPH Prostate enlargement" without mislabeling them as "Kidney stone," for instance, the model demonstrated high performance in these particular categories. Higher numbers off the main diagonal indicate that there were issues distinguishing between "Urethral stricture" and "Bladder stone," nevertheless. Through this analysis, key performance metrics like as accuracy, precision, recall, and F1-score may be computed, allowing for a quantitative assessment of the model's efficacy. The model's remarkable

metrics—accuracy of 0.952, precision of 0.9535, recall of 0.952, and F1-score of 0.952—are also shown in the bar graph. These results show that the Mamdani Fuzzy Inference System has a good mix of accuracy and recall, classifying instances appropriately and with few errors. The Mamdani Fuzzy Inference System performs very well overall across all assessment criteria, demonstrating its capacity for accurate classifications in practical situations.

6 CONCLUSION

The evaluation of the Mamdani Fuzzy Inference System demonstrates exceptional performance in classifying medical disorders based on various input features. The high AUC of 99.80 suggests a significant capacity to distinguish between positive and negative situations, and the steep slope of the ROC curve shows how effective it is at different thresholds. Particularly for categories like "BPH Prostate enlargement" and "Kidney stone," the confusion matrix demonstrates how effectively the program finds occurrences while also pointing out areas of inaccuracy. Furthermore, the model's reliability in generating accurate predictions with minimal mistakes is shown by the good performance measures (accuracy, precision, recall, and F1-score), all of which are above 0.95. All things considered, the Mamdani Fuzzy Inference System shows promise not just for medical diagnostics but also as a useful instrument for enhancing healthcare decision-making, which in turn improves patient outcomes.

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