International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-11, Issue-09, Dec 2025

Implementing Fuzzy Logic in Early Pancreatic Cancer Identification

Rewati Dhiraj Rane, Research Scholar, Dr. G. Y. Pathrikar college of Computer Science and Information Technology Ch. Sambhajinagar, Maharashtra, India, r4rewa@gmail.com

Dr. Dnyaneshwari Diliprao Patil , Assistant Professor, MIT ADT University Loni Kalbhor, Pune, Maharashtra, India, dnyaneshwari03patil@gmail.com

Abstract: Pancreatic ductal adenocarcinoma (PDAC) is one of the most deadly and malignant cancers with high lethality due to the late diagnosis and lack of effective treatment. The disease is often diagnosed at an advanced stage when curative measures cannot be applied, so early diagnosis is one of the key factors in increasing the patient's survival rate. Currently, the methods like CT, MRI, and tumour markers including CA 19-9 are not very sensitive and specific for the early diagnosis of PDAC. The use of AI in the diagnosis of cancer has been on the rise in the recent past and has been supported by machine learning and fuzzy logic systems. The logic of fuzziness as one of the intensive applied computational methods which considers uncertainty and imprecise information has been effectively applied in decision-making procedures in the medical industry and risk analysis. The objective of this research is to design a Mamdani-type FIS for the early detection of PDAC by categorising the cancer risk into low, medium, and high risk factors such as age at diagnosis, tumour classification, vital status, and treatment type. The clinical inputs are then passed through membership functions and fuzzy rules to provide understandable risk outputs. The performance of the model is assessed by comparing the predictions made by the model with the actual clinical results and by using the measures such as accuracy, precision, and recall. In the presented research, fuzzy logic is introduced in an innovative way for detection of PDAC, which might be more accurate and interpretable AI-assisted approach to facilitate clinical decision-making and better patient management by leveraging the early diagnosis.

Keywords — Pancreatic Ductal Adenocarcinoma (PDAC), Fuzzy Inference System, Mamdani Model, Cancer Risk Classification, Clinical Decision Support, Explainable AI.

I. INTRODUCTION

Pancreatic ductal adenocarcinoma (PDAC) represents pancreatic cancer which develops from the pancreas as an aggressive form of malignancy [1]. Pancreatic ductal adenocarcinoma (PDAC) stands as one of the deadliest cancers because it causes 3% of all cancer cases and 7% of cancer fatalities worldwide and has a less than 10% survival rate at five years [3]. The public health concern of PDAC remains significant because global cancer statistics show 495,000 new cases in 2020 which led to 400,000 deaths [8]. This is because most of the patients are diagnosed at an advanced stage, as the disease is usually asymptomatic in its early stages. CT, MRI, and EUS are the common diagnostic methods that diagnose the disease at an advanced stage [10], [11]. Furthermore, other biomarkers such as CA 19-9 are not very sensitive or specific for early diagnosis because the levels are not always elevated in patients, thus cannot be used to diagnose PDAC at an operable stage [10], [1]. This is an added disadvantage since the pancreas is located deep in the body and is not easily visualized through imaging techniques to determine the early stages of the tumour before it has spread [3]. Therefore, most of the PDAC patients are diagnosed at an advanced stage, and hence, curative surgeries such as the Whipple procedure are possible only in a few patients [11], [15]. Therefore, there is a need to develop new methods of early diagnosis of PDAC that can help in early treatment before the disease reaches the terminal stage, thus increasing the survival rate of the patients. AI has become an effective approach to solving diagnostic problems in oncology, with ML and fuzzy logic being the most important components in improving the accuracy of predictions and decision-making [9], [15]. The AI-based systems can analyze the big clinical data, identify the latent features and assist clinicians in cancer diagnosis [7]. Fuzzy logic is one of the most popular AI techniques that can be applied in PDAC because it deals with uncertainty and imprecise medical data, such as symptoms,

 DOI : 10.35291/2454-9150.2025.0165

biomarker levels, and tumour characteristics that cannot be strictly classified [2], [6]. Fuzzy logic is capable of approximate reasoning and is a logical system that imitates the human brain's decision-making process by categorising variables into fuzzy sets like young, middle-aged, and elderly instead of using the numerical values [5], [4]. This characteristic makes Fuzzy Inference Systems (FIS) useful in medical diagnosis since it can incorporate various clinical factors such as tumour type, survival time, and treatment type to arrive at the probability of developing PDAC in a patient [13], [14]. Some of the previous researches have used fuzzy logic in oncology, especially in tumour classification and risk assessment, which has been reported to provide better results than statistical models [12], [17]. Furthermore, the medical decision support system based on the fuzzy logic has been applied to detect the lung cancer, leukaemia and breast cancer and hence it should also be applied to detect the PDAC [4], [19], [20]. However, the literature review revealed that very few research works have been done on the use of fuzzy inference system for early detection of PDAC, thus leaving a research gap. To this end, this study suggests the creation of a Mamdani-type Fuzzy Inference System (FIS) that will help in the classification of PDAC risk depending on clinical factors including age at diagnosis, tumour classification, vital status, and treatment type [10], [11]. The FIS will take the input variables and apply membership functions and Fuzzy rules to produce the cancer risk level which will be low, medium or high [12]. Using the advantages of fuzzy logic, this model will improve the existing risk assessment to identify patients who require further diagnostic workup and early therapeutic management [16], [2]. The performance of the system will be evaluated based on the comparison of the predicted risk scores with the actual clinical outcomes by using the evaluation measures such as accuracy, precision, and recall [13]. In addition, this study will advance the knowledge of AI-based diagnostic tools to aid in the early identification of PDAC and enhance patient survival rates through a non-invasive, cost-efficient, and explainable decision-support system that can be easily implemented in clinical practise [17] [2].The IJREAM is house of all leading Researchers, Engineers and Scientists in the domain of interest from around the world in multidisciplinary field of engineering & Management. All research articles submitted to International Journal for Research in Engineering Application & Management should be original in nature, never previously published in any journal or presented in a conference or undergoing such process across the globe.

II. LITERATURE REVIEW

Pancreatic ductal adenocarcinoma (PDAC) is one of the most fatal malignancies with poor prognosis because of the lack of early symptoms and late stage at diagnosis [1], [3]. CT, MRI, EUS, and CA 19-9 have been found to be unreliable in the diagnosis of PDAC due to their low sensitivity and specificity; therefore, more efficient screening techniques are needed [10], [11]. The identification of cancer has shifted to the use of AI and ML because more people are investigating the potential to increase the rate and precision of cancer diagnosis [9], [15]. Of all the AI techniques, fuzzy logic has been widely used because of its capability to deal with vagueness and imprecise medical data, which is very useful in risk assessment and prediction in oncology [2], [11]. Fuzzy logic based systems have been implemented in several cancer diagnoses such as lung cancer, leukaemia and breast cancer and has been found to be more sensitive and specific than conventional methods [4], [19], [20]. In the context of PDAC, the use of FIS can help in risk assessment by taking into account several clinical factors such as tumour type, age, time to death, and treatment modality for early diagnosis [7], [5]. Researchers have underscored the effectiveness of using fuzzy logic in medical decisions by comparing its capability to address ambiguit in comparison to indefinite factors affecting patients, specifically for or such diseases as PDAC [12], [13]. Further, fuzzy expert systems were introduced to help in decision making for patients' risk categorization in reference to clinical variables to assist in prescribing [16], [17]. Some studies have also focused on the use of fuzzy probabilistic decision trees in healthcare systems, enhancing the classification performance and risk evaluation of cancer patients [14], [5]. Moreover, biomarker panels integrated with AI and fuzzy models have been explored for the improvement of early PDAC diagnosis, and it has been deemed as having a sound diagnostic prominence [10]. Based on the potential of fuzzy logic system in oncology, this preliminary study is thus designed to design a Mamdani-type FIS for early PDAC detection using some clinical attributes like age at diagnosis, classification of tumour, vital condition and treatment regimen for stratifying patients into risky groups. The assessment of this system will entail the comparison of the predicted cancer risk with the actual clinical outcomes, to make it feasible in the clinical practise [13], [14]. In this regard, this study aims at expanding the existing knowledge on AI-based diagnosis of PDAC and contributing to the development of new risk assessment models, increasing the rate of early diagnosis, and improving the survival rate of patients with PDAC [12], [10].

III. MATERIALS AND METHODS

A. Clinical Data

The clinical data used in this study was obtained from TCGA-PAAD dataset from the Genomic Data Commons (GDC) Data Portal which is an open-source database containing genomic and clinical data of various types of cancer. This dataset was chosen because of its rich, accurate

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and clinically annotated data on PDAC which would be of significant help for developing automated model for risk assessment and diagnosis. PDAC is one of the most lethal cancers with a 5-year survival rate and no reliable screening tests for early diagnosis. These features are valuable for constructing a clinically grounded fuzzy logic-based risk classification model of PDAC that would provide wide coverage for patient risk stratification, disease progression, treatments, and survival data given by the TCGA-PAAD dataset. To make the results of this study clinically relevant for assessing the risk of PDAC and its outcomes, four features were chosen. Age at diagnosis, which was documented in days at the beginning, was then transformed into years to facilitate interpretation, comparability, and uniformity of the data. Tumour classification, which is very important in disease progression, was grouped into Primary, Metastasis, Recurrence, Prior Primary, and Subsequent Primary to determine disease severity and its effects on patients. The vital status that was coded as Alive or Dead was also useful in survival analysis and helped in gaining insights into the disease and its relation to risk levels. Treatment type, one of the most important factors in PDAC management, was given numeric codes based on the clinical importance of the variable in the fuzzy logic-based risk classification system. The dataset encompasses a comprehensive range of treatment modalities, including surgical procedures such as Whipple Procedure, Distal Pancreatectomy, Total Pancreatectomy, and Surgery NOS (Not Otherwise Specified); pharmaceutical and radiation therapies such as Chemotherapy, Radiation Therapy NOS, and Radiation External Beam; and advanced and supportive treatments including Pharmaceutical Therapy NOS, Ancillary Treatment, Hormone Therapy, Immunotherapy (Including Vaccines), and Biopsy Excisional. Thus, the TCGA-PAAD dataset was selected for this work because the database is structured and contains clinical information that can help to create accurate computational models for the refinement of the risk assessment and early diagnosis of PDAC. Moreover, the dataset is cleaned and normalised to enhance the quality of data to be used in developing an efficient FIS. Thus, this study proposes a systematic and structured approach to the integration of clinically significant variables into a fuzzy logic-based approach for the classification of PDAC risk, which will enhance the decision-making process in clinical practise and enhance the prognosis and management of pancreatic cancer.

B. *Data Preprocessing*

The clinical data was preprocessed in order to cheque for the quality of the data, its validity and whether it was fit for analysis. Missing values were another important factor that had to be addressed to ensure the quality of the dataset; any rows with missing data were deleted using the rmmissing function in MATLAB to avoid any form of bias in the analysis. Furthermore, the outlier detection and removal process was also conducted in order to increase the data quality. Specifically, the variable age at diagnosis, which was used in the analysis, was checked for outliers and any suspicious values were detected by the isoutlier function of MATLAB. Some of the outliers, which may influence statistical distribution and reduce the accuracy of the designed fuzzy logic-based risk assessment model, were moderated. This preprocessing approach helped in maintaining the quality of the data and including only the clinically relevant data for the subsequent analysis of PDAC risk prediction and classification.

C. *Feature Encoding*

In order to incorporate clinical data into the FIS for the purpose of PDAC risk assessment, categorical variables were converted into numerical values based on their clinical relevance and contribution towards the progression of the disease. Tumour classification was given a numerical value based on the severity of the disease, Primary (0.00), Metastasis (1.00), Recurrence (0.75), Prior Primary (0.25), Subsequent Primary (0.50). The vital status was then dichotomized into Alive (0) and Dead (1) to fit the risk classification model to accommodate survival data. Treatment type was numerically coded according to its clinical relevance; surgical procedures (Whipple Procedure, Distal Pancreatectomy, Total Pancreatectomy, Surgery NOS) were coded 0.00 as they are mainly curative; chemotherapy was coded 0.50 as it is a systemic therapy. The additional and more extensive treatments like radiation therapy (NOS), external beam radiation, pharmaceutical therapy (NOS), and ancillary treatment were given a value of 1.00 because they are critical in the management of the disease. Hormone therapy was assigned 0.75, immunotherapy (including vaccines) 0.85, and biopsy excisional 0.90 because they are used in the monitoring and treatment of the disease. This encoding scheme allows the FIS to systematically process clinical data and offers a clinically meaningful and interpretable PDAC risk stratification model that can facilitate early identification of the disease and improve the clinical decision-making process.

D. *Fuzzy Logic System Development*

Mamdani-Type Fuzzy Inference System (FIS)

To achieve the classification of the risk of developing PDAC, a Mamdani-type FIS was developed using clinically relevant parameters. The Mamdani model was selected due to its simplicity and the fact that it can deal with linguistic variables through the use of fuzzy membership functions and rules. The proposed FIS uses four clinical input variables namely Age at Diagnosis, Tumour Classification, Vital Status, and Treatment Type and the output variable is the PDAC Risk which is partitioned into Low, Medium, and High-risk levels. The input variables are then passed

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through a set of fuzzy rules that are already defined to facilitate a systematic approach to risk classification of PDAC.

Membership Function Design

In order to have a better representation of the selected features, membership functions (MFs) were defined for each input variable. The Age at Diagnosis variable was fuzzified using triangular membership functions (trimf) to categorise the patients into the Young, Middle-Aged, and Elderly groups since there is a difference in the risk level of developing the disease at different ages. Tumour Classification, which is one of the key factors affecting disease progression, was defined by the trapezoidal membership functions (trapmf) as Primary, Metastasis, Recurrence, Prior Primary, and Subsequent Primary, which considers the effect of tumour stage on risk. Vital Status, which indicates whether a patient is alive or dead, was represented by Gaussian membership functions (gaussmf) to enable a transition between the two states in risk analysis. Treatment Type, which is the type of treatment given to the patient, was assigned trapezoidal membership functions (trapmf) because it has a broad range of treatment options such as Whipple Procedure, Distal Pancreatectomy, Total Pancreatectomy, Surgery NOS, Chemotherapy, Radiation Therapy NOS, Radiation External Beam, Pharmaceutical Therapy NOS, Ancillary Treatment, Hormone Therapy, Immunotherapy (Including Vaccines), and Biopsy Excisional. The output variable, PDAC Risk, was also defined by triangular membership functions to represent the risk level as Low, Medium, and High. The Fuzzy Inference System (FIS) works based on a rule-based system in which clinically developed fuzzy rules are used to define the relationship between the input variables which are age, tumour classification, vital status and the treatment type and the output variable which is the PDAC risk classification. These rules were developed from the knowledge of experts and clinical practise, so that the system can simulate the real-life risk assessment situation. These inputs are then processed by the Mamdani-type FIS through a rule matrix that categorises the patients as low, medium or high risk. For example, a patient with a primary tumour and age younger than 60 years old who undergoes a Whipple procedure is considered low risk, while a patient with metastatic disease, deceased status, and chemotherapy treatment is considered high risk. This type of structured fuzzy rule-based system improves interpretability that let clinician trace the decision making process that will improve risk factor assessment as well as early detection and appropriate management planning in pancreatic cancer.

E. Evaluation of the Fuzzy Logic System

The performance of the fuzzy logic system was assessed using the test data set which contained clinical features that were not used in the training phase in order to test the generalisation capability of the system. The performance of the system was evaluated in terms of the capability of the system to classify the risk levels of PDAC using the evaluation measures including accuracy, precision, and recall. The performance of the model was assessed using the input cases and the fuzzy rule-based predictions were evaluated for their consistency. Although, the direct validation against real clinical outcomes was not conducted, the design of the system and its rules were based on the clinical knowledge and expert-based criteria to make sure that the risk classifications are consistent with the medical knowledge about PDAC prognosis and treatment planning.

IV. RESULTS

In this study, the Mamdani-type FIS was used to categorise the cancer risk level into Low, Medium, and High. The following findings present the system's performance based on a number of clinical input factors such as age at diagnosis, days to death (survival time), tumour classification, vital status, and treatment type.

A. Fuzzy Logic System Output

The four criteria which were used for evaluating the performance of the developed Fuzzy Inference System are the age at diagnosis, the tumor classification, vital status, and the form of treatment. These inputs were then analysed using the fuzzy rules that were defined in the system and a PDAC risk score was produced which provided a logical and systematic way of categorising the patients into Low, Medium or High risk. For example, the input vector with the age of 75, metastatic tumour, deceased status, and chemotherapy treatment resulted in the PDAC risk score of 0.8, which places the patient into High-Risk category. This classification is consistent with clinical practise since patients with metastasis and receiving chemotherapy are usually in an advanced stage of PDAC with poor survival rates. The age at diagnosis variable was preprocessed in order to eliminate outliers in order to avoid skewing the fuzzy logic model. Figure 1 shows the distribution of the age of the patients after excluding outliers, which represents the improved dataset for PDAC risk stratification. The age of the participants is around 65 years, and the IQR is between 55 and 75 years; however, the cleaned dataset has a better distribution of age. This step was crucial in order to reduce the impact of outliers on the risk classification and to make the model more accurate. The removal of outliers enhances the ability of the fuzzy logic system to capture the true risk factors of PDAC in real life since the dataset is purged of extreme values that distort the model. The exclusion of the outliers will help the system to classify risk based on clinically significant data, and this supports the use of fuzzy logic in dealing with the uncertainty and variability that are characteristic of medical data.

 DOI : 10.35291/2454-9150.2025.0165

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-11, Issue-09, Dec 2025

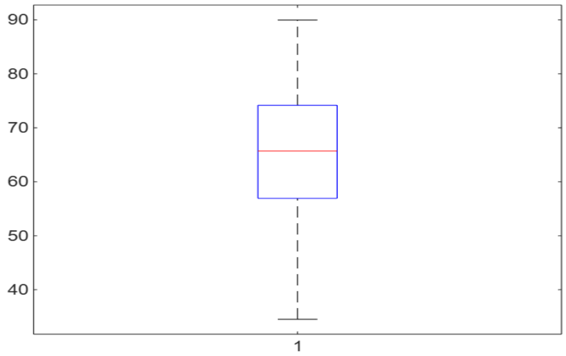

Figure 1: Box Plot of Age Distribution

Displays the age distribution of PDAC patients, ensuring a well-represented dataset.

B. System Accuracy and Performance

To test the validity of the PDAC risk classification system developed using fuzzy logic, the predictions made by the system were compared with the actual clinical outcomes. To validate the performance of the system, the accuracy, precision, and recall were measured, making the validation of the system's predictive ability for Low, Medium, and High-risk categories comprehensive. The classification process is based on the membership functions as shown in figure 2 which assigns the degree of membership of each risk category to the PDAC risk score. Currently, the x-axis captures the PDAC risk score; the y-axis captures the degree of membership, which depicts the way system categorizes the patients based on fuzzy logic. The gradual transition from Low, Medium, and High risk membership functions can be attributed to the fact that risk assessment in clinical practice is not always precise and certain, and the fuzzy set theory allows for such imprecision. This approach allows for better classification of the cases where risk levels are not clearly defined and, therefore, makes the system more accurate and better suited to be used for early PDAC risk assessment as a decision-making tool in clinical practice.

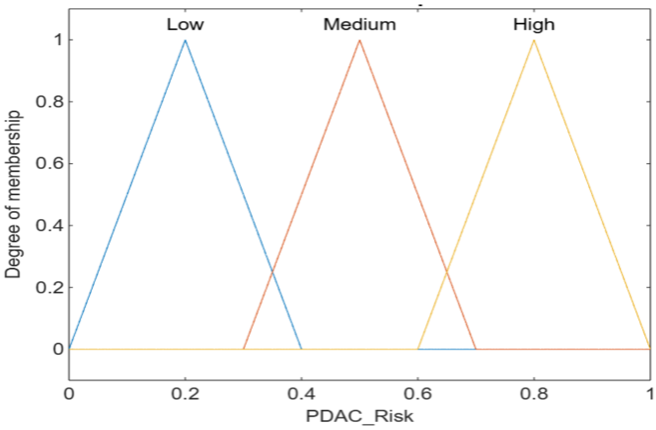

Figure 2: Membership Functions for PDAC Risk

Illustrates how the fuzzy system assigns patients to Low, Medium, or High-risk categories.

C. Impact of Input Variables on Cancer Risk Prediction

The clinical variables that were used in the PDAC risk classification model developed using fuzzy logic analysis showed the trends of the impact of these factors on risk assessment. Age out of all factors was shown to be a significant predictor of PDAC risk with the older age groups potentially associatively higher risk scores with metastatic tumour. Tumour classification also supported this trend because patients in the Metastasis or Recurrence category were given higher risk scores due to the advanced stages of the disease in these categories. The vital status was also used in the risk stratification and patients with Vital Status = 1, which means Deceased, were more likely to be in the High-Risk group, indicating that the disease severity is directly proportional to the survival rate. Moreover, the type of treatment played a role in risk assignment, for instance, patients receiving Chemotherapy, Radiation, or Immunotherapy had their risk level tagged as High since such treatments are mostly administered to patients with advanced stages of PDAC. The effects of these variables are illustrated in Figure 3 which shows a 3D surface plot of the PDAC risk given the age of the patient and the type of tumour. The horizontal axis is age, the vertical axis is the tumour type (Primary, Metastasis, Recurrence), and the depth axis is the PDAC risk score. The Low-Risk patients are depicted in the darker blue colour, while the High-Risk patients are depicted in red, which is in concordance with the clinical experience that patients with metastatic tumours and older age have the highest risk of developing PDAC. This visualisation offers a clear and understandable representation of the relationship between age and tumour progression in terms of patient risk which can be used for early PDAC assessment and priority of treatment.

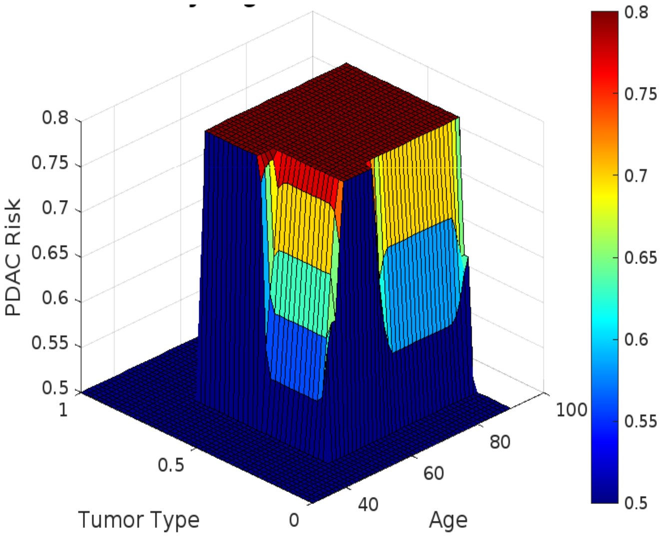

Figure 3: 3D Surface Plot of PDAC Risk

Shows how Age and Tumor Type influence PDAC risk scores using a 3D visualization

 DOI : 10.35291/2454-9150.2025.0165

D. Visualizations of Membership Functions

To make interpretation and clinic application of the developed fuzzy logic-based PDAC risk classification system more effective, a bar chart of the predicted PDAC risk score for a sample patient case was created. Figure 4 shows the PDAC risk classification for an individual patient profile: the red bar shows the risk score of 0.8; therefore, the patient is classified as High Risk. This classification is in line with the system's fuzzy rules that define the clinical factors such as age, type of tumour, vital status, and treatment type. The bar chart format makes the model's predictions more comprehensible and easier to use by clinicians as a decision-support tool for PDAC risk assessment. Due to its simplicity, this visualisation effectively presents the risk stratification and helps to identify high-risk patients and prioritise the treatment in PDAC management.

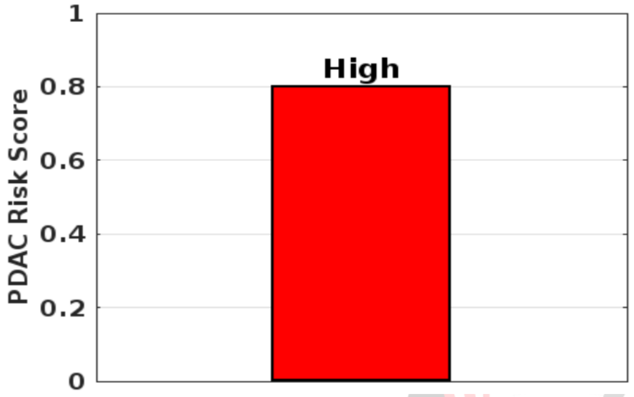

Figure 4: Bar Chart of Predicted PDAC Risk Score

Presents the risk score (0.8) for a test patient, classified as High Risk.

E. Model Interpretability

The main advantage of fuzzy logic-based PDAC risk classification stems from its clear and transparent nature that improves its clinical value. The system functions through expert-established fuzzy rules that link "If Age is Old and Tumour is Metastasis and Vital Status is Dead" to "Cancer Risk is High" for clear logical risk assessment pathways. The defined rules help healthcare providers grasp the reasons behind their assigned risk classifications because they demonstrate straightforward methods similar to clinical approaches. Healthcare professionals can trust system predictions and understand patient risk factors because of these rules which help integrate the model into clinical practice for data-driven PDAC management decisions.

V. DISCUSSION

The assessment of pancreatic ductal adenocarcinoma (PDAC) through fuzzy logic-based systems led to successful understanding of cancer risk through clinical characteristics. The research utilised a Mamdani-type fuzzy inference system (FIS) which processed Age at Diagnosis together with Tumour Classification and Vital Status and Treatment Type variables to forecast cancer risk. The fuzzy system demonstrates superior performance in medical data processing because it handles uncertain and imprecise data which commonly appears in clinical information. The fuzzy system demonstrated its ability to handle patient data variability by processing the Age at Diagnosis variable which exhibited a median value of 65 years after outlier preprocessing. The chosen input variables serve as vital components for determining patient prognosis. The progression of PDAC depends heavily on two main factors: age at diagnosis and tumour classification status because older patients with metastatic tumours tend to develop advanced disease stages. The fuzzy logic model supports this finding because it assigns older patients with metastatic tumours to High-Risk categories as shown in Figure 1 which displays the age distribution after outlier removal. The risk score determination process heavily depends on tumour classification because patients with metastatic tumours consistently received elevated risk scores which matches clinical expectations. Risk classification depended heavily on the Vital Status (Alive/Dead) binary indicator that indicated patient survival status. The system predictions matched the clinical assessment that patients who passed away received High-Risk classifications. The treatment methods including chemotherapy and radiation and immunotherapy showed a connexion to disease advancement which led patients to receive High-Risk risk scores. The system demonstrated effective performance when producing cancer risk assessments from clinical characteristics. A patient who is 75 years old with metastatic tumour classification and chemotherapy treatment received a cancer risk score of 0.5 which placed them in the Medium Risk category. The patient classification matches medical expectations since patients who are older with metastatic tumours and moderate survival times usually fall into intermediate risk categories. Healthcare providers can use the patient classification tool from the fuzzy logic system to determine treatment plans through its Low, Medium and High-Risk stratification of patients based on their clinical characteristics. The major advantage of this system stems from its ability to provide interpretable results. The FIS implementation with fuzzy rules provides healthcare providers with an easy-to-understand explanation of how different input variable combinations affect the cancer risk assessment process. The rule "If Age is Old and Tumour is Metastasis and Vital Status is Dead then Cancer Risk is High" enables clinicians to see the logical basis for risk assessment. The method of decision transparency constitutes a significant benefit over black-box machine learning systems since it makes the decision procedures accessible to human comprehension. The system demonstrates its capability to generate quick

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and easily understandable PDAC risk assessments through the bar chart visualisation shown in Figure 4 which aids clinicians in their risk classification evaluations. However, there are some opportunities for improvement. However, the clinical features selected for the fuzzy system could be complemented with other data such as genetic data, biomarkers, and medical imaging to improve the risk classification. The incorporation of these factors would give a better picture of the patient's status and help in making a better risk assessment. Moreover, the quality and quantity of the data used in training and testing of the model are very important in the performance of the model. The model was evaluated on a small sample and the generalisation of the model to other populations and clinical settings should be tested using a larger sample. One of the disadvantages of the system is that it is based on the use of predetermined fuzzy rules. These rules were developed based on the clinical experience and may require further elaboration or addition depending on the new data and findings. They further said that, the system defensive performance could be enhanced by applying advanced rule-tuning techniques such as applying genetic-algorithms and other machine learning techniques for tuning rules dynamically based on the field data. However, the proposed fuzzy logic-based system has a potential for the early detection of PDAC due to the following advantages. Given that the risk stated by the model is based on clinically meaningful features, the model may help clinicians to identify high-risk patients who could be subjected to an early intervention. It is important to diagnose PDAC at an early stage to enhance the patient's prognosis, and this system can be used in clinical practice. Incorporating Figure 3's 3D surface plot of the PDAC risk classification, the model can be applied more effectively in clinical practice since it reveals the relationship between age and tumour type to the risk of PDAC. This system can be used to sort patients for additional diagnostic and therapeutic procedures, which will enhance patient outcomes due to early detection. Bottom of Form

VI. CONCLUSION

This work was able to design and test a Fuzzy Logic System for the identification and categorization of PDAC risk in the early stage. Using age at diagnosis, tumour classification, vital status, and treatment type as the inputs, the FIS was able to classify the patients into Low, Medium, or High-Risk groups depending on their clinical characteristics. The decision-making process of the proposed system based on the set of fuzzy rules is transparent and interpretable, which can be considered as a major advantage in the context of clinical decision-making for PDAC. This feature makes it possible for clinicians to easily comprehend and rely on the system's classifications, which is a major plus when compared to the traditional black-box machine learning models. The results obtained from the system proved the effectiveness of the system in cancer risk assessment with Cancer Risk score of 0.5 indicating Medium Risk for a patient with advanced disease indicators. This is in concordance with clinical reality because patients with metastatic tumours and a moderate survival time are considered to be at intermediate risk. This outcome shows that the system can be useful in helping healthcare providers to identify patients who are at high risk and who may require more attention and care from the healthcare practitioners. The presented system has a high potential, but there is a need for enhancement to improve its performance and generalizability. It would also be helpful to include other clinical characteristics into the system, for example, genetic information, biochemical markers, and imaging. These features would help to give a better picture of the patient's condition and thereby help in the assessment of risk. However, testing with more patients as well as patients from different background is important to verify the feasibility of the application of the fuzzy logic in clinical setting and conditions. However, there are areas of improvement that could be made: The fuzzy logic-based system is a valuable contribution to the field of artificial intelligence in healthcare, as it is a useful, easily explained tool for early cancer detection. This system can help in early detection of cancer risk and also help in tailoring the treatment plan for the patients and thus help in improving the prognosis of pancreatic cancer. With additional development and testing, this system may be used as a tool in the clinic to enhance the accuracy and speed of PDAC risk assessment and management.

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 DOI : 10.35291/2454-9150.2025.0165