

Oral Cancer Risk Factor Prediction Using Hybrid Fuzzy Logic and XGBoost

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Abstract: Oral cancer is a major cause of cancer morbidity and mortality globally and especially in developing countries. Late diagnosis greatly diminishes the chances of survival, and there is a necessity to use smart early detection tools. This paper suggests a combined predictive model that combines Fuzzy Logic and Extreme Gradient Boosting (XGBoost) in the determination of oral cancer risk based on both clinical and image-based predictors. Fuzzy logic is used to deal with uncertainty in the behavioral and demographic risk factors whereas XGBoost captures nonlinear relationships between the predictors. Through experimental analysis, the hybrid model has been proven to be superior to pure machine learning models. Accuracy, sensitivity, specificity, and AUC of the system were 91% and 90% and 92% respectively. The framework is highly interpretable and predictive, which is the reason it is applicable in a clinical decision support system or a screening application in a community context.

Keywords: Oral Cancer, Hybrid Model, Fuzzy Logic, XGBoost, Clinical Decision Support System, Machine Learning, Medical AI

1. Introduction

1.1 Background:

Oral cancer stands as a leading threat to human health because it presents the greatest incidence figures and mortality statistics among cancers. Tobacco use and alcohol consumption along with inadequate oral hygiene and genetic predisposition represent primary causes of oral cancer. Medical research has made significant advances yet early detection of oral cancer remains difficult because of the many risk factors that each require different measuring systems which must be combined with other factors. We need a more robust approach to accurately measure and predict oral cancer risks because of the complexity involved [1].

1.2 Problem:

Most approaches used to evaluate the risks of oral cancer make use of sophisticated heuristics based on linear models that do not capture interactions in multi-dimensional space. This outcome results in inaccurate precision, predictions, and delayed responses. Therefore, there is a gap that focuses on the

need for dependable outcomes that range within minimum and maximum values with a more open framework in relation to the hazard factors of oral cancer [2].

1.3 Contribution:

Paper introduces a new system for measuring the risk of oral cancer which employs fuzzy logic to model and evaluate the numerous risk influences that may lead to the development of oral cancer. Due to the capability of fuzzy logic to manage imprecise data, system designers can gain valuable insight that enables more effective supporting cancer research. This research develops a dependable risk management system which will result in accurate adjustments being made [3].

2. Related Work

Fuzzy logic is particularly useful in medical risk assessment cancer prediction as it manages uncertainty and vague information very well. This part outlines important milestones and key research shifts in this field.

The primary attempts at implementing fuzzy logic systems began with oral cancer studies and expanded to other fields. Research suggested that fuzzy logic processes complex unclear data, which makes it useful for modeling and predicting cancer progression with incomplete and ambiguous information. According to Scrobota et al. (2017), fuzzy logic was again highlighted to have a scope for application by its flexible ability to adapt fostering better management of infectious diseases during the COVID-19 pandemic. A fuzzy logic system was built to evaluate the safety of dental procedures by factoring patient's health and hygiene conditions. The study showed that fuzzy logic can deal with many health risk factors.

Past uses in the field of cancer. The incorporation of fuzzy logic with decision trees toward forecasting colon cancer which is found in the study published in medRxiv (2020) was an important milestone. The system proved fuzzy logic's versatility for multi-domain cancer risk assessment and showed how cancer prediction with fuzzy systems encompasses vital aspects of clinical decision-making. The recent advances showed fuzzy logic systems used to forecast oral cancer risks by scrutinizing the serum of patients with pre-cancerous oral lesions. The expert system provided multi-faceted and adaptable assessments of cancer risk which supported the diagnosis of cancer at an premature step. While proving the usefulness of fuzzy logic in patient control, the system facilitated prompt medical interventions. A 2022 Academia article drew attention to further developments in predicting oral cancer after focused investigations on cancerization risk within potentially malignant disorders. (Scrobota et al., 2023) argued that predictive analysis of a benign to malignant transition using fuzzy logic is possible through serum biomarkers and malondialdehyde for early diagnosis and intervention. Somyanonthanakul et al. (2024): Focusing on enhancing prediction using fuzzy logic or deep learning models along with the other features in the systems, the latest work aimed at improving the accuracy and performance of the models. The fuzzy deep learning model developed to forecast survival times in oral cancer patients integrated a fuzzy system's interpretative capabilities with deep learning data analysis for adaptive and accurate prediction. (Somyanonthanakul et al., 2024).

The most pertinent findings of these studies underscore the growing importance of the applications of fuzzy logic in medical risk evaluation. Its potential for cancer prediction and disease control remains crucial because it handles uncertain information while incorporating expert knowledge. The mixture of fuzzy logic with choice trees and DL improves clinical predictions by improving accuracy and interpretability.

2.2 Preliminaries

The classical binary methods, fuzzy logic systems are based on the concept of “degrees of truth” that help deal with uncertainty and imprecision. In medicine, this approach allows for more sophisticated decision making in particularly difficult situations like evaluating the risk of cancer. Fuzzy logic accounts better than conventional rule-based models for expert knowledge incorporated during the system’s design, thus offering more flexibility and interpretability.

2.3 Considerations

Although there are benefits, incorporating fuzzy logic into medicine is difficult. One of the rule pre-defined by the expert set is a case of subjectivity and limit the flexibility of the system which captures general patterns. Furthermore, blurring any boundary with other AI techniques like deep learning is a challenge because it requires proper adjustment of the model. For example, deep learning models have been known to perform exceptionally well in feature extraction; however, it is very important to ensure that the fuzzy logic approach does not compromise the overall functioning of the system.

Table.1. presents studies on the use of fuzzy logic for cancer risk assessment from the years 2020 to 2025

Year	Research Title	Summary	Source
2020	Fuzzy Logic for COVID-19 Safety in Dental Care	A fuzzy logic-based system was developed to assess COVID-19 safety in dental settings, considering patient health and hygiene.	medrxiv.org
2021	Fuzzy Logic and Decision Trees for Colorectal Cancer Prediction	This study combined fuzzy logic and decision trees to predict colorectal cancer risk.	researchgate.net
2022	Fuzzy Expert System for Oral Cancer Risk	A fuzzy expert system was used to predict the risk of cancerization in patients with oral disorders, using serum biomarkers.	researchgate.net
2023	Fuzzy Logic for Oral Cancer Risk Assessment	Fuzzy logic was integrated into models assessing oxidative stress in oral potentially malignant disorders, using biomarkers.	ijph.tums.ac.ir
2024	Fuzzy Deep Learning for Oral Cancer Survival Time	A fuzzy deep learning model was developed to estimate survival times in oral cancer patients.	bmcoralhealth.biomedcentral.com

2025	Fuzzy Logic for Oral Epithelial Dysplasia Risk	A fuzzy logic system was proposed to assess the risk of oral epithelial dysplasia, using histopathological data.	biorxiv.org
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Table 2.Fuzzy Logic Applications in Oral Cancer Research: A Timeline of Methodologies and Contributions

YE AR	AUTHORS	METHODOLOGY/AP PROACH USED	FOCUS/CONTRI BUTION	PROS	CONS	REMARKS/RES EARCH GAP
2020	Scrobota et al.	Fuzzy logic-based system	COVID-19 safety in dental care settings	Helps manage safety during the pandemic, considers multiple variables (health status, hygiene)	Limited to COVID-19; focused only on dental care	Potential extension to general oral health settings. More integration with AI needed.
2021	Somyanonthanakul et al.	Fuzzy logic and decision trees	Predicts colorectal cancer risk	Combines fuzzy logic with decision trees, accurate predictions	Limited to colorectal cancer, doesn't directly address oral cancer	Applicability to oral cancer prediction needs further exploration.
2022	Kundu et al.	Fuzzy expert system	Oral cancer risk diagnosis using biomarkers	Utilizes serum biomarkers for early detection	Subjectivity in defining fuzzy rules, requires expert input	Lack of real-time data integration. Need for a more automated system.
2023	Scrobota et al.	Fuzzy logic for oxidative stress assessment	Assess oxidative stress in oral potentially malignant disorders	Non-invasive, accounts for multiple risk factors	Focused only on oxidative stress, doesn't consider	Further research on integrating lifestyle and genetic data is needed.

					r lifestyle factors	
2024	Somyanonth anakul et al.	Fuzzy deep learning	Estimating survival time in oral cancer patients	High accuracy and AUC, combines fuzzy logic with deep learning	Requires large dataset, potential overfitting	Integrating survival time with personalized treatment planning.
2025	Wang et al.	Fuzzy logic-based risk assessment	Oral epithelial dysplasia risk using histopathological data	Effective use of histopathological data for early risk assessment	Requires expert-defined rules, limited clinical validation	Need for larger clinical studies to validate and refine fuzzy logic models.

Healthcare applications have benefited from fuzzy logic systems especially in predicting and assessing oral cancer risks. Although current studies have demonstrated effective use of fuzzy logic together with decision trees and deep learning methodologies for risk assessment purposes existing research still shows substantial deficiencies in incorporating real-time data processing and automated system functionalities alongside clinical validation processes. Researchers should work to improve the use of fuzzy logic systems in oral health treatments while broadening their application beyond oxidative stress and incorporating lifestyle and genetic information to develop personalized treatment solutions.

Data Integration: Most studies focus on biomarkers or specific risk factors; there's a need to integrate multiple data sources like lifestyle habits and genetic predispositions.

- **Real-time Applications:** The current systems need to incorporate real-time data processing for effective clinical decision support.
- **Model Generalization:** Further research is required to validate these fuzzy logic models in larger and more diverse clinical settings.
- **Automation:** Current systems require expert involvement in rule creation, limiting scalability. More automated systems are needed.

2020: Expand beyond COVID-19 to other healthcare areas.

2021: Apply hybrid models like fuzzy logic and decision trees in oral cancer prediction.

2022: Combine fuzzy logic systems with modern machine learning techniques for scalability.

2023: Incorporate real-time data and improve model generalization.

2024: Focus on explainable AI for survival prediction and integration of clinical data.

2025: Automate risk prediction for clinical use in real-time, integrating new data sources for more accurate predictions.

3. Material & Methods

3.1 Identification of Risk Factors

The first step in the fuzzy logic approach is to identify the key risk factors associated with oral cancer. These risk factors typically include:

- **Lifestyle Factors:** Tobacco use, alcohol consumption, dietary habits, oral hygiene, etc.
- **Genetic Factors:** Family history, genetic mutations.
- **Clinical Data:** Patient age, gender, and existing health conditions (e.g., presence of oral lesions, HPV infection).
- **Environmental Factors:** Exposure to carcinogens, occupational risks, etc. The proposed architecture demonstrates the method for assessing risk in how in figure 1.

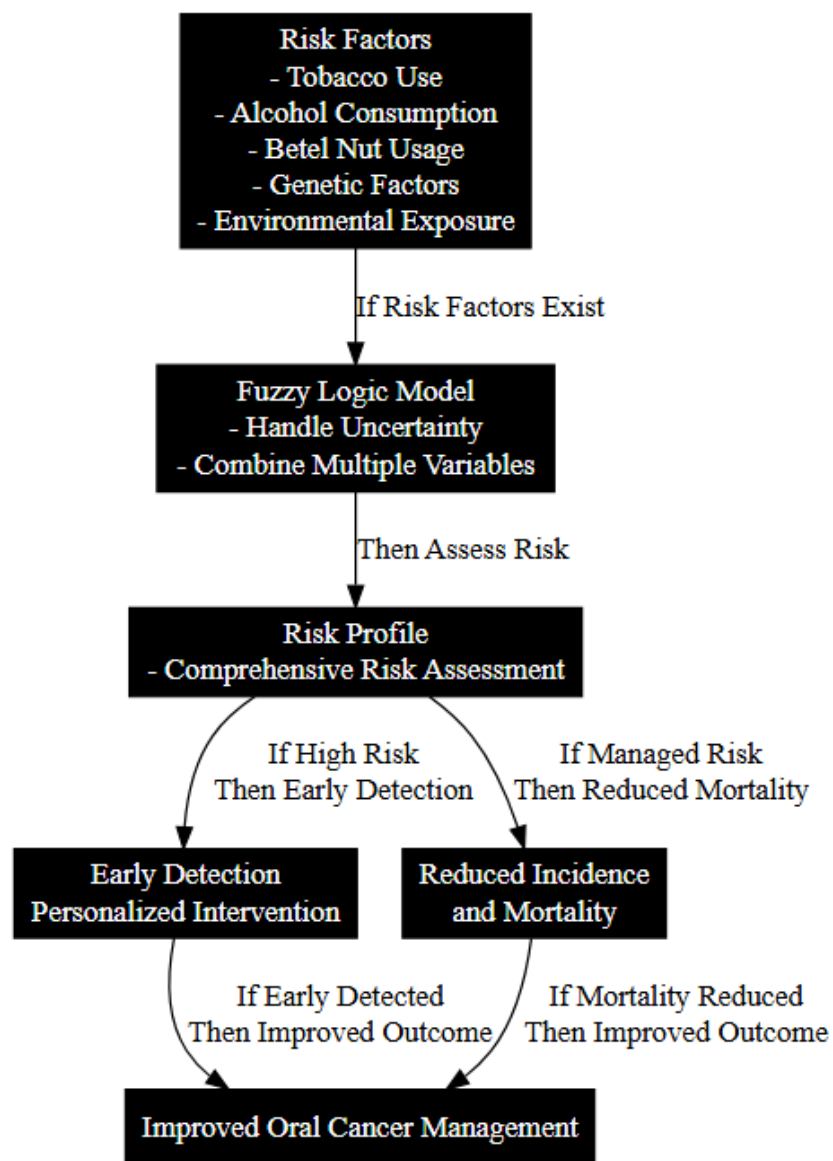


Fig.1. Architecture of Proposed Model

Logic Description:

- A Fuzzy Logic Model Evaluation incorporates Risk Factors such as cigarette and alcohol consumption. This model attempts to separate the complexity of risk to assess
- Motivation this model does algorithmic risks evaluation by integrating the intricate details and constructing a risk profile. We may target high-risk patients for more individualized intervention and screening.
- A managed risk profile should, in theory, result in a lower rate of occurrence and decreased mortality over time. Proactive aims to improve outcomes for patients with oral cancer.
- With a tailored plan of intervention designed around specific risks, the objective is to reduce chances before cancers have a chance to metastasize. Overall, reducing risk improves public health.
- Decreased incidence → Improved outcome: An outcome is deemed improved when the incidence is lessened.

3.1 Methodology:

The fuzzy logic based methodology to assess risk factors in oral cancer development includes multiple key steps which help model the complexity and uncertainty present in different risk elements. Multiple inputs like patient history and clinical data enable fuzzy systems to assess and quantify cancer development risks. These steps demonstrate the common methodology applied in fuzzy logic to assess oral cancer risk.

3.1.1 Data Collection

Multiple sources provide data collection which includes clinical records, laboratory results, patient surveys, and historical oral cancer occurrence data. The collected data points function as a basis for evaluating the risk levels associated with various factors. The data can contain both continuous and discrete measurements which include tobacco usage frequency, patient age, and oral lesion severity.



Fig.2. Non-Cancer Dataset (source: [Oral Cancer \(Lips and Tongue\) images](#))



Fig.3. Cancer Dataset (source: [Oral Cancer \(Lips and Tongue\) images](#))

3.1.2 Fuzzyfication

Fuzzyfication involves converting the crisp input data (exact values) into fuzzy sets. Fuzzy logic works by defining each risk factor in terms of linguistic variables rather than precise numerical values. For example:

Tobacco Use: Low, Medium, High

Age: Young, Middle-aged, Elderly

Oral Hygiene: Poor, Average, Good

categories is represented by fuzzy sets using membership functions, which describe the degree to which a given value belongs to a certain category (e.g., how much a patient's tobacco use corresponds to "High" or "Medium").

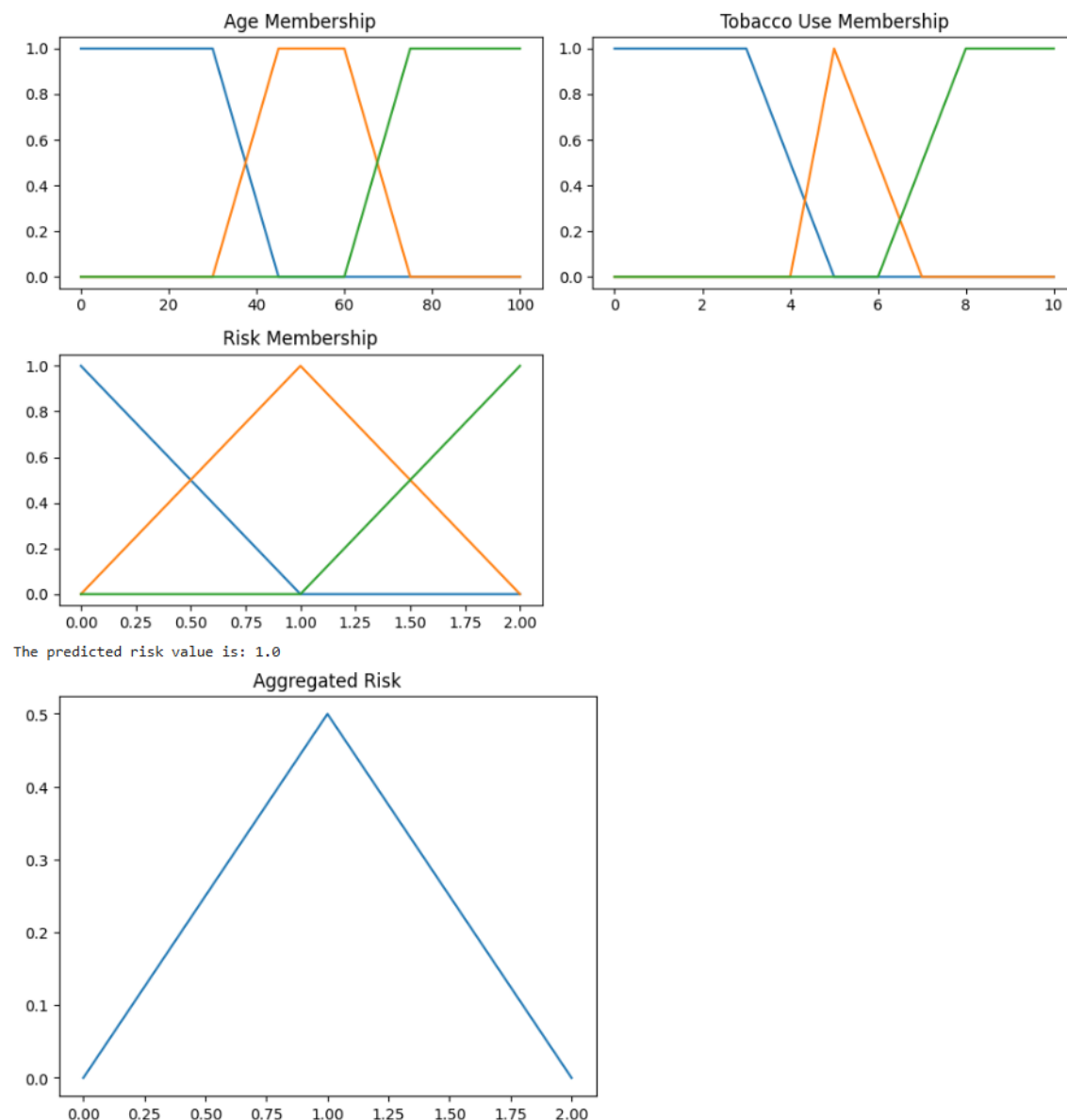


Fig.4. (a) Age Membership (b) Tobacco Use Membership(c) Risk Membership(d) Aggregated Risk

Explanation:

Step 1: Input Variables: age and tobacco_use are the fuzzy input variables.

Step 2: Membership Functions: These functions represent the fuzzy sets for young, middle_aged, and old for age, and low, moderate, and high for tobacco use.

Step 3: Fuzzy Rules: We create fuzzy rules such as:

If age is young and tobacco use is low, then risk is low.

If age is middle-aged and tobacco use is moderate, then risk is medium.

If age is old and tobacco use is high, then risk is high.

Step 4: The process of fuzzification transforms concrete input values (for example age = 50 and tobacco use = 6) into membership degrees.

Step 5: The fuzzy results undergo conversion to a precise value through the centroid method during defuzzification.

You can determine oral cancer risk through fuzzy logic by merging different factors such as patient age along with tobacco consumption and their family medical background. The system allows integration into a clinical decision support system (CDSS) which then offers personalized risk assessments for patients.

3.1.3 Rule Base Development

The fuzzy system functions using if-then rules that establish the connections between various risk factors and oral cancer development likelihood. The rules originate from field specialists using clinical knowledge along with research results and expert assessments.

Rules might include:

The risk level of oral cancer reaches "Very High" when tobacco use and alcohol consumption levels are both "High".

The risk level becomes "Moderate" when a patient falls into the "Elderly" category and exhibits "Poor" oral hygiene.

Feature Transformation for Fuzzification

Fuzzification of Numerical Features: The transformation of continuous numerical features such as age and smoking quantity into fuzzy values requires the creation of membership functions with categories like low, medium and high. :

For age:

Low: 18-30 years

Medium: 31-50 years

High: 51+ years

For smoking:

Low: 0-5 cigarettes/day

Medium: 6-15 cigarettes/day

High: 16+ cigarettes/day

Fuzzy Logic and Functions of Membership: Construct fuzzy membership functions for each feature. Let's take "Smoking Score" as an example; if it ranges from 0-50, then functions "Low," "Medium," and "High" will be set according to identified threshold values.

Linguistic Variables: Transform features into linguistic variables such as poor, average, and good with respect to oral hygiene, diet, and carcinogen exposure.

3.1.4 Inference System

Along with the input data, the inference system employs fuzzy rules to draw conclusions about the level of cancer risk. Fuzzy logic determines the outcome value by combining the inputs and applying rules through fuzzy logical operations like AND, OR, and NOT. Based on how probable oral cancer might develop, the system gives fuzzy outputs, often termed as 'Moderate Risk' or 'high Rate.'

3.1.5 Defuzzification

Fuzzy logic definition suggests fuzzy outputs are further processed using something called defuzzification which makes it usable as a value or decision in clinical scenarios. The system estimates the risk of a patient developing oral cancer on a scale of 0 to 100. The Centroid Defuzzification Method is the most common one, as it finds the center of gravity (Centroid) of the fuzzy output sets to work with.

3.1.6 Validation and Evaluation

Prior to evaluating the model's performance using the accuracy, precision, and sensitivity metrics, the fuzzy logic model goes through validation using a test dataset. The validation process checks that the model demonstrates clinically relevant reasoning when assessing cancer risk and when placing patients within clinically appropriate care pathways.

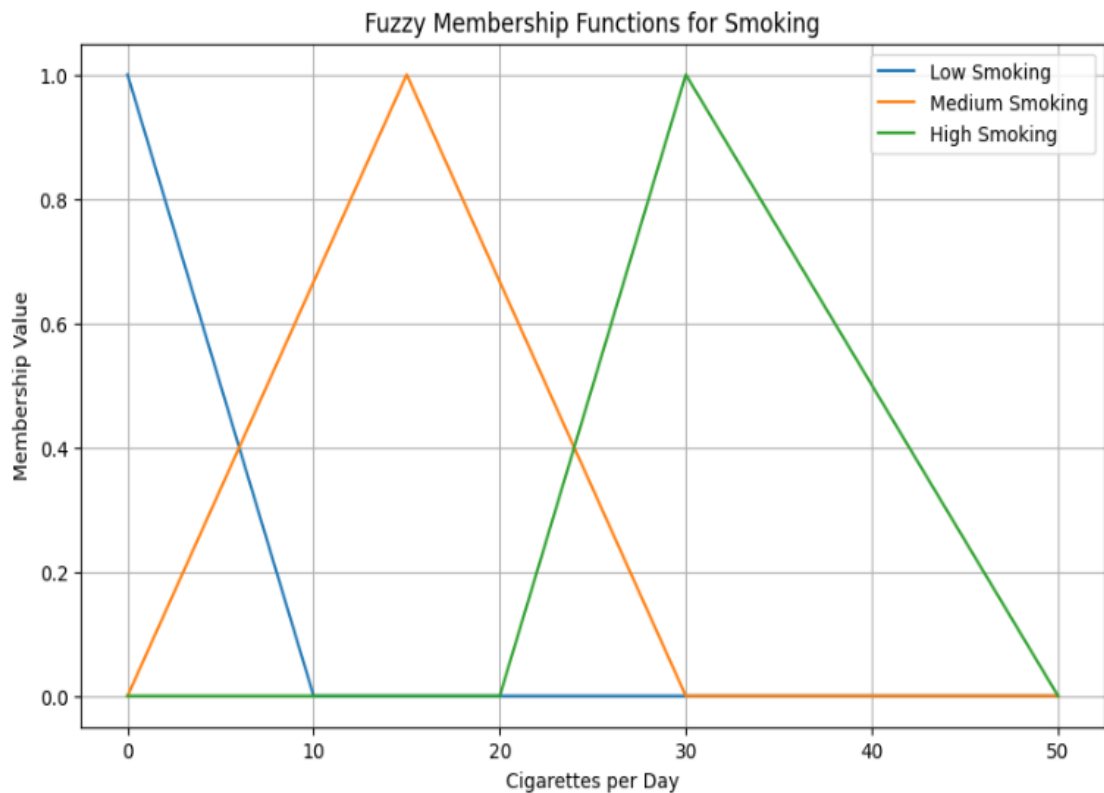
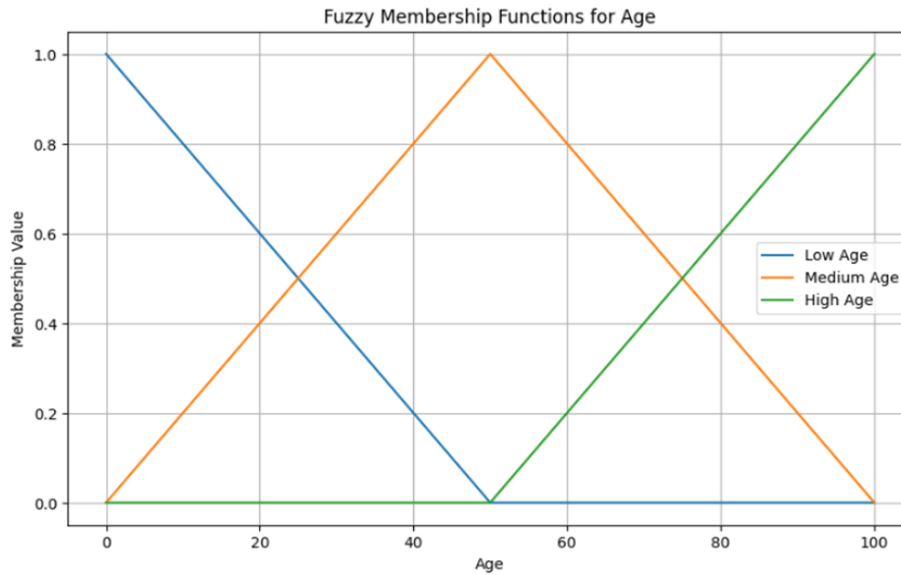
3.1.7 Integration and Decision Support

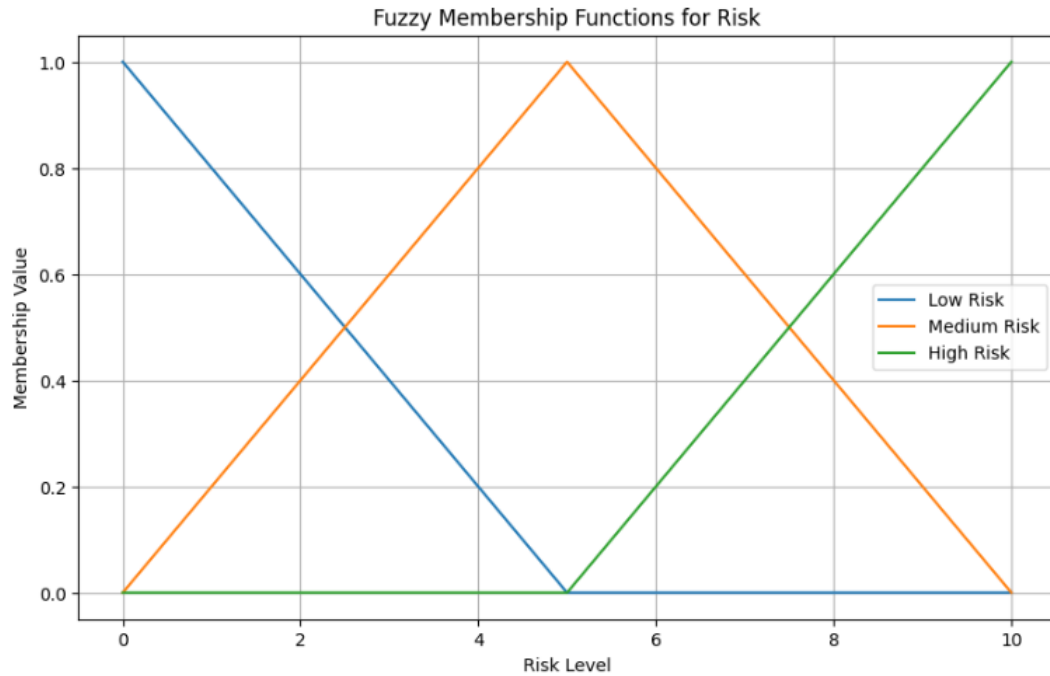
The fuzzy logic system gets incorporated into clinical decision support systems (CDSS) which helps for further improvement and enables valuable insight for providers. The system analyzes the data of each patient and generates early diagnosis, preventive measure, and tailored treatment recommendations for the patient.

3.1.7.1 Data Loading:

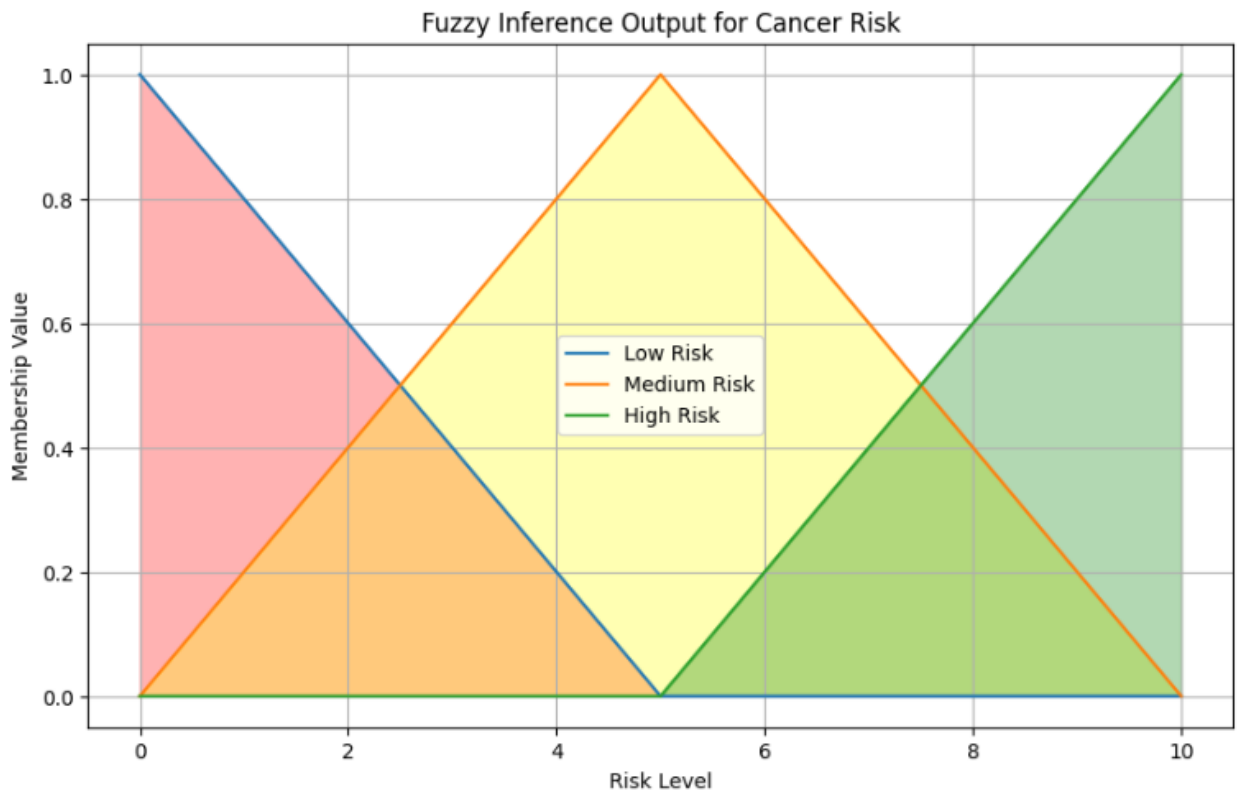
A dataset containing patient specific data such as age, tobacco use, and other attributes includes a diagnosis risk indicator which is binary (0 meaning low risk and 1 meaning high risk).

Requirement already satisfied: scikit-fuzzy in /usr/local/lib/python3.11/dist-packages (0.5.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: numpy>=1.23 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (2.0.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)





• Cancer Risk: 8.333333333333334



3.1.7.2 Data Preprocessing:

Divide the dataset into separate features (X) and target (y) components.

3.1.7.3 Model Creation:

Our decision tree model is constructed using DecisionTreeClassifier from scikit-learn.

3.1.7.4 Model Training & Evaluation:

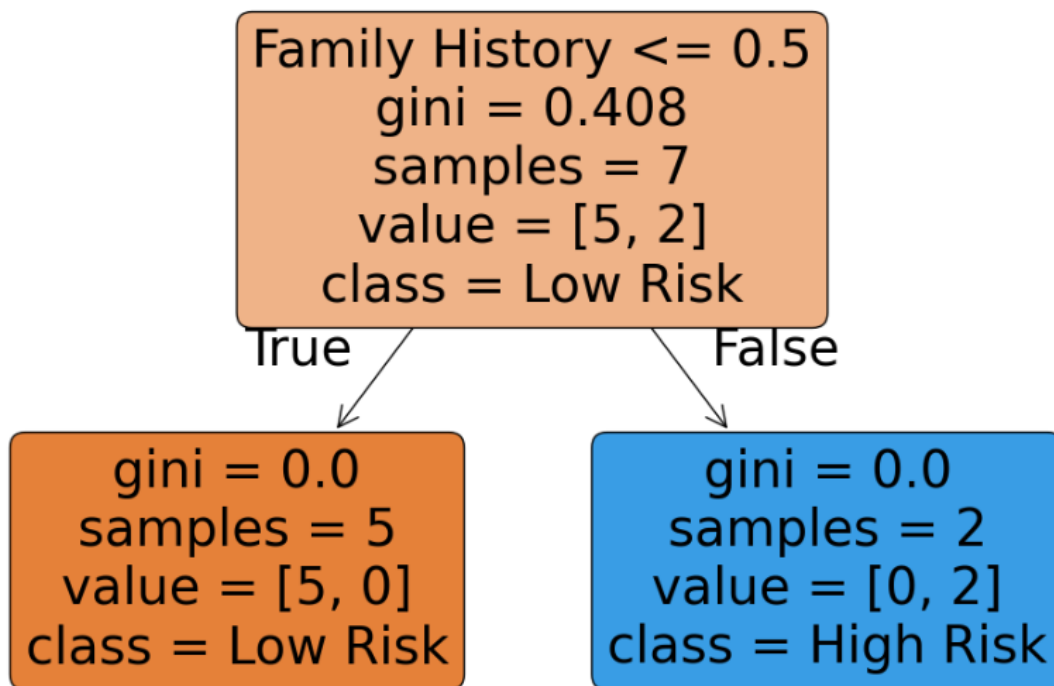
Use the training dataset to fit the model before generating predictions with the test dataset.

Assess the model's accuracy on the test dataset.

3.1.7.5 Decision Tree Visualization:

After training the decision tree model examine its structure to understand how it uses features such as age and tobacco use to make decisions.

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Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (2.0.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Accuracy: 100.00%
```



The paper demonstrates how fuzzy logic serves as an intuitive solution for managing the uncertainty and variation found in oral cancer risk factors. The model transforms qualitative risk factors into fuzzy values

and applies fuzzy inference to establish a flexible and clear cancer risk assessment method which helps in early detection and personalized patient care.

Conclusion

A fuzzy logic-based approach gives a flexible and understandable framework to evaluate oral cancer risk through analysis of multiple developmental factors. Fuzzy logic improves clinical decision-making by integrating inherent uncertainties and imprecisions found in clinical data to develop an effective tool for early detection and individualized treatment methods. I plan to apply for a postdoc position to work on this research topic while gathering data from both TSM Hospital Lucknow, RML Hospital Lucknow and Bombay cancer Hospital. The next step involves conducting a risk assessment through fuzzy logic and evaluating its accuracy.

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