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Analyzing the Cancer Risk of Mortality: using Fuzzy AHP and Fuzzy TOPSIS Method

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***Abstract*— This study aims to assess the various risk factors associated with developing and dying from cancer, utilizing a comprehensive analysis of epidemiological data, genetic predispositions, lifestyle influences, and healthcare access additionally, the study applies the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Fuzzy TOPSIS to prioritize these risk factors based on their relative importance and associated uncertainties.**

***Index Terms*— Cancer risk, Cancer Mortality, Fuzzy AHP, Fuzzy TOPSIS, Genetic Predisposition, Healthcare Access, Lifestyle Factors.**

I. INTRODUCTION

Cancer continues to be one of the primary causes of morbidity and mortality worldwide, presenting a significant public health challenge. According to WHO, cancer accounted for nearly 10 million deaths globally in 2020, representing one out of every six deaths.

The burden of cancer is anticipated to rise with an aging population and lifestyle risk factors such as tobacco usage, physical inactivity, and unhealthy diets persist in proliferating.

The risk of developing or succumbing to cancer is influenced by genetic, environmental, and behavioral elements. Advances in medical research have improved survival rates, yet disparities persist across populations. Understanding these determinants is key to developing effective prevention strategies that promote cancer prevention and control on a global scale.

II. LITERATURE SURVEY

[1] This work presents an improved fuzzy logic model to evaluate the risk of developing cancers of the breast, colon, and lung that outperforms the classic methods. Its best performance rate goes up to 82.72%, indicating the main risk factors: sex, genetics, and smoking. The outputs are supported by ROC analysis, providing accuracy rates from 0.81 to 0.83.

This approach helps in early detection and preventive measures, thus providing valuable insights for individual persons and healthcare providers.

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[2] Xiu Wu 1ORCID,Blanchard-Boehm Denise 1ORCID, F. Benjamin Zhan and Jinting Zhang ,*ORCID This present study is an analysis of LCM versus 30 risk factors of 100 countries for the years ranging from 2006 to 2016 using Fuzzy Inference Modeling and Random Forest Modeling for finding some critical risk factors apart from smoking, which are low physical activity, air pollution, and dietary deficiencies. It does an in-depth analysis pointing to a strong impact of environmental and life-style causes of LCM. The Delphi method and AHP analysis therefore give importance to the environmental variables for developing lung cancer.[3] Ioana SCROBOTĂ Grigore BĂCIUT, Adriana Gabriela FILIP,4BiancaTODOR,2FlorinBLAGA,5 and Mihaela Felicia BĂCIUȚ6In this study, the risk of cancerization in oral potentially malignant disorders was investigated by analyzing serum MDA and proton donors in 16 patients by fluorometric assays. The estimation of cancer risk was made using a multi-criteria decision support system with 25 IF-THEN rules for a scale from 1 to 10. The obtained results indicated that high MDA and low proton donors correspond to a higher cancer risk. For extreme values of risk factors, the maximum risk score was 8.98 out of 10. This approach would contribute to the management of oral cancer in terms of early diagnosis and risk assessment.[4] Ayşegül Büyükavcu,Y. Esra Albayrak, Nazlı Göker This research aims to identify key risk factors for BC and build an RBFCM model to describe those identified along with its cause-and-effect relationships. Expert contributions, along with fuzzy logic, have been used in building the model to point out modifiable variables such as socioeconomic status and advanced maternal age, apart from non-modifiable variables of familial history and breast density. This approach enhances understanding of BC risk factors and supports improved preventive strategies. The model also facilitates sensitivity analysis to evaluate different risk scenarios and their impact on BC.[5] Rhonda M Brand, David D Jones, Henry T Lynch, Randall E Brand, Patrice Watson, Ramesh Ashwathnayaran, and Hemant K Roy Fuzzy logic modeling is applied in this study to evaluate the risk of CRC from smoking in HNPCC patients. It shows that smoking significantly increases the risk due to variable gene type and smoking dose. The approach provides more precise risk estimates than traditional methods, thus offering better support to personalized prevention strategies.[6] Atınç Yılmaz1 and Kürşat Ayan2 This research explores the use of fuzzy logic frameworks for assessing cancer risk and initial diagnoses of breast, lung, and colon cancers. It recognizes the important role that stress plays in the etiology of cancer. Using Takagi-Sugeno fuzzy models with variable coefficients aims to develop the research on the improvement of risk prediction and management in healthcare. These models are consequently used by the developed software to enable doctors and patients to understand and reduce cancer risks more effectively, where current medical resources and practices lack.[7] Georgina Cosma, Giovanni Acampora,David Brown,Robert C. Rees,Masood Khan,A. Graham Pockley The paper introduces a neuro-fuzzy model to predict prostate cancer staging, outperforming traditional methods like the AJCC pTNM Staging Nomogram. Using clinical data, the model improves accuracy in determining whether a patient has Organ-Confined Disease or Extra-Prostatic Disease. This approach offers more precise and personalized predictions, enhancing treatment decision-making.[8] Muhammad Aslam and Mohammed Albassam This paper applies neutrosophic logic to the investigation of the relationship between dietary fat and mortality from prostate cancer in 30 countries and states that a positive correlation exists between dietary fat and deaths due to prostate cancer. Neutrosophic regression, considering uncertainty, is more effective in this context than traditional models of regression.

The authors recommend the use of neutrosophic regression for better estimation of cancer risk and decision-making in uncertain environments.[9] José Carlos R. Alcantud,Gonzalo Varela,Beatriz Santos-Buitrago,Gustavo Santos-García,Marcelo F. JiménezThe study describes a soft set theory-based algorithm to predict the 5-year survival rate in lung cancer patients who have undergone surgical resection. The clinical and functional data-based fuzzy model, in turn, yielded a performance classifier with a survival classification accuracy of 79% that helped the surgeons arrive at well-informed decisions. In general, the approach deals with the complexity and uncertainty of survival analysis to finally have a very precise tool for decision-making surgery.[10] Nivedita, Seema Agrawal and M.K. SharmaThe current research proposes a fuzzy expert system based on ten most informative symptoms for early diagnosis of lung cancer, using Mamdani inference in MATLAB. In the proposed system, stages of cancer are labeled as Low, Medium, and High. It increases the accuracy by diagnosing with main symptoms, not considering data with high dimensions. The model utilizes 15 relevant rules out of 1,000 instances that can be very beneficial in early detection and treatment. Akshitha et al. [11] employed many ML classifiers for detection and prediction of oral cancer. Sharma et al. [12] used ML models for early detection and prediction of breast cancer. Gudipati et al. [13] used ANN model and several combinations of optimizes and activation functions for prediction of breast cancer. Darshan et al. [14] used many computational models for detection of lung cancer. Gagana et al. [15] used ML models for detection and prediction of breast cancer and its stages.

III. METHODOLOGY

A. Fuzzy AHP

The diagnosis of Alzheimer's disease is a very accurate and reliable process of decision-making, which can be considered the most complex and variable entity. The optimization of multi-criteria assessments is carried out with the help of three powerful MCDM methodologies, known as TOPSIS, AHP, and Fuzzy AHP. These methodologies will be described, regarding principles, procedures, and applications for AD diagnosis in the next sections, with the purpose of analysing their strengths and weaknesses and, therefore, their potential to be clinically integrated.

To provide an overview of this study's main methodologies, the subsequent sections are dedicated to the step-by-step explanation of the processes involved in TOPSIS, AHP, and Fuzzified AHP. These methodologies are considered indispensable for the validation of the comparative analysis. The Analytical Hierarchical Process-AHP is a decision-support approach that attempts to solve a problem by

breaking down the problems associated with a solution, then grouping and organizing them in a hierarchy. This will be the most important contribution of the AHP Expert judgment or perception introduces subjectivity into research decision-making. This method also verifies the validity of the data in cognizance of limitations posed by inconsistencies.

However, large uncertainties and doubts in interpretation exist regarding the accuracy of the data taken and the results obtained. The fuzzy AHP method sets only the AHP scale to the scale of the fuzzy

Triangle for which priority is to be available. The Analytic Hierarchy Process (AHP) decomposes decision-making problems into hierarchies:

Step 1: Define Problem and Criteria

The four criteria are as shown in Figure 1.

- Family history of cancer – c1
- Smoking – c2
- Alcohol consumption – c3
- Exposure to carcinogens – c4

Step 2: Develop Pairwise Comparison Matrix

Now use triangular numbers to express the matrix. (1,1,1) for equal (2,3,4) for slightly more importance and more as shown in Table 1. pairwise matrix After pairwise calculate the sum of each column

TABLE I: PAIRWISE COMPARISON MATRIX USING TRIANGULAR FUZZY NUMBERS

Criteria	c1	c2	c3	c4
c1	(1,1,1)	(2,3,4)	(1,2,3)	(2,3,4)
c2	(1/4,1/3,1/2)	(1,1,1)	(1,2,3)	(2,3,4)
c3	(1/3,1/2,1)	(1/3,1/2,1)	(1,1,1)	(1,2,3)
c4	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1,1,1)

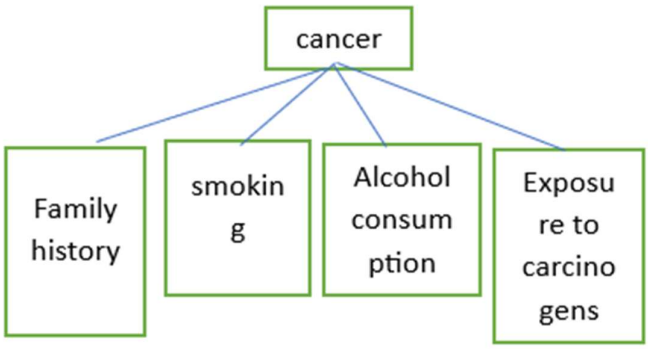

Figure 1. Criteria of cancer

Step 3: Calculate Fuzzy Eigen Vector

Now normalize the matrix by dividing each element by the sum of its column as shown in Table 2 normalized matrix, and then calculate average of each row which is criteria value.

TABLE II: NORMALIZED MATRIX (TRIANGULAR FUZZY NUMBERS)

Criteria	c1	c2	c3	c4
c1	(1,1,1)	(2/8,3/8,4/8)	(1/6,2/6,3/6)	(2/8,3/8,4/8)
c2	(1/4,1/3,1/2)	(1/8,1/8,1/8)	(1/6,2/6,3/6)	(2/8,3/8,4/8)
c3	(1/3,1/2,1)	(1/4,1/2,1)	(1/6,2/6,3/6)	(1/8,2/8,3/8)
c4	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/6,1/2,1)	(1/4,1/3,1/2)

Step 4: Calculate Fuzzy Weights

After averaging we now multiply the criteria value with each value in the column of pairwise matrix and then the sum of each row is obtained which is called weighted sum value. Fuzzy weights =weighted value/criteria value. It is shown in the Table III.

Step 5: Consistency Check Consistency Index

The ranking of criteria is given in Table IV. Consistency Index (CI) and Consistency Ratio (CR) were computed to verify reliability as per (1) and the final calculated values as shown in Table IV.

$$CI = \frac{\lambda_{max} - n}{n-1}, \quad CR = \frac{CI}{RI} \quad (1)$$

where *RI* is the Random Index for *n* criteria.

TABLE III: FUZZY WEIGHTS AND CRITERIA RANKING

Criteria	Fuzzy Weight (l, m, u)	Rank
c1	(0.3, 0.4, 0.5)	1
c2	(0.2, 0.3, 0.4)	2
c3	(0.2, 0.3, 0.4)	3
c4	(0.1, 0.2, 0.3)	4

TABLE IV. FUZZY WEIGHTS AND RANKING

Criteria	Fuzzy Weight (l, m, u)	Weight
c1	(0.3,0.4,0.5)	0.4
c2	(0.2,0.3,0.4)	0.3
c3	(0.2,0.3,0.4)	0.3
c4	(0.1,0.2,0.3)	0.2

B. Fuzzy Geometric Mean

Step 1: consider the given pairwise matrix and convert the numbers into triangular values for the matrix
Step 2: find the geometric mean for all the rows or calculate the geometric mean for each entry.
The geometric mean of fuzzy numbers (a, b, c) and (d, e, f) is calculated as:

$$GM\,(a, b, c, d, e, f) = (\sqrt[3]{a \cdot d}, \sqrt[3]{b \cdot e}, \sqrt[p3]{c \cdot f}) \quad (2)$$

For c1 vs. c2:

• Fuzzy number for c1 vs. c2 is (2,3,4) • Fuzzy number for c2 vs. c1 is (1/4,1/3,1/2) Calculate the geometric mean:

GM (2,1/4) = cube root (2 (1/4)) =cube root (0.5) 0.793

GM (3,1/3) = cube root (3 (1/3)) = cube root (1) =1 GM (4,1/2) = cube root (4 (1/2)) = cube root (2) 1.260

Similarly perform mean for all entries, and then we would be able to construct all the values as in the Table 5.

Or calculate mean for each column by

r1 = $(1*2*1*2)^{1}/4, (1*3*2*3)^{1}/4, (1*4*3*4)^{1}/4 = (1.41, 2.05, 2.63)$

Similarly perform for other columns

Step 3: calculate the fuzzy weights wi

$$Wi = ri*(r1+r2+r3+\ldots\ldots rn)^{-1} \quad (3)$$

Wi = ((1.41+0.84+0.57+0.37),
(2.05+1.18+0.84+0.48),
(2.43+1.56+1.31+0.7))

Wi = $(3.19,4.55,6)^{-1} = (1/6, 1/4.55, 1/3.19) * (1.41, 2.05, 2.43) = (0.235, 0.450, 0.824)$ Similarly calculate all fuzzy weights, which would be demonstrated as it is in the Table VI.

Step 4: calculate the average

After fuzzy weights we will have to calculate the average of weights to get criteria weights, which is used for later calculations hence we are representing those values as shown in Table VII.

TABLE V: GEOMETRIC MEAN

Criteria	c1	c2	c3	c4
c1	(1,1,1)	(0.793, 1, 1.260)	(0.707, 1, 1.442)	(0.793, 1, 1.260)
c2	(1.260, 1.000, 1.000)	(1,1,1)	(0.707, 1, 1.442)	(0.793, 1, 1.260)
c3	(0.707, 1, 1.442)	(0.707, 1, 1.442)	(1,1,1)	(0.793, 1, 1.260)
c4	(0.793, 1, 1.260)	(0.793, 1, 1.260)	(0.707, 1, 1.442)	(1,1,1)

TABLE VI: GEOMETRIC MEAN AND FUZZY WEIGHTS

criteria	geometric mean	fuzzy weights
c1	(1.41,2.05,2.43)	(0.235,0.450,0.824)
c2	(0.84,1.18,1.56)	(0.14,0.259,0.489)
c3	(0.57,0.84,1.31)	(0.095,0.184,0.410)
c4	(0.37,0.48,0.70)	(0,061,0.105,0.219)

Step5: Normalizing values
if the sum of weights is greater than 1 then normalize the weights by dividing each column by sum of the weights. Now based on the normalized value gives ranks or priority to the factors, which is as follows in Table VIII.
Step6: after assigning rank to highest criteria, we get the decision of which factor is important, so to find out the factor that is important we would be depicting ranks as in Table XI.
From this we can conclude that from fuzzy ahp geometric mean it is assigned that family history has very strong importance in risk of cancer mortality and then smoking, alcohol consumption and more.

TABLE VII: AVERAGED WEIGHTS

criteria	c1	c2	c3	c4
c1	(0.5,0.33,0.25)	(1,1,1)	(0.5,0.66,0.75)	(1,1,1)
c2	(0.125,0.111,0.125)	(0.50,0.33,0.25)	(0.5,0.66,0.75)	(1,1,1)
c3	(0.33,0.25,0.33)	(0.33,0.25,0.33)	(1,0.5,0.33)	(1,1,1)
c4	(0.25,0.33,0.5)	(0.25,0.33,0.5)	(0.33,0.5,1)	(1,1,1)

TABLE VIII: AVERAGE AND NORMALIZED WEIGHTS

criteria	avg weights	normalized
c1	0.503	0.435
c2	0.296	0.256
c3	0.230	0.199
c4	0.128	0.111

TABLE IX: FINAL RANKING BASED ON FUZZY GEOMETRIC MEAN

criteria	rank
c1	1
c2	2
c3	3
c4	4

C. Fuzzy TOPSIS

This method works using fuzzy logic and helps in choosing the best alternative in a multicriteria system.
Step1: construct the fuzzy decision matrix
Decision matrix or pairwise comparison matrix both holds same meaning.
Step2: normalize fdm
To normalize the decision matrix, we will have to find the maximum value of each column. Max value under c1: (2,3,4), Max value under c2: (2,3,4), Max value under c3: (1,2,3), Max value under c4: (1,1,1)
Divide every fuzzy value in the decision matrix by its maximum value.
Step3: determine FPIS (fuzzy positive ideal solution) and FNIS (fuzzy negative ideal solution), thereby these values are shown in the Table 10.
Step4: calculate distance of every alternative from fpis and fnis

d+ = root (1/3[(0.5-1) 2 + (0.33 − 1)2 + (0.25 − 1)2] + ... [1/3(1 − 1)2 + (1 − 1)2 + (1 − 1)2] = 0.750
d- = root (1/3[(0.5-0.5) 2 + (0.33 − 0.33)2 + (0.25 − 0.25)2] + ...[1/3(1 − 0.5)2 + (1 − 0.33)2 + (1 − 0.25)2] = 0.98
Similarly perform all the alternatives, which in turn would be represented as it is shown in the Table 11.
Step5: calculate closeness coefficient for all the values.
Cc = di-/di-+di+
Cc1 = 0.98/0.75+0.98 = 0.566
Similarly calculating all the closeness value we get, Cc2=0.404, Cc3=0.426, Cc4=0.410
Step6: rank the alternative
Now for the closeness coefficient rank the criteria value and determine the best alternative.

$$CC_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{3}$$

where Di− and Di+ are distances from FNIS and FPIS, respectively which values are then calculated and shown as in Table 12.
From the fuzzy topsis method we conclude that the family history of cancer is the best alternative and the risk factor is more when family history of cancer is detected.

TABLE X: FPIS AND FNIS VALUES

criteria	fpis	fnis
c1	(1,1,1)	(0.5,0.33,0.25)
c2	(1,1,1)	(0.5,0.33,0.25)
c3	(1,1,1)	(0.33,0.25,0.33)
c4	(1,1,1)	(0.25,0.33,0.5)

TABLE XI: DISTANCE FROM FPIS AND FNIS

criteria	d+	d-
c1	0.75	0.98
c2	1.15	0.7798
c3	1.09	0.8108
c4	1.03	0.718

TABLE XII: CLOSENESS COEFFICIENT AND RANKING

criteria	CC	rank
c1	0.566	1
c2	0.404	4
c3	0.426	2
c4	0.41	3

IV. RESULTS

The results from Fuzzy AHP and Fuzzy Geometric Mean show that family history of cancer has the highest weight and priority order in being the most critical risk factor for cancer mortality. These are followed in importance by smoking and alcohol consumption, with smoking being very slightly more significant than alcohol consumption. Among the assessed risk factors, exposure to carcinogens is the least important. This conclusion is continuously supported by the methods of Fuzzy AHP and Fuzzy TOPSIS, underlining that the genetic predisposition factor sharply affects the risk of cancer.
Both Fuzzy AHP and Fuzzy Geometric Mean determination provide complete evidence that family cancer history is the most deciding risk factor for cancer mortality. This proves that in both methods, family history has been listed first, hence being of utmost relevance when assessing the risk of cancer. This result shows that genetic susceptibility is a powerful influencing factor in the development of cancer and indicates that any individual with a family medical history of the disease has a remarkably higher risk compared with a person without family medical history. On the other hand, smoking and alcohol consumption are considered some of the major risk factors, but rank after family history. The second most important is smoking, and alcohol intake is almost as strong. Carcinogenic exposure is still relevant, but it is the slightest among the factors analysed. Such results demand measures of active prevention, taking into account genetic predisposition, along with health public interventions addressed to a decrease of smoking and alcohol, with minimal carcinogen exposure. This

study demonstrates that family cancer history has the highest weight in cancer mortality risk. Public health interventions should focus on genetic counselling, smoking cessation, and alcohol reduction programs to minimize risk.

V. RECOMMENDATIONS

Based on the findings, the recommendations proposed are: Improve genetic screening programs, Implement comprehensive genetic cancer testing among those with family cancer histories, especially cancers classified as high-risk, such as breast, colon, and prostate cancers.

- Public Health Interventions for Modifiable Risks:
- Advocate for smoking cessation, alcohol reduction programs, and awareness campaigns to reduce lifestyle-induced cancer risks.
- Improve early detection systems;
- Implement fuzzy logic decision-support systems in hospitals and clinics to enhance risk prediction and early diagnosis.
- Improve Occupational and Environmental Safety: Also, develop stricter guidelines on exposure to carcinogenic materials in industries and the environment.
- Future Research Expansion: Include larger data sets as well as other risk factors like diet, obesity, radiation exposure, and socio-economic indicators. Understand hybrid models, comprising fuzzy logic with machine learning, for better predictive performance.

VI. CONCLUSION

The major risk factors contributing to cancer mortality were analyzed in the present study by a structured multi-criteria decision-making framework involving Fuzzy AHP, Fuzzy Geometric Mean, and Fuzzy TOPSIS. Integration of fuzzy logic supported a better handling of uncertainty and expert subjectivity, hence offering a much more robust and realistic prioritization of cancer risk factors. Among all three approaches, the family history of cancer turned out to be the strongest risk factor across them, thus pointing to genetic predisposition as the leading factor in the development and mortality from cancer. This finding underlines the crucial need for early genetic screening, assessment for hereditary cancer syndromes, and personalized prevention.

The second most impactful risk factor was smoking, closely followed by alcohol consumption, indicating the strong influence of modifiable lifestyle behaviors. Exposure to carcinogens ranked last but remained a major contributor to cancer mortality risk, a finding that again underlines the need for environmental and occupational health regulations. In sum, the integrated fuzzy-based analytical approach strengthens the view that genetic and lifestyle variables are at the core of any explanation of cancer mortality risk. The obtained insights may lead policymakers, healthcare practitioners, and researchers to formulate specific interventions in the form of genetic counseling programs, lifestyle modification campaigns, and carcinogen-free work environments.

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