Turkish Journal of Science & Technology
20(2), 583-593, 2025

Research Paper
https://doi.org/10.55525/tjst.1344862

Evaluating Prostate Cancer Diagnosis Using the Adaptive Neural Fuzzy Inference System (ANFIS): A Comparative Analysis of Diagnostic Accuracy

Orhan DALILIÇ[1*], Naime DEMİRTAŞ[2], Abdullah DEMİRTAŞ[3]

[1] Department of Mathematics, Faculty of Arts and Science, Bingöl University, Bingöl, Türkiye
[2] Department of Mathematics, Faculty of Arts and Science, Mersin University, Mersin, Türkiye
[3] MNE Minhalıççık District Directorate of National Education, Eskişehir, Türkiye
[*1] odalkilic@bingol.edu.tr, [2] naimedemirtas@mersin.edu.tr, [3] abdullah.demirtas@meb.gov.tr

(Geliş/Received: 17/08/2023; Kabul/Accepted: 25/09/2025)

Abstract: This study explores the application of the Adaptive Neural Fuzzy Inference System (ANFIS) in evaluating prostate cancer diagnosis outcomes. Prostate cancer remains one of the most prevalent cancers among men globally, where early and accurate detection is critical for effective treatment. Despite advancements, diagnosing prostate cancer is inherently complex due to the variability in clinical data and the need for precise interpretation. In this research, ANFIS—a hybrid methodology integrating fuzzy logic and neural networks—was employed to analyze a clinical dataset and develop a diagnostic model. The ANFIS framework excels in handling uncertainty and nonlinear relationships, making it particularly suited for medical diagnostics. The model's performance was rigorously assessed using multiple evaluation metrics, including accuracy, sensitivity, and specificity. The results demonstrate that ANFIS achieves high diagnostic accuracy, significantly reducing unnecessary biopsies by 45.45% compared to traditional methods. This highlights its potential as a reliable decision-support tool in clinical settings. By leveraging ANFIS, clinicians can enhance diagnostic precision, optimize resource allocation, and improve patient outcomes. The study underscores the transformative role of intelligent systems in advancing prostate cancer management.

Key words: Fuzzy logic, prostate cancer, ANFIS.

Uyarlanabilir Sinirsel Bulanık Çıkarım Sistemini (ANFIS) Kullanarak Prostat Kanseri Tanısının Değerlendirilmesi: Tanısal Doğruluğun Karşılaştırmalı Analizi

Öz: Bu çalışma, prostat kanseri teşhis sonuçlarını değerlendirmede Adaptive Neural Fuzzy Inference System'in (ANFIS) uygulamasını araştırmaktadır. Prostat kanseri, erken ve doğru tespitin etkili tedavi için kritik öneme sahip olduğu, küresel olarak erkekler arasında en yaygın kanserlerden biri olmaya devam etmektedir. İlerlemelere rağmen, prostat kanseri teşhisi klinik verilerdeki değişkenlik ve kesin yorumlama ihtiyacı nedeniyle doğası gereği karmaşıktır. Bu araştırmada, bulanık mantık ve sinir ağlarını entegre eden bir hibrit metodoloji olan ANFIS, bir klinik veri setini analiz etmek ve bir teşhis modeli geliştirmek için kullanılmıştır. ANFIS çerçevesi, belirsizlik ve doğrusal olmayan ilişkileri ele almada mükemmeldir ve bu da onu özellikle tıbbi teşhisler için uygun hale getirir. Modelin performansı, doğruluk, duyarlılık ve özgüllük dahil olmak üzere birden fazla değerlendirme metriği kullanılarak titizlikle değerlendirilmiştir. Sonuçlar, ANFIS'in yüksek teşhis doğruluğuna ulaştığını ve geleneksel yöntemlere kıyasla gereksiz biyopsileri %45,45 oranında önemli ölçüde azalttığını göstermektedir. Bu, klinik ortamlarda güvenilir bir karar destek aracı olarak potansiyelini vurgulamaktadır. ANFIS'ten yararlanarak, klinisyenler tanısal hassasiyeti artırabilir, kaynak tahsisini optimize edebilir ve hasta sonuçlarını iyileştirebilir. Çalışma, prostat kanseri yönetimini ilerletmede akıllı sistemlerin dönüştürücü rolünü vurgulamaktadır.

Anahtar kelimeler: Bulanık mantık, prostat kanser, ANFIS

1. Introduction

The real world is often characterized by imprecise and vague information. Fuzzy logic acknowledges this inherent fuzziness and provides a formal framework to handle it [1]. It recognizes that many concepts and variables in everyday life are not easily defined by precise boundaries or crisp categories. Instead, they exhibit degrees of membership or degrees of truthfulness, which can be effectively captured using fuzzy logic. Unlike classical logic, which relies on crisp, binary values (true or false), fuzzy logic allows for gradual membership degrees between 0 and 1, enabling a more nuanced representation of information and reasoning. Fuzzy sets and fuzzy rules are used to model linguistic variables and capture the vagueness inherent in many real-world problems [2-7]. Fuzzy logic provides a flexible and interpretable way to handle uncertain information.

[*] Corresponding author: odalkilic@bingol.edu.tr. ORCID Number of authors: [1] 0000-0003-3875-1398, [2] 0000-0003-4137-4810, [3] 0000-0001-9096-7888

There has been a substantial surge in interest in the development of intelligent systems that excel in making accurate predictions and informed decisions across a diverse range of domains [8-12]. Among the various methodologies employed to meet these objectives, the Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out as a particularly prominent and extensively utilized approach. Although ANFIS is not a novel technique per se, its relevance and efficacy persist due to its unique ability to seamlessly integrate the adaptive learning features of neural networks with the interpretative and reasoning capabilities of fuzzy logic systems. This hybrid methodology is instrumental in addressing complex problems characterized by uncertainty, imprecision, and nonlinearity.

The strength of ANFIS lies in its dual nature: it combines the adaptive, data-driven learning processes of neural networks, which can adjust and improve based on input data, with the rule-based, human-interpretable structure of fuzzy logic. This integration allows ANFIS to create models that not only capture intricate relationships within data but also provide explanations and insights into the decision-making process. As a result, ANFIS has proven to be an invaluable tool across various applications, including pattern recognition, where it helps in classifying and identifying complex patterns; control systems, where it aids in managing and optimizing dynamic processes; and time series prediction, where it forecasts future values based on historical data. Its versatility and robustness in handling diverse types of data and problem scenarios have cemented ANFIS as a widely accepted and effective method in both academic research and practical applications [13-17]. The ANFIS model is organized into five distinct layers, each serving a specific function that contributes to the overall system's ability to model complex data relationships. These layers are as follows:

- **Input Layer**

The input layer represents the fundamental entry point of the ANFIS architecture, where raw numerical data are introduced into the system. Each node within this layer corresponds to one independent variable from the dataset, and its primary role is to transfer the input directly to the subsequent fuzzy layer without modification. Although this stage does not perform complex operations, it plays a decisive role in determining how accurately and effectively the information will be processed in later stages. The quality of data transmission at this stage directly influences the reliability of fuzzification, rule evaluation, and ultimately the prediction capacity of the entire model. In this sense, the input layer forms the structural foundation upon which all subsequent computational processes are built.

- **Fuzzy Layer**

Once the raw data are introduced, they enter the fuzzy layer, where crisp numerical inputs are transformed into linguistic representations through the application of predefined membership functions. Each node in this layer embodies a membership function, mapping input values into fuzzy sets such as "low," "medium," or "high," with degrees of membership ranging continuously between 0 and 1. This fuzzification process provides a flexible and human-interpretable means of representing uncertainty and imprecision that inevitably exist in real-world data. By enabling the system to work with degrees of truth rather than binary judgments, the fuzzy layer establishes the basis for adaptive reasoning and prepares the ground for rule-based inference in the following stages.

- **Normalization Layer**

The outputs generated by the fuzzy layer are not immediately suitable for direct comparison across different rules, as their magnitudes may vary significantly. The normalization layer addresses this issue by scaling and proportionally adjusting the fuzzy membership degrees. Through this process, the firing strengths of the rules are normalized, ensuring that each rule contributes fairly to the reasoning mechanism. This step is crucial to prevent distortions in rule evaluation that may arise from disproportionate membership values. By harmonizing the fuzzy signals, the normalization layer enhances the coherence and stability of the decision-making process, thereby increasing the overall accuracy and robustness of the ANFIS model.

- **Rule Layer**

At the rule layer, the normalized inputs are combined according to a set of predefined fuzzy logic rules. Each node in this layer represents an individual rule that connects input conditions with an associated outcome, for example: "If variable A is high and variable B is low, then the output is moderate." The degree to which each rule is activated is determined by the firing strength, which reflects the compatibility between the current inputs and the conditions specified in the rule. This mechanism allows the system to evaluate multiple fuzzy scenarios simultaneously, capturing complex relationships among input variables. The rule layer can thus be regarded as the central reasoning component of ANFIS, where the abstract fuzzy descriptions of input data are transformed into structured logical assessments.

- **Output Layer**

The final stage of the ANFIS structure is the output layer, where the consequences of all activated rules are aggregated to produce a single crisp output. In this layer, each rule's suggested output is weighted by its firing strength, and a defuzzification process—often realized through a weighted average—is applied to transform the fuzzy inferences into a precise numerical value. This final output represents the model's decision, prediction, or classification result. The significance of the output layer lies in its ability to synthesize diverse fuzzy evaluations into an interpretable and actionable result, bridging the gap between human-like fuzzy reasoning and the precision required in computational applications.

To optimize the performance of ANFIS, a hybrid learning algorithm is employed, which typically combines gradient descent-based backpropagation with least-squares estimation. This dual mechanism enables the system to iteratively fine-tune both the antecedent (membership functions) and consequent (rule outputs) parameters of the model. In practice, the training process begins by feeding the clinical dataset—comprising PSA, fPSA, prostate volume, and age—into the ANFIS structure. The network calculates the discrepancy between the predicted outcomes and the actual diagnostic results, after which the backpropagation method adjusts the nonlinear parameters of the membership functions, while the least-squares estimation updates the linear parameters of the rules. Through this iterative refinement, the system progressively minimizes the error and improves its predictive capacity.

The effectiveness of this learning process was quantitatively assessed using the Root Mean Square Error (RMSE), which is widely recognized as a reliable indicator of model accuracy. In our study, the training RMSE reached a minimal value of 4.29991×10^{-6}, signifying an exceptionally small average deviation between predicted and actual values. Such a remarkably low RMSE demonstrates that the ANFIS model was able to capture the underlying nonlinear relationships in the data with high precision. The small error value is attributed to the strong generalization ability of the hybrid optimization process, which effectively balances parameter adaptation while avoiding overfitting.

Furthermore, the ANFIS findings directly support the objectives of this study by providing a robust predictive framework for prostate cancer diagnosis. The model not only achieved high diagnostic accuracy but also substantially reduced unnecessary biopsies by accurately stratifying patients according to their risk levels. This outcome underscores the clinical relevance of ANFIS: while conventional diagnostic methods may lead to overdiagnosis and invasive procedures, the ANFIS-based system offers a more reliable and data-driven alternative. Thus, the integration of ANFIS in medical decision-making highlights both the methodological rigor of this work and its potential to contribute significantly to improving patient care.

Prostate cancer remains one of the most prevalent cancers among men globally, with early and accurate diagnosis being pivotal for effective treatment and improved patient outcomes. Current diagnostic methods rely on a combination of clinical parameters such as prostate-specific antigen (PSA), free PSA (fPSA), prostate volume (PV), age, and biopsy results [18-20]. These tests generate vast amounts of heterogeneous data, including clinical measurements, laboratory results, and imaging findings, which pose significant challenges for integration and interpretation. To address these challenges, intelligent systems capable of handling complex patterns and uncertainties have garnered increasing attention in recent years [21-25]. Among these, the Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out as a promising approach, leveraging the synergistic strengths of neural networks and fuzzy logic [29-34].

This study explores the potential of ANFIS to evaluate prostate cancer diagnosis results, aiming to enhance diagnostic accuracy and efficiency. By integrating diverse diagnostic data and expert knowledge, ANFIS can provide clinicians with actionable insights, streamline decision-making, and reduce unnecessary procedures such as biopsies. The outcomes of this research may pave the way for advanced intelligent systems in prostate cancer management, ultimately improving patient care and resource utilization.

Table 1. Key Diagnostic Parameters and Challenges.

Parameter	Role in Diagnosis	Challenges
PSA	Biomarker for prostate cancer screening	High false-positive rates, leading to unnecessary biopsies
fPSA	Improves specificity when combined with PSA	Limited standalone diagnostic value
Prostate Volume (PV)	Correlates with cancer risk and biopsy outcomes	Variability in measurements across imaging modalities
Age	Significant risk factor for prostate cancer	Non-modifiable, complicates risk stratification
Biopsy	Gold standard for definitive diagnosis	Invasive, associated with complications, and overused in low-risk cases

2. Preliminaries

In this section, the concepts of fuzzy set and ANFIS are reminded.

Throughout this paper, $U = \{u_1, u_2, \dots\}$ is an initial universe set, 2^U is the power set of U.

Definition 2.1. [1] A fuzzy set F over U is a set defined by $\mu_F: U \to [0,1]$. μ_F is called the membership function of F. Thus, a fuzzy set F over U can be represented in Equation 1 as follows:

$$F = \{\mu_F(u)/u: u \in U\} \tag{1}$$

Throughout the paper, the family of all fuzzy sets over U are represented by $2^{F(U)}$.

Definition 2.2. [1] Let F_1 and F_2 be two fuzzy sets over U. Then,

- $F_1 \tilde{\subseteq} F_2 \Leftrightarrow \mu_{F_1}(u) \leq \mu_{F_2}(u);\ \forall u \in U$,
- $F_1 = F_2 \Leftrightarrow F_1 \tilde{\subseteq} F_2$ ve $F_2 \tilde{\subseteq} F_1$,
- $F_1 \tilde{\cap} F_2 = \{min\{\mu_{F_1}(u), \mu_{F_2}(u)\}/u: u \in U\}$,
- $F_1 \tilde{\cup} F_2 = \{max\{\mu_{F_1}(u), \mu_{F_2}(u)\}/u: u \in U\}$,
- $F_1^c = \left\{\left(1 - \mu_{F_1^c}(u)\right)/u: u \in U\right\}$.

The Adaptive Network-Based Fuzzy Inference System (ANFIS) is a sophisticated artificial system that integrates the Takagi-Sugeno (T-S) fuzzy model [26] with advanced learning algorithms. ANFIS leverages the strengths of both neural networks and fuzzy logic to offer a powerful framework for solving complex prediction problems. At its core, ANFIS combines the backpropagation learning capabilities of neural networks with the inference capabilities of fuzzy logic, creating a hybrid system that is adept at handling both qualitative and quantitative data.

The architecture of ANFIS involves the use of fuzzy rules within the Takagi-Sugeno model, which are structured to handle different types of input data. Initially, the input data is processed through fuzzification, where it is mapped into fuzzy sets using membership functions. These membership functions are designed to represent the degree of truth of various inputs within a given range, converting precise numerical inputs into fuzzy values that can be more easily manipulated within the fuzzy system.

Once fuzzified, the data is distributed across the network according to a set of fuzzy rules. These rules, which are typically represented in the form of If-Then statements, dictate how the inputs interact with the system and how they should be processed to produce an output. The ANFIS model uses these rules to perform inference, combining the fuzzy inputs in a manner that reflects the logical relationships described by the rules. This inference process is critical for capturing the underlying patterns and relationships within the data, enabling the system to make informed predictions.

The final stage involves the computation of outputs based on the aggregated results of the fuzzy rules. ANFIS employs a defuzzification process to convert the fuzzy outputs into precise, actionable results. This process involves calculating a weighted average of the rule outputs, where the weights are determined by the firing strengths of the rules. The result is a crisp output that reflects the system's prediction or decision based on the input data.

The adaptability and performance of ANFIS are enhanced through its hybrid learning algorithm, which typically combines gradient descent-based backpropagation with least-squares estimation. This learning mechanism allows ANFIS to continuously adjust the parameters of the membership functions and fuzzy rules, improving its accuracy and effectiveness in modeling complex, nonlinear relationships. The flexibility of ANFIS in handling various types of data and its ability to provide interpretable results make it a valuable tool in a wide range of applications, including time series prediction, system identification, and control systems [27-28].

By integrating these components, ANFIS not only improves prediction performance but also offers a clear and interpretable model of the underlying data relationships, making it a robust choice for addressing complex problems involving uncertainty and imprecision.

ANFIS has two types of parameters: the input and output parameters, which connect the fuzzy rules to each other. The training of the model is achieved through the optimization of these parameters. Fundamentally, ANFIS consists of five layers.

Input Layer: Each node in this layer transmits the input signals to another layer without applying any summation or activation operation.

Fuzzifying Layer: In the layer referred to as the fuzzification layer, each node transfers its signal to the next layer. The signal received at each node is dependent on the input values and the type of membership function used. The outputs of these nodes (N_{1i}) in this layer are defined by Equation (2) and Equation (3) as follows:

$$N_{1i} = \mu_{A_i}(u), \quad i = 1,2 \tag{2}$$

$$N_{1i} = \mu_{B_{i-2}}(u), \quad i = 3,4 \tag{3}$$

Implication Layer Normalizing Layer: Each node in this layer is labeled as Π and represents the product of all input signals. The output of the node is calculated using Equation (4) as follows:

$$N_{2i} = w_i = \mu_{A_i}(u)\mu_{B_i}(u), \quad i = 1,2 \tag{4}$$

Moreover, each node in this layer is represented by a circle and labeled as N. In the i-th node, the normalized threshold value of the i-th rule is calculated using Equation (5) as follows:

$$N_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{5}$$

Defuzzyifying Layer: The layer known as the defuzzification layer calculates the output value for each rule. Each i-th node in this layer is an adaptive node with a node function that computes the consequent weight values. The node output is calculated using Equation (6) as follows:

$$N_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i u + q_i v + r_i), \quad i = 1,2 \tag{6}$$

Output Layer: The output of the ANFIS is obtained by summing the output values corresponding to each rule obtained in the defuzzification layer. The output of the network is calculated using Equation (7) as follows:

$$N_{5i} = f = \sum \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i}, \quad i = 1,2 \tag{7}$$

3. Experimental Study

In this section, the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) to analyze critical clinical parameters—namely, prostate-specific antigen (PSA), free prostate-specific antigen (fPSA), prostate volume (PV), and AGE—is meticulously detailed. These parameters are pivotal in the diagnosis and management of prostate cancer, a disease characterized by significant variability in clinical presentation and progression. Accurate analysis of these parameters is essential for distinguishing between malignant and benign conditions, guiding clinical decisions, and determining the need for further diagnostic procedures, such as biopsies. The dataset utilized in this study was obtained from Necmettin Erbakan University Meram Medicine Faculty and comprises 44 samples collected from 29 patients diagnosed with prostate cancer and 15 healthy controls. This dataset is instrumental in developing and validating the ANFIS model, as it provides a robust basis for training and testing the system.

For the purposes of this study, the dataset was divided into two subsets: 33 patients' data was used for training the ANFIS model, while the remaining 11 patients' data was reserved for testing. The ANFIS model employed a Sugeno-type adaptive fuzzy logic system to predict which patients would require a biopsy based on their clinical parameters. Multiple approaches and numbers of iterations were tested to optimize the rule base, ultimately leading to the selection of a hybrid optimization method that demonstrated the best alignment with experimental findings. The model was trained over 1000 iterations, refining its parameters to enhance predictive accuracy.

The performance of the ANFIS model was assessed using the Root Mean Square Error (RMSE) of the training dataset, which is a crucial metric for evaluating model accuracy. The minimal training RMSE achieved was 4.29991×10^{-6}, indicating a very low average discrepancy between the predicted and actual values. This minimal RMSE underscores the model's high accuracy in fitting the training data, reflecting its potential effectiveness in practical applications. Figure 2 illustrates the analysis of relationships between clinical parameters and susceptibility to prostate cancer, providing visual insights into the model's findings.

The clinical data employed in this study were obtained from Necmettin Erbakan University Meram Medicine Faculty and carefully divided into training and testing subsets. Specifically, data from 33 patients were allocated for training the ANFIS model, while the remaining 11 patients were reserved for testing to evaluate its generalizability. Although the dataset is relatively small, it reflects real-world clinical limitations, where data availability is often constrained by ethical considerations, patient consent, and the invasive nature of diagnostic procedures such as biopsies. Despite this limitation, the ANFIS model demonstrated robust predictive performance, as evidenced by the minimal RMSE and strong correlation results. This outcome highlights the model's capacity to extract meaningful patterns even from limited data, which is particularly valuable in medical applications where datasets are typically heterogeneous and not easily scalable. Looking ahead, ANFIS modeling should be considered in future studies involving larger and more diverse datasets, as its hybrid architecture uniquely combines interpretability with adaptive learning. This makes it a powerful and scalable tool for enhancing diagnostic decision-making, reducing unnecessary procedures, and ultimately supporting precision medicine in prostate cancer management and beyond.

The significance of incorporating ANFIS into clinical practice lies in its ability to enhance diagnostic accuracy, particularly in the context of complex and uncertain medical data. The integration of ANFIS can potentially address gaps in traditional diagnostic methods by offering a sophisticated approach to modeling and predicting clinical outcomes. This is crucial for improving patient management and ensuring timely intervention. The need for accurate diagnostic tools is underscored by the challenges associated with prostate cancer detection and the importance of early and precise diagnosis. By emphasizing the role of ANFIS in this context, the study highlights its potential impact on advancing diagnostic practices and supporting clinicians in making informed decisions based on comprehensive data analysis. Figure 2 shows the analysis of the relationships between clinical parameters for prostate cancer and susceptibility to cancer.

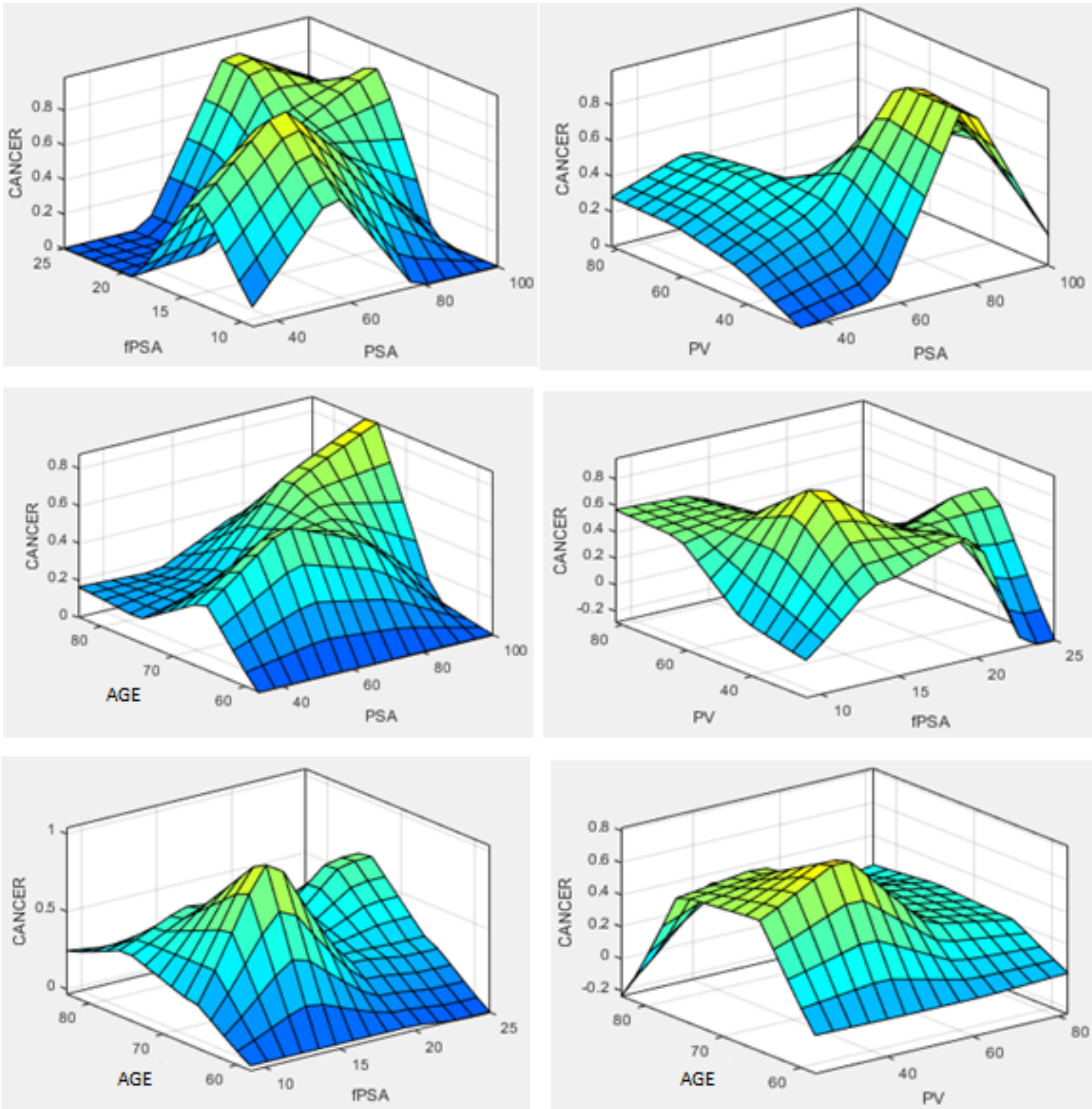

Figure 2. Relationships between clinical parameters and susceptibility to cancer.

The performance of the ANFIS model using a Sugeno-type adaptive fuzzy logic system was rigorously evaluated by analyzing the correlation coefficients R^2 for both the training and testing datasets. The value R^2, also known as the coefficient of determination, provides a measure of how well the predicted outcomes correlate with the actual data with a value closer to 1 indicating a better fit.

Figure 3 presents the correlation R^2 for the training dataset. This figure illustrates the relationship between the actual and predicted values during the model training phase. The x-axis represents the actual values, while the y-axis represents the predicted values by the ANFIS model. Each point on the scatter plot corresponds to a patient case, and the proximity of these points to the line of best fit indicates the accuracy of the model's predictions. The figure demonstrates that the ANFIS model achieved a high value R^2 during training, suggesting that it effectively learned the underlying patterns in the training data, thereby minimizing prediction error.

Figure 4 shows the correlation R^2 for the testing dataset. Similar to Figure 3, the x-axis represents the actual values, and the y-axis represents the predicted values by the ANFIS model for the testing data. The scatter plot in this figure is crucial as it evaluates the model's generalizability to new, unseen data. The clustering of data points around the line of best fit in Figure 4 indicates that the ANFIS model maintains high predictive accuracy even on the testing dataset, confirming its robustness and reliability.

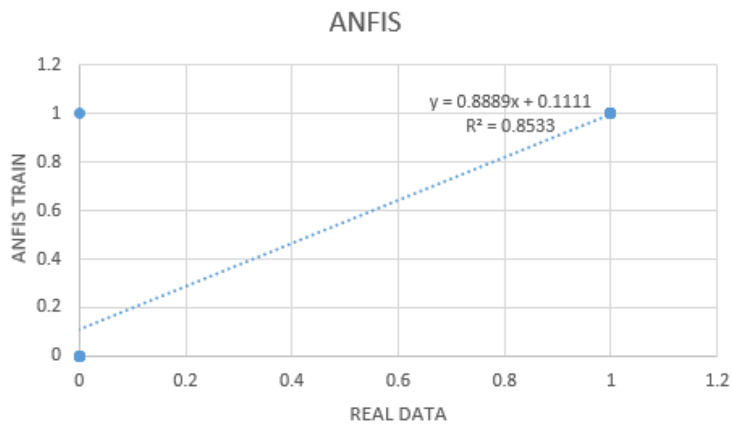

Figure 3. ANFIS training correlation relationship.

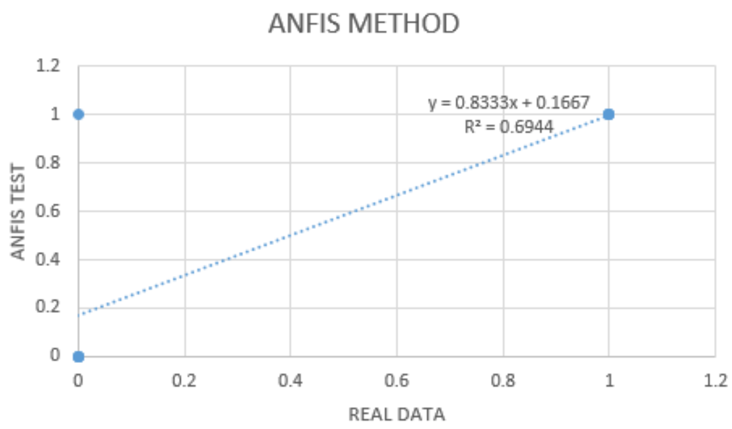

Figure 4. ANFIS testing correlation relationship.

Together, Figures 3 and 4 highlight the model's proficiency in both learning from the training data and accurately predicting outcomes for the testing data. The high values R^2 in both figures underscore the ANFIS model's capability to predict prostate cancer presence with significant accuracy and minimal error. These visual representations affirm the model's effectiveness and its potential application in clinical settings for aiding in the diagnosis and management of prostate cancer.

5. Comparison Analysis

In this section, according to the test data based on the trained ANFIS model, it was discussed whether the patients needed a biopsy procedure. Of the 11 patients considered as test data, 5 have prostate cancer. Based on the results obtained, the patient analysis sent to the biopsy procedure is given in Table 2 as follows:

Based on the results obtained from Table 2, it has been determined that unnecessary biopsies can be prevented significantly. In conclusion, avoiding unnecessary biopsy procedures is of paramount importance in the context of prostate cancer. This approach carries significant benefits for both patients and healthcare systems.

Firstly, unnecessary biopsies can lead to physical discomfort and potential complications for patients. Biopsy procedures involve inserting a needle into the prostate gland, which can cause pain, bleeding, and infection. By minimizing the number of biopsies performed, we can reduce the associated risks and improve the overall patient experience.

Secondly, unnecessary biopsies impose a burden on healthcare systems. These procedures require significant resources, including medical personnel, equipment, and laboratory analysis. By implementing more targeted approaches, such as multiparametric magnetic resonance imaging (MRI) or prostate-specific antigen (PSA) testing, we can allocate these resources more effectively and optimize the utilization of healthcare facilities.

Furthermore, reducing unnecessary biopsies is crucial in addressing the challenges of diagnosis and treatment in prostate cancer management. Prostate cancer is characterized by its often-slow progression, and many cases may not necessitate immediate intervention. Unnecessary biopsies can lead to the detection of clinically insignificant tumors, resulting in potential over-treatment and associated side effects. Adopting a more selective and precise approach to biopsies can help differentiate between aggressive cancers that require treatment and indolent tumors that can be safely monitored.

Table 2. Biopsy process decision analysis based on ANFIS-test data.

Decision-maker	Doctor	ANFIS
Total number of patients	11	11
Number of patients recommended biopsy	11	6
Percentage of unnecessary biopsies	%54.55	%9.1

The Adaptive Neuro-Fuzzy Inference System (ANFIS) can significantly contribute to this selective approach by enhancing risk stratification and decision-making processes. ANFIS combines neural network learning with fuzzy logic, enabling it to model complex, nonlinear relationships and handle uncertainties in clinical data. By integrating various risk factors, such as age, family history, and prostate-specific antigen (PSA) levels, ANFIS can improve the accuracy of risk assessments. This advanced modeling capability allows clinicians to better identify patients who are at higher risk for aggressive cancer and, therefore, would benefit most from a biopsy.

Furthermore, ANFIS can assist in distinguishing between cases that require immediate treatment and those that can be managed through active surveillance. By providing more accurate predictions and classifications, ANFIS reduces the likelihood of unnecessary biopsies and interventions, thereby minimizing the risk of overdiagnosis. Additionally, ANFIS can support shared decision-making between patients and healthcare professionals by offering more nuanced and reliable information about individual risk profiles. Educating patients about the potential risks and benefits of biopsy procedures, supported by ANFIS-derived insights, empowers them to make informed choices about their healthcare.

6. Conclusion

The evaluation result generated by ANFIS provides a comprehensive and personalized assessment of the prostate cancer patient's condition. Furthermore, the ANFIS evaluation result enables clinicians to tailor treatment strategies with unprecedented precision. It empowers medical professionals to make informed decisions regarding the most suitable therapeutic interventions, taking into consideration factors such as the patient's risk profile, response to previous treatments, and potential side effects. By leveraging the power of ANFIS, healthcare providers can offer prostate cancer patients a higher level of personalized care. The evaluation result serves as a compass, guiding physicians in navigating the complex landscape of treatment options and helping patients embark on a journey towards improved outcomes and enhanced quality of life. In summary, the ANFIS evaluation result in prostate cancer patients represents a advancement in the field of medical analysis. It embodies a transformative shift towards more precise and personalized approaches, heralding a new era of patient-centric care and providing hope for improved treatment outcomes in the battle against prostate cancer.

References

[1] Zadeh LA. Fuzzy sets. Inf Control 1965; 8: 338–353.
[2] Dalkılıç O, Demirtaş N. Algebraic operations of virtual fuzzy parameterized soft sets and their application in decision-making. Cumhuriyet Sci J 2021; 42(4): 878–889.
[3] Zhang F, Ma W, Ma H. Dynamic chaotic multi-attribute group decision making under weighted T-spherical fuzzy soft rough sets. Symmetry 2023; 15(2): 307.
[4] Gwak J, Garg H, Jan N. Hybrid integrated decision-making algorithm for clustering analysis based on a bipolar complex fuzzy and soft sets. Alex Eng J 2023; 67: 473–487.
[5] Nawaz HS, Akram M. Granulation of protein–protein interaction networks in Pythagorean fuzzy soft environment. J Appl Math Comput 2023; 69(1): 293–320.
[6] Akram M, Martino A. Multi-attribute group decision making based on T-spherical fuzzy soft rough average aggregation operators. Granul Comput 2023; 8(1): 171–207.
[7] Khalil AM, Zahran AM, Basheer R. A novel diagnosis system for detection of kidney disease by a fuzzy soft decision-making problem. Math Comput Simul 2023; 203: 271–305.
[8] Hu H, Xu J, Liu M, Lim MK. Vaccine supply chain management: An intelligent system utilizing blockchain, IoT and machine learning. J Bus Res 2023; 156: 113480.
[9] Shimizu R, Saito Y, Matsutani M, Goto M. Fashion intelligence system: An outfit interpretation utilizing images and rich abstract tags. Expert Syst Appl 2023; 213: 119167.
[10] Njoku JN, Nwakanma CI, Amaizu GC, Kim DS. Prospects and challenges of Metaverse application in data-driven intelligent transportation systems. IET Intell Transp Syst 2023; 17(1): 1–21.
[11] Chesnokov AM. Pattern regions as a basis for logical inference in columns-based intelligent systems. J Pharm Negat Results 2023; 407–422.
[12] Rabin MRI, Hussain A, Alipour MA, Hellendoorn VJ. Memorization and generalization in neural code intelligence models. Inf Softw Technol 2023; 153: 107066.
[13] Olayode IO, Tartibu LK, Alex FJ. Comparative study analysis of ANFIS and ANFIS-GA models on flow of vehicles at road intersections. Appl Sci 2023; 13(2): 744.
[14] Yu H, Dai Q. AE-DIL: A double incremental learning algorithm for non-stationary time series prediction via adaptive ensemble. Inf Sci 2023; 636: 118916.
[15] Ahmed IE, Mehdi R, Mohamed EA. The role of artificial intelligence in developing a banking risk index: An application of adaptive neural network-based fuzzy inference system (ANFIS). Artif Intell Rev 2023; 1–23.
[16] Zardkoohi M, Molaeezadeh SF. Long-term prediction of blood pressure time series using ANFIS system based on DKFCM clustering. Biomed Signal Process Control 2022; 74: 103480.
[17] Salehi S. Employing a time series forecasting model for tourism demand using ANFIS. J Inf Organ Sci 2022; 46(1): 157–172.
[18] Southwick PC, Catalona WJ, Partin AW, Slawin KM, Brawer MK, Flanigan RC, Loveland KG. Prediction of post-radical prostatectomy pathological outcome for stage T1c prostate cancer with percent free prostate specific antigen: A prospective multicenter clinical trial. J Urol 1999; 162(4): 1346–1351.
[19] Van Cangh PJ, De Nayer P, Sauvage P, Tombal B, Elsen M, Lorge F, Wese FX. Free to total prostate-specific antigen (PSA) ratio is superior to total-PSA in differentiating benign prostate hypertrophy from prostate cancer. Prostate 1996; 29(S7): 30–34.
[20] Egawa S, Soh S, Ohori M, Uchida T, Gohji K, Fujii A, Koshiba K. The ratio of free to total serum prostate specific antigen and its use in differential diagnosis of prostate carcinoma in Japan. Cancer 1997; 79(1): 90–98.
[21] Perincheri S, Levi AW, Celli R, Gershkovich P, Rimm D, Morrow JS, Sinard J. An independent assessment of an artificial intelligence system for prostate cancer detection shows strong diagnostic accuracy. Mod Pathol 2021; 34(8): 1588–1595.
[22] Raciti P, Sue J, Ceballos R, Godrich R, Kunz JD, Kapur S, Fuchs TJ. Novel artificial intelligence system increases the detection of prostate cancer in whole slide images of core needle biopsies. Mod Pathol 2020; 33(10): 2058–2066.
[23] Rouvière O, Souchon R, Lartizien C, Mansuy A, Magaud L, Colom M, Crouzet S. Detection of ISUP ≥ 2 prostate cancers using multiparametric MRI: Prospective multicentre assessment of the non-inferiority of an artificial intelligence system as compared to the PI-RADS V2.1 score (CHANGE study). BMJ Open 2022; 12(2): e051274.
[24] Parwani AV. Commentary: Automated diagnosis and Gleason grading of prostate cancer – are artificial intelligence systems ready for prime time? J Pathol Inform 2019; 10.
[25] Van Booven DJ, Kuchakulla M, Pai R, Frech FS, Ramasahayam R, Reddy P, Arora H. A systematic review of artificial intelligence in prostate cancer. Res Rep Urol 2021; 31–39.
[26] Jang JS. ANFIS: Adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern 1993; 23(3): 665–685.
[27] Karaboga D, Kaya E. Training ANFIS using artificial bee colony algorithm for nonlinear dynamic systems identification. In: Proc 22nd Signal Process Commun Appl Conf (SIU). IEEE 2014; 493–496.
[28] Jang JS, Sun CT. Neuro-fuzzy modeling and control. Proc IEEE 1995; 83(3): 378–406.
[29] Cobbinah M, Abdulrahman UFI, Emmanuel AK. Adaptive neuro-fuzzy inferential approach for the diagnosis of prostate diseases. Int J Intell Syst Appl 2022; 14(1).

[30] Zekri M. A review of medical image classification using adaptive neuro-fuzzy inference system (ANFIS). J Med Signals Sens 2012; 2(1): 49–60.
[31] Haznedar B, Arslan MT, Kalinli A. Optimizing ANFIS using simulated annealing algorithm for classification of microarray gene expression cancer data. Med Biol Eng Comput 2021; 59: 497–509.
[32] Ramana PV, Rosalina KM. Optimizing weak grid integrated wind energy systems using ANFIS-SRF controlled DSTATCOM. Sci Rep 2025; 15(1): 13662.
[33] Awasthi D, Khare P, Srivastava VK. ANFISmark: ANFIS-based secure watermarking approach for telemedicine applications. Neural Comput Appl 2025; 37(14): 8677–8693.
[34] Mirzaaghabeik H, Mashaan NS, Shukla SK. A predictive model for the shear capacity of ultra-high-performance concrete deep beams reinforced with fibers using a hybrid ANN-ANFIS algorithm. Appl Mech 2025; 6(2): 27.