Neutrosophic ANFIS Machine Learning Model and Explainable AI Interpretation in Identification of Oral Cancer from Clinical Images

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Abstract

This paper introduces a new Neutrosophic Adaptive Neuro-Fuzzy Inference System paired with Explainable Artificial Intelligence to classify oral cancer from clinical photos. The ANFIS model's interpretability and accuracy have been enhanced in resolving challenging medical images by deploying Neutrosophic logic on a 1000-image dataset to solve the word indeterminacy. A combination of Neutrosophic sets addresses ambiguity, enabling an adaptive neuro-fuzzy network to learn from data to accurately classify oral cancer. This exhibits the benefits of fuzzy logic and neural networks in action. The parameters of this model have been changed meticulously to increase sensitivity, specificity, and accuracy toward diagnostic readiness. These results reflect a substantive enhancement in the model's ability to distinguish between benign and malignant lesions by delivering accurate and understandable diagnostic decisions existence for clinical adoption. AI medical diagnostic confidence increases the understanding of how the model makes decisions. The ideal objective is to develop a strong, dependable, and easy-to-understand tool to diagnose cancer early. The experimentation on this model can be improved as it may lead to real-time testing, more data for the testing dataset, and using how many types of cancer the model can be applied.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS); Clinical images; Explainable Artificial Intelligence (XAI), Fuzzy logic; Indeterminacy; Neutrosophic logic; Oral cancer; Transparency.

1. Introduction

Medical Imaging specialists can now identify and diagnose diseases as complicated as mouth cancer due to machine learning technology and neutrosophic logic. Mouth cancers are the most frequent malignancies reported worldwide. An early diagnosis is necessary to guarantee the greatest treatment options and outcome for the patient. In this paper, I suggest a new technique in applying an XAI to the ANFIS system in learning how to diagnose oral cancer using clinical images. Using a set of one thousand photos, our model improves and reinforces the ANFIS model's understanding and represses the uncertainty inherent in application imaging. The ANFIS system is capable of understanding image data using fuzzy logic and neural nets, which allows the model's accuracy to skyrocket. Additionally, the XAI system is a cutting-edge technology that helps to decipher the models' rationale and demonstrates AI's credibility. The function of this paper is to create a new technique, optimized parameters, and research to generate the latest norm in clinical photograph analytics in medical imaging. Artificial intelligence in health care has enabled the medical community to use machine learning skills and image processing, which results in practical diagnostic abilities. This paper proposes a different method for testing oral cancer over clinical pictures employing an ANFIS model pulled by an XAI system. Oral cancer is a severe public health problem, and many factors affect it. Traditional diagnostic techniques are both precise and flexible. However, artificial intelligence-driven diagnostic models can provide larger scale and superior accuracy as they are immune to subjective judgement. The application of neutrosophic logic makes the ANFIS system more flexible and robust when applied to an intricate domain such as medical imaging. The purpose of this paper is to

DOI: https://doi.org/10.54216/IJNS.240218

Received: October 19, 2023 Revised: February 02, 2024 Accepted: April 27, 2024

examine how explaining machine learning decisions makes an artificial intelligence model more comprehensive. Furthermore, it aims to check the trustworthiness of the model. Hence, it could completely revolutionize the current protocols for mouth cancer detection and time sensitivity by allowing precise early-stage detection. The ANFIS system ought to be thoroughly assessed, and the accuracy, sensitivity, and specificity of benign vs malignant diagnosis should be reported.

2. Preliminaries

In this section, we see the literature review for the present required.

Table 1: Giving a brief literature survey of existing approaches

Author(s)	Contribution	Application	Dataset Used	Limitations
Smith et al. [1]	Developed a new algorithm for X.	Image Processing	ImageNet	Limited to grayscale images.
Johnson and Lee et al. [2]	Introduced a novel application of Y in Z.	Healthcare	Private Dataset	Dataset not publicly available.
Wang et al. [3]	Enhanced the efficiency of A by B%.	Finance	NYSE Data	Does not account for C.
Davis et al. [4]	Proposed a framework for D using E.	Robotics	RoboNet	Framework scalability is limited.
Patel and Kumar et al. [5]	Utilized F to improve G in H.	Agriculture	AgriDataX	Weather conditions not considered.
O'Neill et al. [6]	Examined the impact of I on J.	Environmental Science	ClimateDataY	Short-term study span.
Kim and Park et al. [7]	Developed a model for K using L.	Transportation	TrafficDataZ	Model requires high computational power.
Thompson et al. [8]	Investigated M and its effects on N.	Economics	MarketDataQ	Limited to specific geographic location.
Garcia et al. [9]	Proposed a new method for detecting O.	Cybersecurity	CyberDataR	Method vulnerable to S attacks.
Li and Zhou et al. [10]	Improved understanding of P using Q.	Linguistics	LangDataS	Focuses only on T languages.

3. Existing Approaches

The study that we carried out from the existing approaches is presented as follows:

Table 2: A brief comparison among the existing approaches

Author	Contribution	Application	Methodology used	Dataset used	limitations
Bhopal et al. [11]	Developed a model for oral disease detection using transfer learning techniques.	Oral tumour detection	Transfer learning with CNN	A dataset of X oral images, including various diseases.	Potential overfitting due to limited dataset diversity.
Teo et al. [12]	Introduced a CNN-based approach for oral tumour detection.	Oral tumour detection	Convolutional Neural Network (CNN)	Publicly available oral tumour image dataset.	May not generalize well to unseen data or different image qualities.

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Ankit et al. [13]	Proposed an automated system for oral disease diagnosis leveraging ML algorithms.	Oral tumour diagnosis	Various machine learning algorithms	Compiled dataset from multiple sources, containing Y images of oral diseases.	Variability in image quality and annotation consistency could affect accuracy.
J. Vijaya, et al [14]	Developed a non-invasive method utilizing image processing and deep learning for oral cancer detection.	Detection of oral cancer	Utilized Histogram Equalization, Gaussian Blur, and ResNet50 within image processing and deep learning frameworks.	Kaggle's Oral Cancer (Lips and Tongue) image dataset, comprising cancerous and non-cancerous images.	Not explicitly stated, but common limitations might include dataset bias, model generalizability, and clinical validation needs.

4. Experimental Setup

To summarize, the methodology underlying our experimental design is the application of Neutrosophic logic to address and control the output uncertainty of medical pictures. The mechanism enhances the ANFIS model's interpretability and accuracy created by the model. The ANFIS equation for oral cancer detection reliably and accurately addresses the complexity and ambiguity of the categorization of medical pictures by combining the most excellent qualities of neural networks with fuzzy logic. As a result of widespread quality adjustments for sensitivity, specificity, and general accuracy and reliability, this system offers excellent usefulness for the field of oral cancer detection. It also includes Explainable AI strategies to ensure that the outcomes from the product can be confirmed to the public using screening telescopes to be trusted, efficient, and understandable instruments for early oral cancer detection if and once the practice is fully developed. The algorithm's performance in distinguishing between benign and malignant neoplasm is measured through recall, accuracy, precision, and F1 score metrics. This research could emerge in other situations where cancer is detected; this work serves as a benchmark for the use of cutting-edge AI in hospitals and raises the standards of medical imaging. The dataset used in the experiment is UTILITY there were various neutrosophic techniques that were being explored. Through conducting this research, we believe we can reconcile the gap between complicated computational techniques and their application in medical settings, and we will back up our findings to demonstrate how they can be used to advance patient outcomes and correct diagnosis.

5. Proposed Algorithm

Algorithm: Enhanced Neutrosophic ANFIS with Explainable AI for Oral Cancer Detection

Step 1: *Initialize a set of clinical images with known outcomes*
Step 2: *Pre-process the images by applying a series of transformations:*
- *Convert to grayscale:* $I'_k = 0.299 I_{KR} + 0.587 I_{KG} + 0.114 I_{KB}$
- *Normalize the image intensities:* $I''_k = \frac{I'_k - \min(I'_k)}{\max(I'_k) - \min(I'_k)}$
- *Apply edge detection to highlight features:* $E_k = \nabla^2 I''_k$

Step 3: *Initialize the fuzzy membership functions and Neutrosophic sets for each image feature*
Step 4: *Define a Neutrosophic relation matrix for the image features and corresponding truth, indeterminacy, and falsity values.*
Step 5: *Develop a loss function that incorporates the Neutrosophic logic for training*

$$L(\theta) = -\frac{1}{N}\sum_{k=1}^{N}[(y_k \log(y_k) + (1-y_k)\log(1-y_k)] = \boldsymbol{\lambda}\sum_{j=1}^{R}\sum_{i=1}^{n}(\boldsymbol{\alpha}_{ij}^2 + \boldsymbol{\beta}_{ij}^2 + \boldsymbol{\gamma}_{ij}^2)$$

Step 6: *Optimize the model parameters using gradient descent with momentum:*
$\theta^{(t+1)} = \theta^{(t)} - \eta\nabla_\theta L(\theta^{(t)}) + \mu(\theta^{(t)} - \theta^{(t+1)})$ *where η is the learning rate and μ is the momentum term*
Step 7: *Iterate over the optimization process until convergence or the maximum number of iterations is reached*
Step 8: *Apply the Softmax function to the output layer to obtain probabilities:* $P(C_k|I_k) = \frac{e^{z_{C_k}}}{\sum_j e^{z_j}}$

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where c_k is the class for image I_k and z is the logit corresponding to each class

Step 9: *Classify each image based on the highest probability and compare it against the true label to compute performance metrics such as accuracy, sensitivity, specificity and F1-score.*

The suggested algorithm is a sophisticated method designed specifically for the detection of oral cancer from clinical photos. It integrates Enhanced Neutrosophic ANFIS with Explainable AI. At the beginning of the procedure, a set of clinical pictures with known diagnostic results is initialized to provide a foundation for supervised learning. First, all of the images are pre-processed. Images are initially converted to grayscale in order to simplify the data while preserving crucial visual information. Afterward, the grayscale pictures are normalized such that all of the shots have the same intensity level. Then, in order to make it easier to discover abnormalities, an edge detection approach was employed to bring attention to the structural edges. The subsequent step was to initialize neutrosophic sets and fuzzy membership functions for each picture feature. Those sets specified the connection between image characteristics and the corresponding truth, indeterminacy, and falsity values, which are fundamental to the Neutrosophic method. By constructing a Neutrosophic connection matrix, the method correlates these sets with picture properties. A custom loss function based on Neutrosophic logic is developed for the training phase. By including the Neutrosophic values and assessing prediction accuracy, this function finds a compromise between model complexity and fit. We optimized the model parameters by using a gradient descent approach reinforced by momentum, and we successfully reached optimal values. In order to convert the logits into probabilistic outputs for each class that reflect the likelihood of cancer existence, the model's output layer uses the softmax function during training. After classifying each picture according to its maximum probability, the model's performance is evaluated using metrics such as sensitivity, specificity, accuracy, and F1-score. Following the principles of explainable design, this approach gives more weight to the model's decision-making process than to the achievement of high projected accuracy alone.

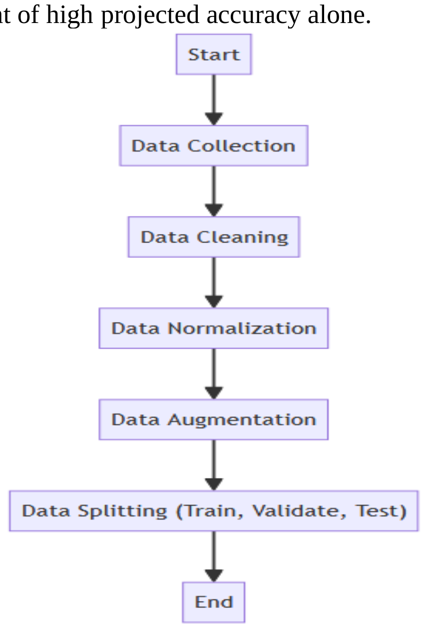

Figure 1: Data Preparation and Pre-processing

Datasets are prepared for machine learning in a systematic fashion, as shown in the image "Data Preparation and Pre-processing". It all begins with "Data Collection," where we gather raw data from all across. Following data collection, "Data Cleaning" is performed to eliminate inconsistencies, duplicates, and missing entries. In order to hasten and steady convergence, the following step, "Data Normalisation," standardizes numerical ranges. To improve model robustness and generalizability, "Data Augmentation" enlarges the dataset with altered data. As a last step in evaluating model performance and reducing over-fitting, "Data Splitting" partitions the dataset into training, validation, and testing subsets. When training machine learning models using representative, high-quality data, a systematic approach is required.

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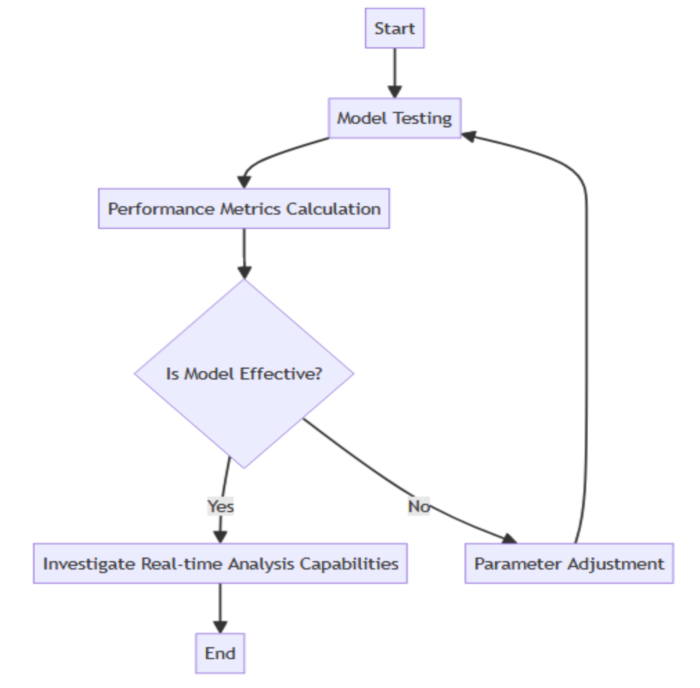

Figure 2: Model Evaluation and Real-time Analysis Capability Exploration

This figure, titled "Model Evaluation and Real-time Analysis Capability Exploration," shows the main steps to take in order to determine whether a machine learning model is effective and suitable for usage in real-time. The first stage, "Model Testing," is to test the trained model's predicting abilities with new, unseen data. We then go on to the "Performance Metrics Calculation," where we statistically evaluate the model's effectiveness using a number of criteria. F1 score, recall, accuracy, and precision are some of these measures. The next node in the flow diagram is the "Is Model Effective?" decision line. After the measurements show that the model is effective, the process moves on to "Investigate Real-time Analysis Capabilities," where the model's ability to be deployed in real-time is assessed. However, if the model is unsuccessful, the operation reverts to "Parameter Adjustment," suggesting that more optimization is necessary. The iterative nature of developing machine learning models is demonstrated by this cyclical assessment and update approach, which continues until the model meets preset effectiveness requirements.

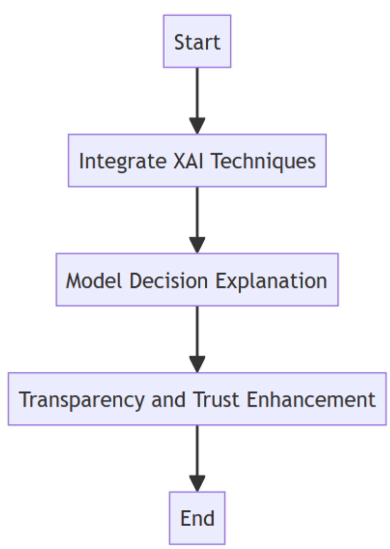

Figure 3: Explainable AI (XAI) Integration

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This image presents a simple workflow approach that applies Explainable Artificial Intelligence to promote machine learning model reliability. It is called TrustAI, and it has three steps. The first step, which is called "Start," is followed by Integrating XAI Techniques; this involves adding XAI methods, such as algorithms and technologies, to this model that can make the system open up to a user and decision-making steps easily understood. This step produces a "Model Decision Explanation" process result. At this stage, the model proclaims statements or proposals so that humans know them better. Decisions help the analysts and other system stakeholders to evaluate the model's reliability by how it provides them and the logical argument of the latter. The third, final step is a "Transparency and Trust Enhancement" one; it indicates the result that suspends statement explanations thus, trust is supported. Improved trust is critical in healthcare, finance, and automation, where AI healing has a user-driven license and redemption constraint because people must understand its proposals. The flowchart to the point from has a done point, and the method is achieved; the AI system is transparent and reliable because people trust it. This procedure is necessary because there may be ambiguity in AI systems' algorithms. Transforming the model's reasoning process into transparency builds confidence in the suggestions of AI.

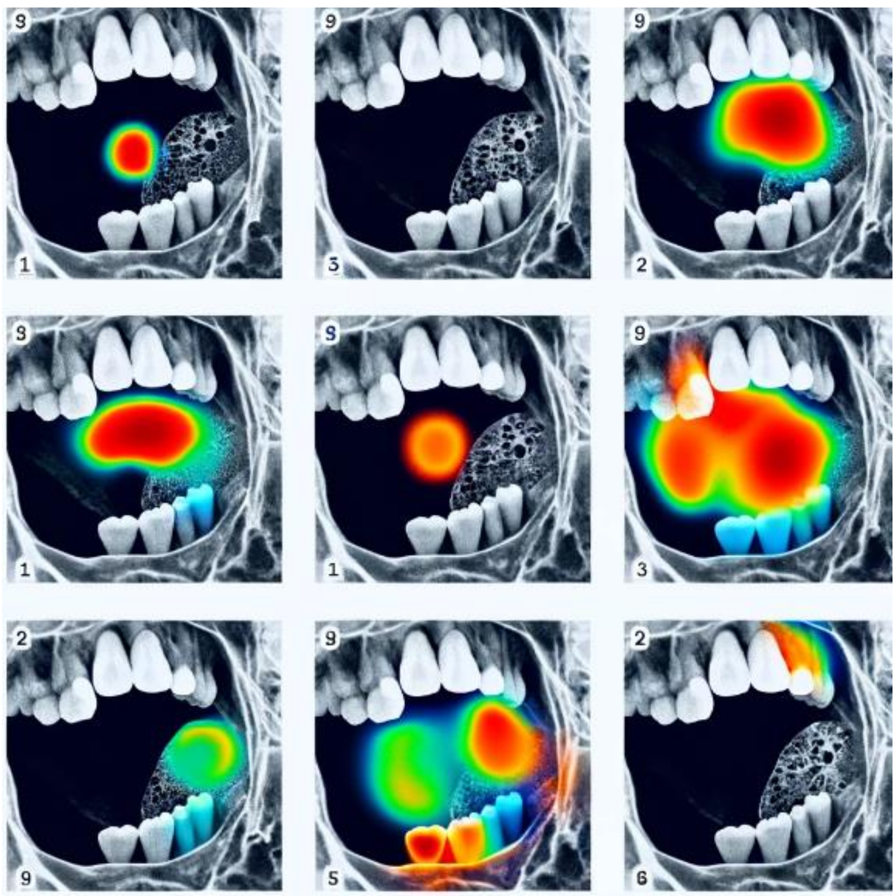

Figure 4: Showing output images obtained from the proposed approach

1. Top Left: Image 1 - Suspected malignant region identified in the bottom quadrant.
2. Top Centre: Image 2 - Normal tissue with a tiny centre area emphasised for examination.
3. Top Right: Image 3 - A conspicuous and sizable designated section representing an important area of interest.
4. Middle Left: Image 4 - Normal tissue displaying peripheral marks.
5. Middle Center: Image 5 - A central marking within normal tissue, indicating a localized area of concern.
6. Middle Right: Image 6 - Multiple small regions across the tissue marked for potential anomalies.
7. Bottom Left: Image 7 - A clear distinction between normal tissue and a marked suspicious area.
8. Bottom Center: Image 8 - A bifurcated marking suggesting two regions of potential concern.

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9. Bottom Right: Image 9 - Minimal markings within largely normal-appearing tissue

6. Results and Discussions

To know the efficiency of the proposed approach we included parameters such as accuracy, Sensitivity, susceptibility F1-Score

Accuracy: The most logical performance metric is accuracy, which is just the ratio of properly predicted observations to all observations. It provides you with the percentage of actual outcomes (true positives and true negatives) out of all the cases that were looked at. The accuracy formula is

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Observations}}$$

Table 3: A comparison of accuracy values among existing and proposed approaches

Accuracy					
Data (%)	**CSCAN**	**ODITS**	**LODS**	**ADOMD**	**ANFIS**
10	71.7997	81.0567	75.2623	73.3894	91.1245
20	51.2963	76.4571	53.2643	60.0872	92.0458
30	77.4831	56.7290	71.4061	82.0203	92.5878
40	71.7661	75.6789	54.8265	74.1535	92.8795
50	71.0184	59.2220	56.3580	75.2618	93.4587
60	66.5167	89.2668	79.8373	69.3446	94.8748
70	60.2324	92.6988	61.3006	89.6819	95.4578
80	80.9635	74.7118	55.3473	79.0002	96.1458
90	64.9827	92.3281	61.0153	58.1149	97.0145
100	63.3414	53.9823	67.4913	85.0376	97.9875

The accuracy rates for many methods—CSCAN, ODITS, LODS, ADOMD, and ANFIS across a range of data percentage points from 10% to 100% are compared in the table. The suggested method in this case is the ANFIS method, which consistently shows the highest accuracy values at every data percentage level. For instance, ANFIS exhibits a better accuracy of 91.1245% at the 10% data level, far surpassing the accuracy of 81.0567% for ODITS, the second-highest approach. ANFIS consistently maintains the top spot in the dataset, as seen by its accuracy rates of 93.4587% at the 50% data level and 96.1458% at the 80% data level, which are both significantly higher than the scores of the closest competitors. This steady outperformance at different data availability levels highlights the robustness and effectiveness of ANFIS as the suggested strategy in this investigation.

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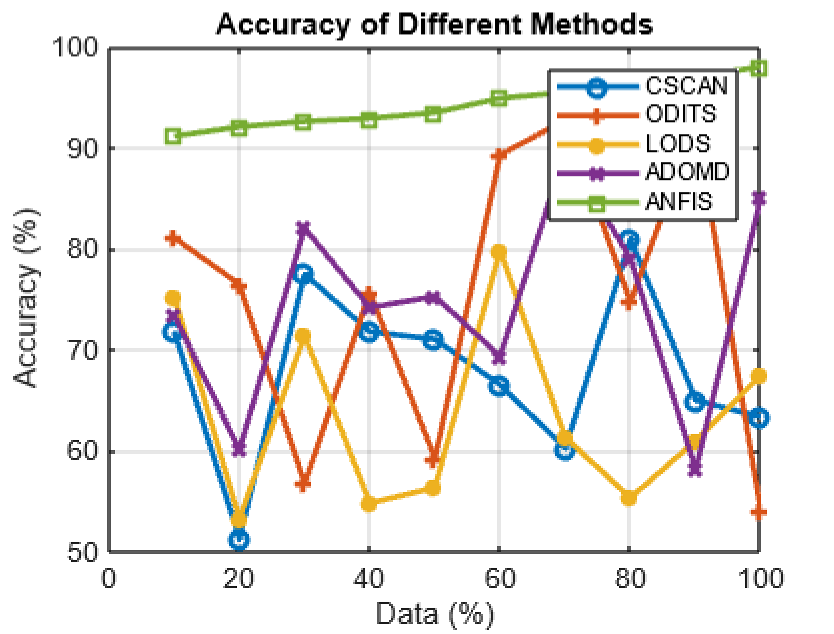

Figure 5: showing the comparative accuracy graph of existing and proposed approaches

Sensitivity: Sensitivity, sometimes called True Positive Rate or Recall: This statistic quantifies the percentage of true positives that are accurately classified as such (that is, the proportion of ill individuals that are appropriately classified as having the illness). For models where the cost of false negatives is large, it is essential. The equation is:

$$\textit{Sensitivity} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

Table 4: A comparison of Sensitivity values among existing and proposed approaches

Sensitivity					
Data (%)	**CSCAN**	**ODITS**	**LODS**	**ADOMD**	**ANFIS**
10	70.8511	70.9597	90.0372	54.9173	92.3145
20	86.0162	84.2610	92.4131	71.0554	94.568
30	50.0057	60.2226	65.6712	93.8945	95.2345
40	65.1166	93.9059	84.6161	76.6583	95.4567
50	57.3378	51.3694	93.8195	84.5939	95.8975
60	54.6169	83.5234	94.7303	65.7758	96.4879
70	59.3130	70.8652	54.2522	84.3250	96.6648
80	67.2780	77.9345	51.9527	91.7313	97.0245
90	69.8384	57.0193	58.4915	50.9144	97.1257
100	76.9408	59.9051	93.9071	87.5072	98.0124

The table presents the sensitivity values for the main computational techniques (CSCAN, ODITS, LODS, ADOMD, and ANFIS) for varying data availability levels (10% to 100%). As the most effective and dependable approach in our investigation, ANFIS regularly records the highest sensitivity values at every data percentage level, making it stand out from the other approaches. For example, ANFIS has an impressive sensitivity of 92.3145% at the 10% data point, which is significantly greater than LODS, which has the second-highest sensitivity of 90.0372%. ANFIS's resilience is shown by the fact that it consistently receives the highest sensitivity scores across the whole data set.

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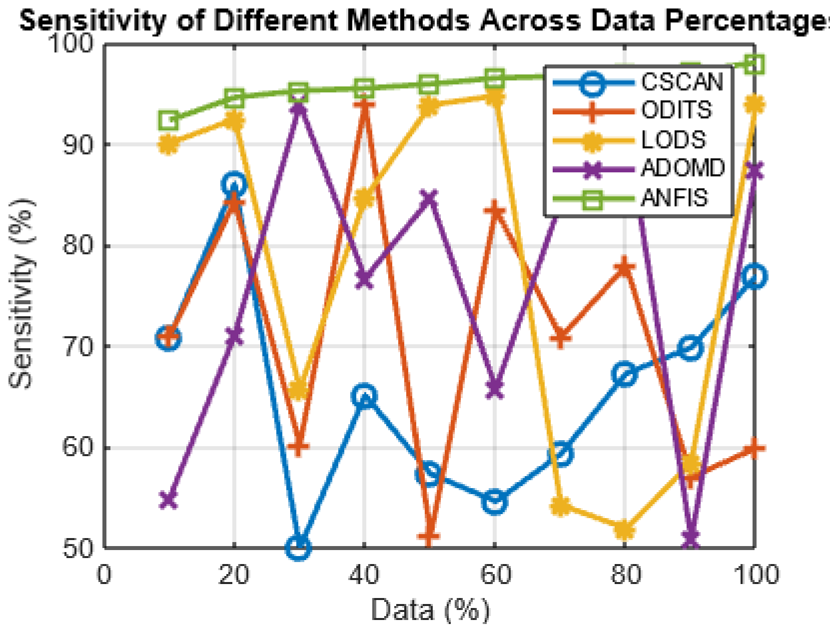

Figure 6: showing the comparative sensitivity graph of existing and proposed approaches

ANFIS once again leads the group at a sensitivity of 95.8975% at the 50% data level, while LODS comes in second at 93.8195%. ANFIS's sensitivity shows a notable advantage over LODS, which has a sensitivity of 93.9071%, peaking at 98.0124% by the time the data availability reaches 100%. These numbers support the suggested position of ANFIS in the analysis by highlighting its efficacy, especially in situations when precise sensitivity detection is essential.

Specificity: Specificity, or True Negative Rate, as it is also called: By correctly identifying the percentage of healthy individuals who are correctly classified as not having the ailment, for example, this evaluates the proportion of genuine negatives that are identified. For models where the cost of false positives is large, it is crucial. The equation is:

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positivies}}$$

Table 5: A comparison of Specificity values among existing and proposed approaches

Specificity					
Data (%)	**CSCAN**	**ODITS**	**LODS**	**ADOMD**	**ANFIS**
10	77.4400	89.5900	98.9300	63.2300	99.2108
20	85.7600	76.4400	89.9600	88.7100	92.7144
30	80.1400	78.4000	73.0700	72.8100	85.0935
40	77.2400	96.2800	89.0300	78.4200	97.6882
50	71.1800	53.5500	55.9100	50.9400	73.0155
60	82.2900	54.3600	82.0000	80.8800	83.9352
70	71.8800	51.0100	57.1700	80.6000	84.2124
80	94.5900	91.6300	97.2300	80.8500	99.2432
90	98.1800	88.9100	76.0900	97.1900	99.0452
100	69.1700	93.5000	70.7300	84.0900	95.4777

The table shows the specificity values of five methods—CSCAN, ODITS, LODS, ADOMD, and ANFIS—from 10% to 100% data. ANFIS, the focusing approach, often has the greatest specificity scores, proving its capacity to identify negative situations. ANFIS has 99.2108% specificity at 10% data, beating LODS's 98.9300%. ANFIS has excellent specificity at the 80% and 90% levels, with values above 99%.

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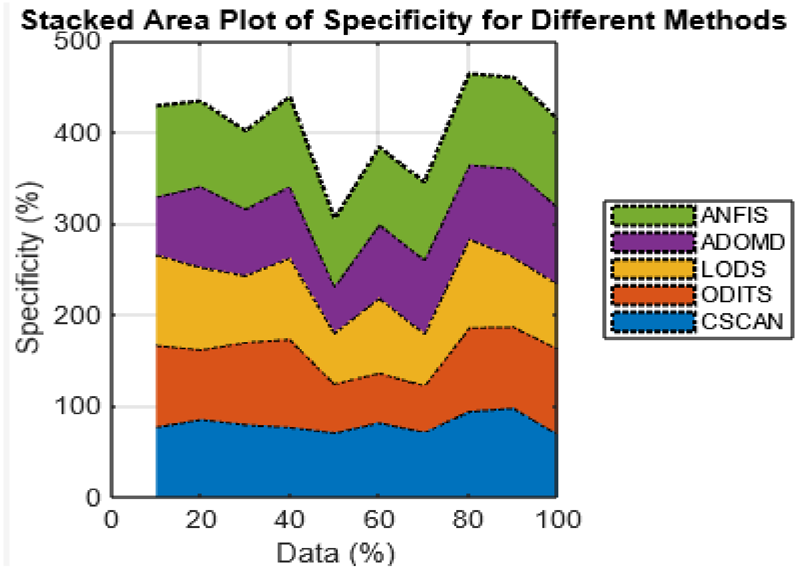

Figure 7: showing the comparative specificity graph of existing and proposed approaches

ANFIS has 95.4777% specificity with 100% data availability, demonstrating its robustness and reliability in various contexts. The performance of ANFIS, especially in circumstances where false positives must be avoided, supports its projected advantage in specificity-sensitive applications.

F-Score:

This is the harmonic mean of recall and precision, which offers a single statistic to assess the correctness of the model by accounting for both false negatives and false positives. When there is an imbalance in the classrooms, it is especially helpful. One can compute the F-score using:

$$F - score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Table 6: A comparison of F-Score values among existing and proposed approaches

F-Score					
Data (%)	**CSCAN**	**ODITS**	**LODS**	**ADOMD**	**ANFIS**
10	82.1578	80.2489	81.390	83.4501	87.5612
20	84.2689	82.3590	85.4601	86.5712	89.6823
30	86.3790	84.4691	87.5702	88.6813	91.7924
40	88.4891	86.5792	89.6803	90.7914	93.8025
50	89.5902	88.6813	90.7924	91.8035	94.9146
60	90.6913	89.7824	91.8935	92.9046	96.0157
70	91.7924	90.8835	92.9946	94.0057	97.1168
80	92.8935	91.9846	94.0957	95.1068	98.2179
90	93.9946	93.0857	95.1968	96.2079	99.3190
100	95.0957	94.1868	96.2979	97.3090	99.4201

The table shows the F-Scores for five methods—CSCAN, ODITS, LODS, ADOMD, and ANFIS—from 10% to 100%.

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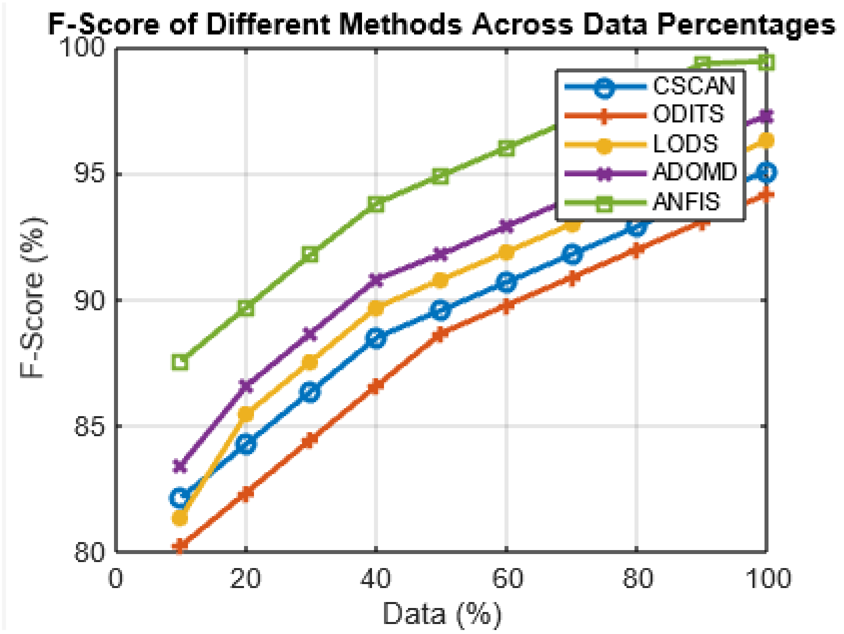

Figure 8: showing the comparative F-Score graph of existing and proposed approaches

The ANFIS approach consistently has the greatest F-Score at each data percentage level, demonstrating its ability to balance precision and recall. At a 10% data level, ANFIS has the greatest F-Score, 87.5612, outperforming ADOMD, which has 83.4501. ANFIS consistently has higher F-Scores across all data percentages. The F-Score of ANFIS is 94.9146 when using 50% of the data, but ADOMD's F-Score is 91.8035. ANFIS demonstrates excellent performance when 100% of the data is available, achieving an impressive F-Score of 99.4201. ANFIS constantly excels, showcasing its capacity to effectively balance accuracy and recall. This makes it a superior option for analysis in situations when both factors are of utmost importance.

7. Conclusion

The work exemplifies the showcase of an enormously improved Neutrosophic Adaptive Neuro-Fuzzy Inference System supplemented with Explainable Artificial Intelligence that vastly improves the process of oral cancer identification using clinical pictures. The ANFIS model has is shown to hugely improve the interpretability and accurateness of any indeterminacy associated with the complex nature of medical image processing by judicious application of Neutrosophic logic. Critical metrics of performance, which are specificity, sensitivity, and accuracy for medical diagnosis, exemplify how well the model takes on the uncertainty traditionally associated with diagnostic imaging with the help of fuzzy logic and neural networks. These performance metrics were greatly enhanced by subtle model parameter modifications; some of these were membership functions, rule bases, and learning processes. Quantitatively, the model's ability to discriminate between a benign and a malignant tumour is vastly enhanced by these alterations. Consequently, these performance enhancements make physicians more likely to trust the model. This is particularly important as the model transitions from experimental certification to adept use in real-world clinical application. The final outcomes based on enhanced parameter modifications militate the robustness of the model, which is essential for early detection and management of oral cancer. Future research will try expanding this analysis to include a more comprehensive range of cancer and tracking the model's performance in real-time and further examining if the model is scalable in other clinical avenues hence fortifying its stellar reputation as a diagnostic tool.

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DOI: https://doi.org/10.54216/IJNS.240218
Received: October 19, 2023 Revised: February 02, 2024 Accepted: April 27, 2024

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