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A Hybrid Fuzzy Soft Prediction Model for Transforming Acoustic Voice Data into Linguistic Knowledge

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Abstract

This paper demonstrates the diagnostic modeling of 20 patients denoted as a universe set U = {x1, x2, ..., x20} and its parameter set denoted as E = {VPI, FF, A}, where “VPI” represents the Vocal Perturbation Index, “FF” represents the Fundamental Frequency of the patient, and “A” represents Age. Mathematical prediction models are designed and applied using two well-established mathematical frameworks called Fuzzy Set Theory, which deals with degrees of membership in modeling uncertainty and vagueness in the interval [0,1], and Soft Set Theory, a parametric approach to modeling vagueness. A mapping F: E → F(U) is constructed for the analysis of uncertainty in vocal health assessment, where F(U) denotes the complete lattice of fuzzy subsets of U. In this paper, patients voice recordings are obtained, acoustic features are extracted and embedded in a structured dataset. A triangular membership function is applied in the formulation of the mathematical prediction model to define fuzzy partitions over the parameter space. Here, each crisp data point is converted to corresponding degrees of membership in predefined linguistic classes through the process of fuzzification, and the resulting mathematical inferences provide a rigorous foundation for subsequent approximate reasoning and the decision-support process in vocal health diagnostic assessment.

Keywords: Fuzzy soft set; Vocal health; Acoustic parameters; Fuzzification; Uncertainty modeling; Diagnostic systems

1. Introduction

Vocal disorders constitute a major clinical concern because they can impair communication, occupational performance, and quality of life. Although acoustic analysis offers a non-invasive pathway for assessing vocal function, clinical interpretation remains difficult because voice measures vary continuously and are influenced by physiology, age, environment, and recording conditions. Consequently, rigid thresholding and purely crisp classifications may lose severity information, particularly in borderline cases. Acoustic perturbation and intensity-related measures have been shown to differ between speakers with and without voice disorders, supporting their diagnostic relevance (Brockmann-Bauser et al., 2018). Yet, uncertainty persists in mapping numerical indicators such as fundamental frequency (F0/FF) and perturbation indices to clinically meaningful judgments. Computational intelligence provides tools for modeling such uncertainty in medical decision support (Kacprzyk et al., 2020; Pedrycz, 2020). Fuzzy set theory models gradual transitions via membership functions on [0,1] (Zadeh, 1965), and fuzzy decision-making in multi-criteria environments has a classical foundation in the work of Bellman and Zadeh (1970). Core theory and engineering practice for membership design and fuzzy reasoning are well established (Klir & Yuan, 1995; Ross, 2017). Interpretable rule-based inference particularly Mamdani-type systems supports linguistic-to-decision mappings that align with clinician reasoning (Mamdani, 1977), while uncertain rule-based fuzzy systems further address uncertainty in rules and measurements (Mendel, 2017).

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Soft set theory provides a parameterized framework for handling vagueness (Molodtsov, 1999), and its hybridization with fuzzy sets yields fuzzy soft sets that combine graded membership with parameter dependence (Maji et al., 2001). Conceptual precision is essential when applying soft-set operations in practice (Singh & Onyeozili, 2012), and algebraic extensions such as soft semirings contribute formal tools for parameterized information processing (Feng et al., 2010). Recent research has improved fuzzy-soft efficiency through parameter reduction methods, including correlation-based (Ma et al., 2020) and distance-based approaches (Qin et al., 2023). Moreover, aggregation operators such as OWA enable flexible multi-criteria fusion (Yager, 1988, 2013).In vocal risk diagnosis, fuzzy-soft modeling has shown promise (Sanabria et al., 2023), and structured diagnostic frameworks (e.g., ICD-11) motivate transparent decision support in healthcare (World Health Organization, 2019). This study develops a hybrid fuzzy-soft prediction model that transforms acoustic voice data (FF, VPI) and age into linguistic knowledge via triangular membership functions and a fuzzy-soft mapping $F:E\to F(U)$, supporting uncertainty-aware and interpretable vocal health assessment.

2. Preliminaries

This section presents the fundamental mathematical concepts and definitions underlying the integrated aggregated weighted fuzzy–soft diagnostic prediction model. The preliminaries provide the theoretical basis for fuzzy membership modelling, soft set parameterization, fuzzy–soft structures, and α-cut discretization.

2.1. Fuzzy Sets

Definition 2.1 Fuzzy Set (Zadeh, 1965): Let U be a non-empty set. A fuzzy set A on U is defined by a membership function

$$\mu_A: U \to [0,1], \text{ i.e,}$$

$$A = \{(x, \mu_A(x)) | x \in U, 0 \le \mu_A(x) \le 1\}. \qquad (1)$$

Where $\mu_A(x)$ represents the degree of membership of element x in A.

If $\mu_A = 1$, then x fully belongs to A.

If $\mu_A = 1$, then x does not belong to A.

If $0 < \mu_A(x) < 1$, then x partially belongs to A and $\mu_A(x)$ establishes the degree of membership from x to A. A fuzzy set can be discrete or continuous. For discrete fuzzy sets, $\mu(x)$ can be expressed as follows:

$$\mu_A(x) = \frac{1}{|x_i|} \sum_{i=1}^{m} \mu_A(x_i) \qquad (2)$$

where m is the number of elements in U.

Example 2.1 Assume that $U = \{x_1, x_2, x_4, x_5, x_6\}$ represent six patients.

Define a fuzzy set A representing altered voice by

$$\mu_A(x_1) = 0.19, \quad \mu_A(x_2) = 0.34, \quad \mu_A(x_3) = 0.81$$

$$\mu_A(x_4) = 0.76, \quad \mu_A(x_5) = 0.44, \quad \mu_A(x_6) = 0.92$$

Then patient x_6 exhibits the highest degree of vocal alteration. Moreover, an important notion in fuzzy sets called the α-cut sets, which corresponds to any fuzzy set A, may be considered as an intermediate set that connect between fuzzy sets and ordinary sets, is a crisp subset of A defined by:

$$A_\alpha = \{x \in U : A(x) \ge \alpha, \alpha \in (0,1]\} \qquad (3)$$

$A_1 = \{x \in U : A(x) \ge 1\}$ is called the core of the fuzzy set A, while

$\text{Supp } A = \{x \in U : A(x) > 0\}$ is called the support of the fuzzy set. It is important to note that each fuzzy set can be related to a collection of crisp sets using the concept of α-level set.

2.2. Soft Sets

Soft set theory was pioneered by Molodtsov, (1999) as a method for dealing with vagueness. Molodtsov showed in his paper that the theory can be successfully applied to several areas; for example, game theory, Perron-integration, Riemann integration, the smoothness of functions, etc. Also, he showed that soft set theory is free from the parametrization insufficiency syndrome of other theories developed for vagueness. A soft set can be represented by a Boolean valued information system and thus can be used to represent a data set.

Definition 2.2 Soft Set (Molodtsov, 1999): A soft set F_A over $X \subseteq U$, denoted by F_A^X or (F, A), is a set defined by:

$f_A^X: E \rightarrow S^X$ such that $f_A^X(e) = \emptyset$ if $e \notin A$. Hence, f_A^X is called approximation function of F_A^X, and the value $f_A^X(e)$ is a set called e-element of F_A^X for all $e \in E$. Thus, a soft set over X can be expressed by

$$F_A^X = \{(e, f_A^X(e): e \in E, f_A^X(e) \in S^X\}. \qquad (4)$$

Example 2.2: Let $U = \{x_1, x_2, x_3, x_4\}$ be a set of recorded voice samples and $E = \{e_1 =$ High Pitch, $e_2 =$ Low Pitch, $e_3 =$ Breathiness$\}$ be the set of observed vocal features. A soft set F can be defined as:

$$F = \{(e_1, \{x_1, x_2\}), (e_2, \{x_3, x_4\}), (e_3, \{x_2, x_3\})\}$$

3. Materials and Methods

In soft computing systems, the universe of discourse represents the complete set of objects under investigation, while parameters represent measurable attributes used for evaluation (Molodtsov, 1999; Feng et al., 2010). For the recording of the voices, these were performed and collected in a controlled clinical environment by an expert in Phonoaudiology through a study conducted by the Faculty of Health Sciences in Nigeria using professional condenser microphones and digital recording devices. Patients were instructed to sustain vowel phonation for at least five seconds under standardized conditions. The system functions at a sampling signal rate of 4.41×10^4Hz with a quantization depth of 16-bits.

3.1. System Design and Computational Flowchart

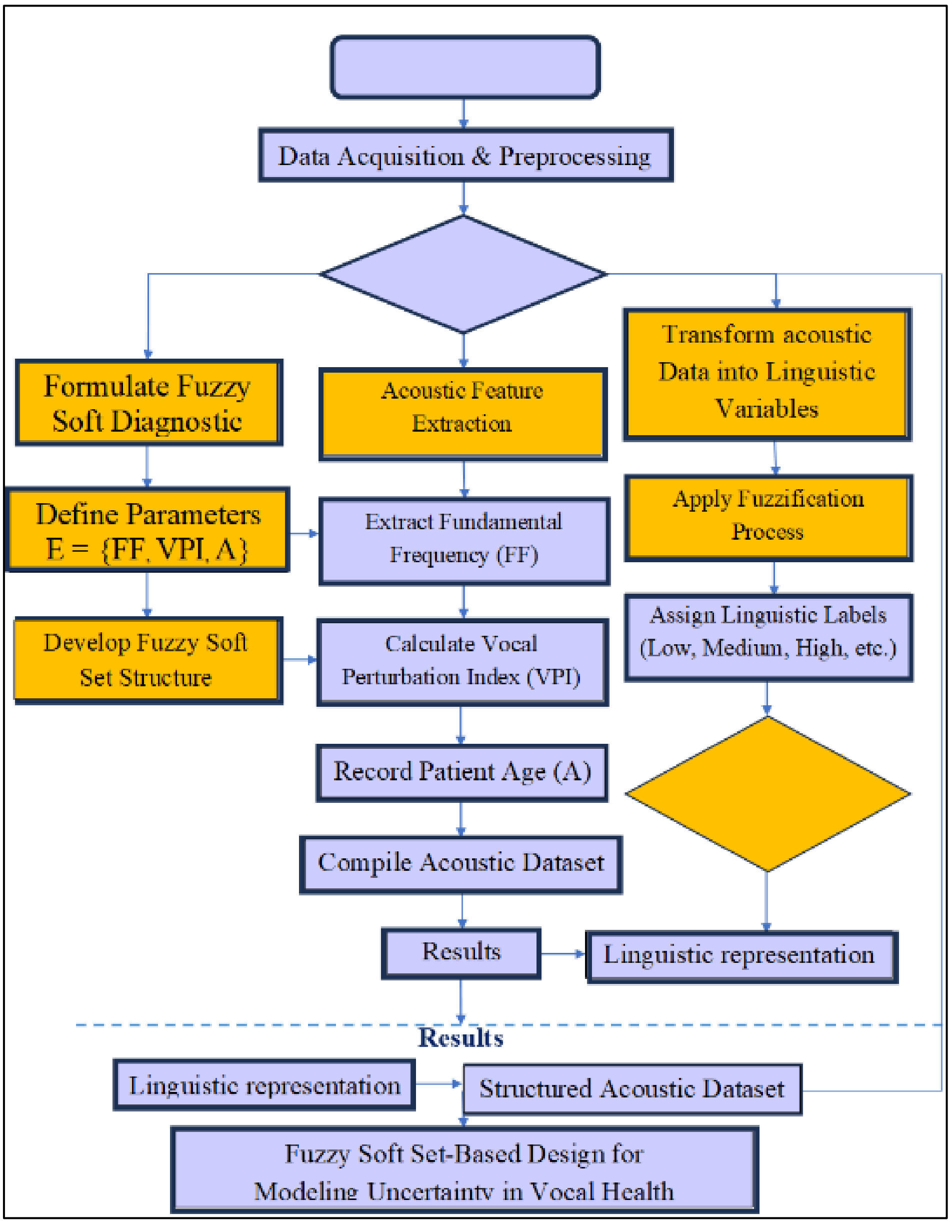

Figure 1 Mathematical flowchart showing the sequential processing stages of the proposed fuzzy soft diagnostic model, including data acquisition, feature extraction, fuzzy soft mapping, and fuzzification of acoustic parameters

4. Results

In this section, we present a soft expert system obtained from a dataset collected during the evaluation of the tone of voice of 20 patients from the Faculty of Health Sciences. From each preprocessed voice signal, the dataset obtained contains the observed values of the following acoustic parameters; (i) fundamental frequency (FF) which reflects the vibration rate of the vocal folds and serves as a primary indicator of pitch. It is estimated using time domain and frequency domain analysis techniques, (ii) the vocal perturbation index (VPI) quantifies cycle-to-cycle variations in vocal fold vibration. It is computed by analyzing temporal fluctuations in pitch periods, and Age, which is included as a demographic factor due to its influence on vocal fold elasticity and respiratory efficiency. Patient age is obtained through medical records. Our purpose is to design a soft expert system using fundamental frequency, vocal perturbation index, and Age as input values, while the output value will be the voice risk.

Let the universe of discourse be:

$$U=\{x_1, x_2, \dots, x_{20}\}, \qquad (6)$$

Then the extracted parameter vector is

$$E(x) = \{(FF(x), VPI(x), Age(x)) \qquad (7)$$

Parameter extraction was implemented using Praat-based algorithms and the crisp dataset

obtained from 20 patients are given below:

Table 1 The input values of 20 patients

Patient	**FF(Hz)**	**VPI**	**Age**
x_1	288	1.407	53
x_2	207	2.250	29
x_3	221	1.390	38
x_4	159	1.791	25
x_5	188	1.486	53
x_6	220	0.674	39
x_7	176	2.000	44
x_8	150	4.602	38
x_9	261	2.358	18
x_{10}	244	3.062	38
x_{11}	195	1.615	51
x_{12}	236	2.750	50
x_{13}	240	2.494	20
x_{14}	209	0.868	29
x_{15}	210	1.486	29
x_{16}	162	4.258	54
x_{17}	227	1.000	38
x_{18}	225	2.952	63
x_{19}	231	1.089	61
x_{20}	202	1.250	42

4.1. Fuzzification of Acoustic Parameters

The fuzzy membership functions are defined using triangular structures with linear growth and decay segments. Each linguistic variable is characterized by lower, central, and upper bounds, which determine the gradual transition between adjacent classes. Since the soft set theory cannot be applied directly to the dataset obtained, we first proceed to fuzzify the factors through membership functions, which are constructed using the following linguistic variables:

4.1.1. Membership Function Design for FF

For each parameter, three triangular membership functions were constructed.

For the Fundamental Frequency (FF), we have; AT (Altered Tone), NT (Normal Tone) and ST (Stable Tone) and so the mathematical formulation for each linguistic variable is given by:

$$\mu_{AT}(x) = \begin{cases} 0, & x \leq 10 \text{ or } x > 200 \\ \frac{(2x-20)}{190}, & 10 < x \leq 105 \\ \frac{2(200-x)}{190}, & 105 < x \leq 200 \end{cases} \quad (7)$$

$$\mu_{NT}(x) = \begin{cases} 0, & x < 190 \text{ or } x > 275 \\ \frac{3(x-190)}{127.5}, & 190 \leq x \leq 232.5 \\ \frac{3(275-x)}{127.5}, & 232.5 < x \leq 275 \end{cases} \quad (8)$$

$$\mu_{ST}(x) = \begin{cases} 0, & x < 265 \text{ or } x > 400 \\ \frac{2(x-265)}{135}, & 265 \leq x \leq 332.5 \\ \frac{2(400-x)}{135}, & 332.5 < x \leq 400 \end{cases} \quad (9)$$

Fuzzification results for fundamental frequency

Each crisp value was converted into fuzzy memberships using the membership functions defined in equations (7,8 and 9) above. For each patient, we computed the 3 membership values (AT, NT, ST) and the results are given below:

Patient $\mathbf{x_1}$:

$$FF_1 = 288\text{Hz},$$

For the FF membership, we have;

$FF_1 \rightarrow AT$:

$$\mu_{AT}(288) = 0. \text{ Since } (x_1 > 200)$$

$FF_1 \rightarrow NT$:

$$\mu_{NT}(288) = 0. \text{ Since } (x_1 > 275)$$

$FF_1 \rightarrow ST$:

$$\mu_{ST}(288) = \frac{2(x_1-265)}{135} \text{ since } 265 \leq 288 \leq 332.5,$$

$$\mu_{ST}(288) = \frac{2(288-265)}{135} = \frac{46}{135} = 0.341 \text{ to 3dp.}$$

Thus,

$$\text{FF triple for } x_1 = \{AT{:}0, NT{:}0, ST{:}0.341\} \quad (10)$$

Patient $\mathbf{x_2}$:

$$FF_2 = 207$$

For the FF membership, we have;

$FF_2 \rightarrow AT$:

$$\mu_{AT}(207) = 0. \text{ Since } (x_2 > 200)$$

$FF_2 \rightarrow NT$:

$\mu_{NT}(207) = \frac{3(x_2-190)}{127.5}, \quad 190 \le x_2 \le 232.5$ $\qquad \mu_{NT}(207) = \frac{3(207-190)}{127.5} = \frac{51}{127.5} = 0.400$ to 3dp.

$FF_2 \rightarrow ST$:

$$\mu_{ST}(207) = 0 \text{ since } x_2 < 265$$

Thus,

$$\text{FF triple for } x_2 = \{AT{:}0, NT{:}0.400, ST{:}0\} \tag{11}$$

Patient $\mathbf{x_{20}}$:

$$FF_{20} = 202$$

For the FF membership, we have;

$FF_{20} \rightarrow AT$:

$$\mu_{AT}(202) = 0. \text{ Since } (x_{20} > 200)$$

$FF_{20} \rightarrow NT$:

$$\mu_{NT}(202) = \frac{3(x_{20} - 190)}{127.5}, \quad 190 \le x_{20} \le 232.5$$

$$\mu_{NT}(202) = \frac{3(202 - 190)}{127.5} = \frac{36}{127.5} = 0.280$$

$FF_{20} \rightarrow ST$:

$$\mu_{ST}(202) = 0 \text{ since } x_{20} < 265$$

Thus,

$$\text{FF triple for } x_{20} = \{AT{:}0, NT{:}0.280, ST{:}0\} \tag{12}$$

Membership Function Model for VPI

For the vocal perturbation index (VPI), we have; NV (Normal Voice), RV (Rough Voice) and AV (Altered Voice). The mathematical formulations models are constructed below:

$$\mu_{NV}(x) = \begin{cases} 0, & 2x < 0.4 \text{ or } 2x > 4 \\ \frac{(5x-1)}{4.5}, & 0.4 \le 2x \le 2.2 \\ \frac{5(2-x)}{4.5}, & 2.2 < 2x \le 4 \end{cases} \tag{13}$$

$$\mu_{RV}(x) = \begin{cases} 0, & 2x < 3.4 \text{ or } 2x > 6.2 \\ \frac{(5x-8.5)}{3.5}, & 3.4 \le 2x \le 4.8 \\ \frac{(15.5-5x)}{3.5}, & 4.8 < 2x \le 6.2 \end{cases} \tag{14}$$

$$\mu_{AV}(x) = \begin{cases} 0, & x < 2.7 \text{ or } x > 6.3 \\ \frac{(5x-13.5)}{9}, & 2.7 \le x \le 4.5 \\ \frac{(31.5-5x)}{9}, & 4.5 < x \le 6.3 \end{cases} \tag{15}$$

Fuzzification results for Vocal Perturbation Index (VPI)

Each crisp value was converted into fuzzy memberships using the membership functions defined in equations (13, 14 and 15) and the results of the linguistic variables are shown below:

$VPI_1 = 1.407$ from table 3.1 above, we have;

$VPI_1 \rightarrow NV$:

$$\mu_{NV}(1.407) = \frac{5(2-x_1)}{4.5}, \quad \text{since } 2.2 < 2x_1 \leq 4.$$

$$\mu_{NV}(1.407) = \frac{5(2-1.407)}{4.5} = \frac{2.965}{4.5} = 0.659.$$

$VPI_1 \rightarrow RV$:

$$\mu_{RV}(1.407) = 0. \text{ Since } (2x_1 < 3.4)$$

$VPI_1 \rightarrow AV$:

$$\mu_{AV}(1.407) = 0. \text{ Since } (x_1 < 2.7)$$

Therefore, VPI triple for x_1 implies;

$$VPI_1: NV = 0.659, RV = 0, AV = 0 \qquad (16)$$

$$\mathbf{VPI_2 = 2.25}$$

$VPI_2 \rightarrow NV$:

$$\mu_{NV}(2.25) = 0, \qquad 2x_2 > 4.$$

$VPI_2 \rightarrow RV$:

$$\mu_{RV}(2.25) = \frac{(5x - 8.5)}{3.5}, \quad 3.4 \leq 2x_2 \leq 4.8$$

$$\mu_{RV}(2.25) = \frac{(5\times 2.25 - 8.5)}{3.5} = \frac{2.75}{3.5} = 0.786.$$

$VPI_2 \rightarrow AV$:

$\mu_{AV}(2{,}25) = 0. \text{ Since } (x_2 < 2.7)$

Therefore, VPI triple for x_2 implies;

$$VPI_2 = \{ NV: 0, RV: 0.786, AV: 0\} \qquad (17)$$

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$$\mathbf{VPI_{20} = 1.250}$$

$VPI_{20} \rightarrow NV$:

$$\mu_{NV}(1.250) = \frac{5(2-x_{20})}{4.5}, \qquad 2.2 < 2x_{20} \leq 4.$$

$$\mu_{NV}(1.250) = \frac{(2-1.250)}{4.5} = \frac{3.75}{4.5} = 0.830.$$

$VPI_{20} \rightarrow RV$:

$$\mu_{RV}(1.250) = 0. \text{ Since } (2x_{20} < 3.4)$$

$VPI_{20} \rightarrow AV$:

$$\mu_{AV}(1.250) = 0. \text{ Since } (x_{20} < 2.7)$$

Therefore, VPI triple for x_{20} implies;

$$VPI_{20} = \{ NV: 0.830, RV: 0, AV: 0\} \qquad (18)$$

Membership Function Model for Age

The membership function for the AGE is partitioned into three parts, namely: Young (Y), Middle(M) and Old (O). The mathematical formulations are designed constructively to be:

$$\mu_Y(x) = \begin{cases} 0, & x < 15 \text{ or } x > 35 \\ \frac{(2x-30)}{20}, & 15 \le x \le 25 \\ \frac{(70-2x)}{20}, & 25 < x \le 35 \end{cases} \qquad (19)$$

$$\mu_M(x) = \begin{cases} 0, & x < 30 \text{ or } x > 50 \\ \frac{2(x-30)}{20}, & 30 \le x \le 40 \\ \frac{2(50-x)}{20}, & 40 < x \le 50 \end{cases} \qquad (20)$$

$$\mu_O(x) = \begin{cases} 0, & x < 45 \text{ or } x > 65 \\ \frac{2(x-45)}{20}, & 45 \le x \le 55 \\ \frac{2(65-x)}{20}, & 55 < x \le 65 \end{cases} \qquad (21)$$

Fuzzification results for Age.

The membership values obtained using the crisp dataset in table 3.1, after fuzzification are given below:

$$\mathbf{Age_1 = 53}\,.$$

$Age_1 \rightarrow Y$:

$$\mu_Y(53) = 0 \text{ since } x_1 > 35$$

$Age_1 \rightarrow M$:

$$\mu_M(53) = 0,\ (x_1 > 50).$$

$Age_1 \rightarrow O$:

$$\mu_O(53) = \frac{2(x_1-45)}{20},\ \text{ since } \ 45 \le x_1 \le 55.$$

$$\mu_O(53) = \frac{2(53-45)}{20} = \frac{16}{20} = 0.8.$$

Therefore, Age triple for x_1:

$$\text{Age}_1 : Y = 0, M = 0, O = 0.8 \qquad (22)$$

$$\mathbf{Age_2 = 29},$$

$\text{Age}_2 \rightarrow \text{Y}$:

$$\mu_Y(29) = \frac{(70 - 2x_2)}{20}, \quad 25 < x_2 \leq 35$$

$$\mu_Y(29) = \frac{(70 - 2 \times 29)}{20} = \frac{12}{20} = 0.6$$

$$\text{Age}_2 \rightarrow \text{M}: \mu_M(29) = 0,$$

since $x_2 < 30$

$$\text{Age}_2 \rightarrow \text{O}: \mu_O(33) = 0.$$

Therefore, Age triple for x_2:

$$\text{Age}_2 : Y = 0.6, M = 0, O = 0. \qquad (23)$$

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$$\mathbf{Age_{20} = 42}$$

$\text{Age}_{20} \rightarrow \text{Y}$:

$$\mu_Y(42) = 0 \text{ since } x_{20} > 35$$

$\text{Age}_{20} \rightarrow \text{M}$:

$$\mu_M(42) = \frac{2(50 - x_{20})}{20}, \qquad 40 < x_{20} \leq 50$$

$$\mu_M(42) = \frac{2(50 - 42)}{20} = \frac{16}{20} = 0.8$$

$\text{Age}_{20} \rightarrow \text{O}$:

$$\mu_O(42) = 0, \;\; \text{since } x_{20} < 45.$$

Therefore, Age triple for x_{20}:

$$\text{Age}_{20} : Y = 0, M = 0.8, O = 0 \qquad (24)$$

Combined fuzzification results for the universe of discourse

$$U = \{x_1, x_2, \ldots, x_{20}\},$$

that is, equations (10,11,12,16,17,18,22,23,24) are summarized below:

x_1= {ST:0.341, NV:0.659, O:0.8}

x_2= {NT:0.400, RV: 0.786, Y:0.6}

x_{20}= {NT:0.280, NV:0.830, M:0.8}

However, the results are further summarized in the table below:

Table 2 Fuzzification Results

Patient	AT	NT	ST	NV	RV	AV	Y	M	O
x_1	0.0	0.0	0.341	0.659	0.0	0.0	0.0	0.0	0.8
x_2	0.0	0.400	0.0	0.0	0.790	0.0	0.6	0.0	0.0
x_3	0.0	0.729	0.0	0.677	0.0	0.0	0.0	0.8	0.0
x_4	0.0	0.280	0.0	0.830	0.0	0.0	0.0	0.8	0.0
x_5	0.126	0.0	0.0	0.571	0.0	0.0	0.0	0.0	0.8
x_6	0.0	0.706	0.0	0.527	0.0	0.0	0.0	0.9	0.0
x_7	0.250	0.0	0.0	0.0	0.430	0.0	0.0	0.6	0.0
x_8	0.526	0.0	0.0	0.0	0.0	0.943	0.0	0.8	0.0
x_9	0.0	0.329	0.0	0.0	0.94	0.0	0.3	0.0	0.0
x_{10}	0.0	0.729	0.0	0.0	0.055	0.201	0.0	0.8	0.0
x_{11}	0.053	0.118	0.0	0.427	0.0	0.0	0.0	0.0	0.6
x_{12}	0.0	0.920	0.0	0.0	0.500	0.030	0.5	0.0	0.0
x_{13}	0.0	0.824	0.0	0.0	0.866	0.0	0.5	0.0	0.0
x_{14}	0.0	0.447	0.0	0.742	0.0	0.0	0.6	0.0	0.0
x_{15}	0.0	0.471	0.0	0.571	0.0	0.0	0.6	0.0	0.0
x_{16}	0.400	0.0	0.0	0.0	0.0	0.866	0.0	0.0	0.9
x_{17}	0.0	0.870	0.0	0.890	0.0	0.0	0.0	0.8	0.0
x_{18}	0.0	0.824	0.0	0.0	0.211	0.14	0.0	0.0	0.2
x_{19}	0.0	0.965	0.0	0.988	0.0	0.0	0.0	0.0	0.4
x_{20}	0.432	0.0	0.0	0.232	0.131	0.0	1.0	0.0	0.0

5. Discussion

We present the fuzzification of the crisp dataset of the 20 patients using the membership functions defined above. The fuzzification process successfully transforms raw acoustic measurements into structured linguistic representations. Each patient record is characterized by membership values associated with predefined vocal health categories. The resulting fuzzy soft representation enables the integration of heterogeneous parameters within a unified prediction model. The gradual transitions between linguistic classes reflect the continuous nature of vocal variation. Furthermore, the fuzzy soft structure provides an interpretable interface for medical practitioners, as diagnostic information is expressed in qualitative terms rather than rigid numerical thresholds. At this stage, the constructed model establishes a reliable foundation for subsequent reasoning and decision-making processes.

Table 3 Parameter Used in the Fuzzy Soft Prediction Model.

Symbol	Parameter Name	Description
U	Universe of Patients	Collection of all patients whose vocal data are analyzed.
E	Parameter Set	Set of diagnostic parameters used in the fuzzy soft prediction model.
FF	Fundamental Frequency	Frequency of vocal fold vibration measured in Hz; indicates pitch characteristics.
VPI	Vocal Perturbation Index	Quantifies cycle-to-cycle variation in vocal fold vibration.
A	Age	Age of the patient; incorporated to model physiological vocal variation.
μ_{AT}	Abnormal Tone Membership	Fuzzy membership function describing abnormal fundamental frequency levels.
μ_{NT}	Neutral Tone Membership	Fuzzy membership function describing neutral pitch characteristics.
μ_{ST}	Stable Tone Membership	Fuzzy membership function describing stable pitch patterns.
μ_{NV}	Normal Voice Membership	Fuzzy membership function representing normal vocal perturbation levels.
μ_{RV}	Rough Voice Membership	Fuzzy membership function representing rough voice conditions.
μ_{AV}	Altered Voice Membership	Fuzzy membership function representing altered vocal states.
μ_{Y}	Young Membership	Fuzzy membership function for young age category.
μ_{M}	Middle-aged Membership	Fuzzy membership function for middle-age category.
μ_{O}	Old Membership	Fuzzy membership function for old age category.

6. Conclusion

This study presents a fuzzy soft set based design for modeling uncertainty in vocal health assessment. The approach integrates acoustic feature extraction, parameterized fuzzy representation, and linguistic transformation of data. By formulating a fuzzy soft diagnostic model and applying it to real patient voice recordings, the study demonstrates the feasibility of uncertainty aware vocal analysis. The fuzzification stage enables the conversion of crisp measurements into meaningful qualitative descriptors, which serves as a prerequisite for intelligent inference.

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