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Harnessing fuzzy logic framework to quantify diagnostic uncertainty in medical decision support

S. Leelavathy[1] ✉, J Ramprasath[2], I. Mettildha Mary[3], R. Nagendran[4], and R N Devendra kumar[5]

ABSTRACT

Medical diagnosis has become increasingly difficult, requiring sophisticated systems to manage decision-making uncertainty. The proposed medical diagnosis utilizing fuzzy logic framework (MD-FLF) addresses medical data imprecision and ambiguity by employing fuzzy inference techniques. Clinical data ambiguity is often overlooked by conventional diagnosis models. Such models include probabilistic classifiers and threshold-based decision trees. The models use accurate input-output correlations. However, fuzzy inference simplifies incremental membership assignment and rule-based reasoning in MD-FLF. This enhances the system's diagnostic ambiguity detection. The framework uses fuzzy rules to represent complicated non-linear interactions between symptoms and diagnostic data. This improves framework interpretation. MD-FLF models' ambiguity and non-linear relationships between diagnostic inputs and outputs provide interpretable recommendations for complex disorders. Rule-based methods and expert knowledge produce these results. Experimental evaluations showed that MD-FLF improved reliability by 97.68%, uncertainty by 96.84%, ambiguity by 43.56%, patient variability by 98.26%, and diagnostic accuracy by 97.82%. The paradigm addresses uncertainty to increase diagnostic reliability, precision, and confidence while eliminating ambiguity and offering clinical decision-making insights. MD-FLF outperforms deterministic techniques in medical diagnostic decision support systems and is stable and interpretable.

KEYWORDS

fuzzy logic; medical diagnosis; decision support system; uncertainty quantification; diagnostic accuracy; fuzzy inference system

1 Introduction

Medical illnesses are usually non-linear, symptoms fluctuate, and patient data is confusing[1]. These variables complicate and unpredict medical diagnosis. Clinical symptoms overlap, information is unclear, and medical practitioners' subjective interpretations produce uncertainty[2]. Advanced computational methods for uncertainty management and decision-making improvement are needed[3]. While there could exist situations under which the classical deterministic methods applied in diagnosing the conditions work out to be very effective, the imprecision and fuzziness the real-world data about medical cases carry cannot be handled by it[4]. A true mathematical system that successfully handles these problems is fuzzy logic, which

1 Department of AI&DS, Panimalar Engineering College, Chennai 600123, India.
2 Department of Information Technology, Dr. Mahalingam College of Engineering and Technology, Pollachi 642003, India.
3 Department of Computer Science and Engineering (Cyber Security), Dr. N.G.P. Institute of Technology, Tamil Nadu 641048, India.
4 Department of Computer Science and Engineering, Sri Ramakrishna Institute of Technology, Tamil Nadu 641010, India.
5 Department of Computer Science and Engineering, Sri Ramakrishna Institute of Technology, Tamil Nadu 641010, India.
✉ Address correspondence to S. Leelavathy, sivakumarleelavathy4@gmail.com

hails from the concept of Zadeh on fuzzy sets[5]. Fuzzy logic is easier to describe in ambiguity and uncertainty than classical logic, which has only a true/false value[6].

It is very applicable for usage in medical decision support systems, where accurate classifications are hard to achieve since illnesses and their symptoms are very complex[7]. Fuzzy logic may help interpret clinical descriptors with linguistic ambiguity as mild, moderate, or severe[8]. To avoid all the issues, the MD-FLF is the framework of medical diagnosis utilizing fuzzy logic[9]. The fuzzy inference algorithms in the medical decision support system provide a systematic way of handling uncertainty and enhancing diagnostic accuracy[10]. Using expert knowledge to frame fuzzy rules, the framework models links between diagnostic inputs like symptoms or test findings and outputs like possible conditions using a rule-based technique[11]. Such rules are then subjected to fuzzy inference algorithms to produce concise suggestions that are easy to understand and apply[12].

The important advantage that MD-FLF has over others is its ability to treat imprecise input data, such that it does not create outcomes that would be unintelligible[13]. Even though heuristic thought and subjective estimation by medical persons are ubiquitous, they result in unstable and variable diagnostic outputs[14]. Because MD-FLF formalizes this kind of reasoning, there is a full guarantee that the final diagnosis properly models the uncertainty inherent within subjective assessments[15]. Overlapping diagnostic criteria is another typical problem with diseases that share symptoms, an issue the framework is designed to prevent. Respiratory symptoms include Ref. [16]. Difficult breathing and coughing can indicate various medical conditions, such as asthma and pneumonia[17]. With Fuzzy logic used to put forward probabilistic evaluations, MD-FLF avoids diagnostic ambiguity in general, as opposed to the traditional systems that might struggle to differentiate such possibilities[18].

Using "if-then" rules that experts have created, fuzzy rule-based reasoning is a computational method that can handle input data that is not exact, uncertain, or articulated verbally. Fuzzy logic variables may have different degrees of membership in different categories, unlike binary logic variables (temperature above 100 degrees Fahrenheit). Patient temperature membership values include "normal" and "slightly high". Fuzzy rule-based inference engines allow this framework to handle such gradations. Fuzzy sets and membership functions help understand these gradations. Clinical environments may simulate diagnostic uncertainty like overlapping symptoms or opposing test findings, enabling more adaptable and realistic decision-making.

Medical diagnosis utilizing a fuzzy logic framework (MD-FLF) was created to solve practical concerns, including overlapping diagnostic criteria and patient variability. Clinical data is non-linear and inaccurate; hence, the framework uses fuzzy logic to account for patient presentations and symptom intensity. MD-FLF should be able to handle diagnostic inputs that overlap across conditions and do not meet rigorous thresholds utilizing rule-based inference and fuzzy membership functions. By modeling the gradient in symptom severity and understanding hidden clinical circumstances, the system models the intricacy of real-world diagnosis. The architecture was created to simplify personalized evaluations to improve decision assistance for patients with diverse characteristics.

Motivation: The motivation of this research is to minimize medical diagnosis uncertainty, which frequently leads to ambiguous symptoms, patient variability, and overlapping diagnostic criteria.

The pressing need to minimize uncertainty inspired this investigation. Conventional methods cannot handle complexity, frequently leading to erroneous diagnoses or prolonged therapy. Fuzzy logic describes medical data imprecision and ambiguity more effectively. Fuzzy inference systems in decision support systems improve diagnostic accuracy, reliability, and confidence to improve patient outcomes in complicated clinical situations.

Problem statement: Uncertainty arising from ambiguous symptoms, patient variability, and overlapping diagnostic criteria threatens the efficacy of medical diagnosis. The traditional approach, deterministic in nature, cannot address impreciseness and vagueness appropriately in clinical data, resulting in possibilities of misdiagnosis and delaying remedies. A strong framework is hence required to make uncertainty explicitly modeled and manageable to improve the precision, reliability, and confidence level of diagnostic decision-making.

Objectives:

- Development of the MD-FLF framework that explicitly models and manages uncertainty using fuzzy logic, addressing challenges like ambiguous symptoms, patient variability, and overlapping diagnostic criteria.
- Integrating expert-driven fuzzy rules to capture non-linear relationships in medical data provides interpretable and reliable diagnostic recommendations for complex conditions.
- Demonstration of improved diagnostic accuracy and decision confidence through experimental evaluations, showcasing the framework's effectiveness compared to traditional deterministic methods.

Figure 1 displays fuzzy logic healthcare prediction. Standard data and health records generate a knowledge discovery dataset. A prediction model is trained using this dataset. The model fuzzifies, processes, and defuzzes input data to provide clean output. Fuzzy logic's ability to handle uncertainty and ambiguity in medical data improves projections and decision-making.

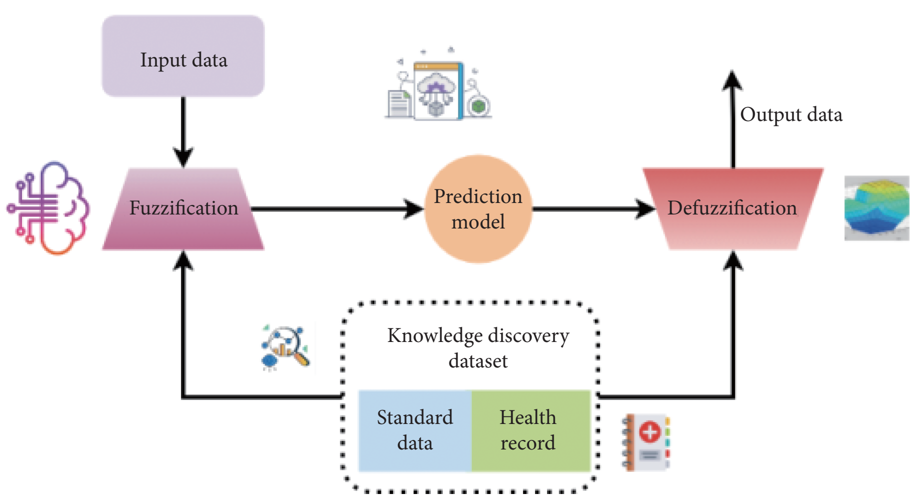

Fig. 1 Fuzzy forecasting for healthcare.

This paper is structured as follows: Section 2 studies the related medical diagnosis work. In Section 3, the proposed methodology of MD-FLF is explained. In Section 4, the efficiency of MD-FLF is discussed and analyzed. Finally, in Section 5, the paper concludes with future work.

2 Related work

Compared with more traditional methods, the first experimental evaluations of MD-FLF show it significantly improves the accuracy of diagnosis. Testing the system on real-world datasets with complicated situations demonstrated its ability to handle ambiguity and improve clinical decision-making. The findings show that MD-FLF decreases the probability of incorrect diagnosis and boosts doctors' confidence in their judgments (Table 1).

Table 1 Simulation of related work

Ref No.	Methods	Advantages	Limitations
[19]	Machine learning models (MLM)	-Combining fuzzy logic with machine learning enhances adaptability and automates rule generation; -Improves diagnostic accuracy by learning from complex, multi-modal data.	-Integration requires substantial computational resources and high-quality datasets for training; -The interpretability of machine-learned rules.
[20]	Deep learning techniques (DLT)	-Integrating deep learning with fuzzy logic enables automatic feature extraction; -Improved scalability and the ability to handle high-dimensional and complex medical data by.	-Deep learning models can be computationally intensive and less interpretable; -Ensuring transparency and trustworthiness in critical clinical decision-making scenarios is challenging.
[21]	Support vector machine (SVM)	-Integrating SVM with fuzzy logic provides robust performance on small, structured datasets; -Effective handling of non-linear relationships and uncertainty in medical diagnosis by.	-SVMs struggle with scalability in large datasets and the manual tuning of hyperparameters; - kernel selection can be complex, potentially limiting flexibility in dynamic clinical environments.
[22]	Data mining (DM)	-DM uncovers hidden patterns, trends, and relationships in large medical datasets; -Enabling informed decision-making and improving the precision of medical diagnoses.	-Significant preprocessing efforts are required to handle noisy or incomplete data; -Privacy concerns may arise due to the sensitive nature of medical information.
[27]	Uncertainty quantification in multi-label classification using automatic ECG diagnosis	Handles complex diagnostic tasks with overlapping labels; improves interpretability of model predictions under uncertainty.	Limited scalability across heterogeneous datasets; uncertainty estimation relies on threshold sensitivity.
[28]	Distance measure under complex picture fuzzy sets for decision-making and diagnosis	Captures more nuanced hesitation and contradiction in decision processes; enhances fuzzy modeling in medical contexts.	Computational complexity increases with multi-dimensional data; lacks adaptability in dynamic decision environments.
[29]	AUQantO (actionable uncertainty quantification optimization) integrated into deep learning for medical image classification	Enhances clinical decision-making by providing actionable confidence scores; improves risk-aware model deployment.	Requires high computational resources for optimization; model-specific tuning limits generalizability across architectures.
[30]	Uncertainty quantification in densenet for myocardial infarction detection via ECG	Integrates uncertainty modeling with a deep CNN structure; improves trust in automated ECG interpretation.	DenseNet complexity can lead to overfitting with smaller datasets; interpretation of uncertainty layers remains abstract for clinical users.

In summary, in medical diagnostics, combining fuzzy logic with ML, DL, SVM, and data mining increases diagnostic accuracy, quantifies uncertainty, and gives suggestions that are easy to understand. Problems that may arise include privacy problems in healthcare applications, high-quality data requirements, interpretability difficulties, and computing needs. The MD-FLF framework identifies significant deficiencies in the existing literature about medical diagnostic systems. Many current methodologies mostly depend on traditional statistical models or machine learning methods that, although attaining substantial predicted accuracy, often function as opaque systems with restricted interpretability. Many of these models ignore linguistic ambiguity and expert reasoning. Fixed thresholds in traditional rule-based systems fail to reflect clinical data's complex and non-linear relationships. The research found a lack of computationally robust and clinically appropriate diagnostic uncertainty representation. MD-FLF combines fuzzy logic with expert-generated rule sets to meet this demand. This allows the system to handle ambiguous inputs and provide intelligible outputs using human-like reasoning.

3 Proposed method

Fuzzy logic solutions might transform medical diagnostics by eliminating uncertainty and ambiguity in demanding healthcare settings. These systems use advanced inference algorithms, patient data, and expert knowledge to provide consistent, adaptable, and pragmatic diagnoses. Fuzzy logic systems may enhance patient care, decision-making, and collaboration in difficult medical settings by merging artificial intelligence and human understanding.

Contribution 1: quantifying uncertainty in medical diagnosis: This article really depicts medical data confusion and ambiguity[19]. The quantification-based MD-FLF is explained here. This includes individual variances, overlapping diagnostic criteria, and poorly reported symptoms.

Including symptoms and test results, a fuzzy logic-based diagnostic system delivers a quantified diagnosis with a defined uncertainty level (Fig. 2). Processing medical input data the fuzzification layer converts crisp medical data into fuzzy sets, encapsulating medical ambiguity and vagueness. Experts created the rule base with medical diagnostic IF-THEN guidelines. These soft rules imply diagnosis using inference engine fuzzy output from input data. Maintaining uncertainty, the defuzzification layer finally converts this fuzzy output into a clear, useful diagnosis. While technology as a whole provides more precise and adaptable diagnostic suggestions, fuzzy logic helps one manage challenging medical situations.

$$k_f e :\rightarrow \mathrm{Xz}\left[a^{'} * \mathrm{var}\right] + V[\mathrm{ki} - \mathrm{sz}] - \mathrm{Cs}\left[\alpha\gamma^{'} - \mathrm{ab}^{''}\right] \tag{1}$$

The MD-FLF framework employs an equation 1 model to measure uncertainty by establishing a

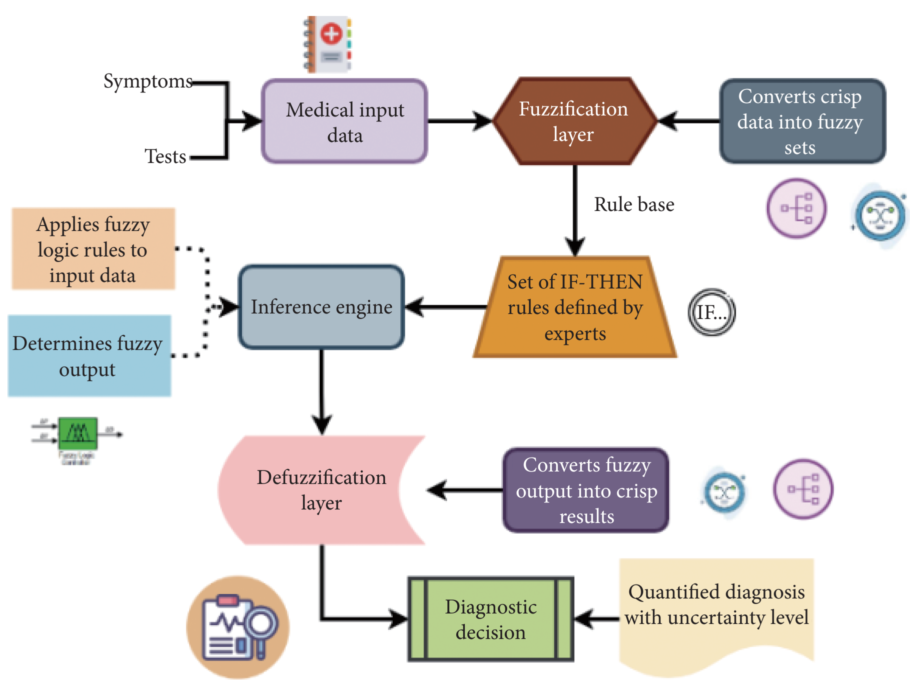

Fig. 2 Fuzzy logic diagnostic framework: Bridging uncertainty in medical decision-making.

correlation between diagnostic factors ($k_f e$), $Xz\left[a' * \text{var}\right]$ and patient-specific volatility $V[ki - sz]$), along with the reduction of overall ambiguity ($Cs\left[\alpha\gamma' - ab''\right]$). It logically encodes the fuzzy logic concepts to provide solid uncertainty quantification and decision-making help.

$$Z_x se\left[\text{lo} - \text{snw}''\right] :\rightarrow \text{La}\left[\partial' * 6v\right] + \text{Vs}\left[\alpha\vartheta' - \text{Evs}\right] \tag{2}$$

Within the MD-FLF framework, Eq. (2) represents $Vs\left[\alpha\vartheta' - \text{Evs}\right]$ the impact of diagnosis uncertainty ($\left[\text{lo} - \text{snw}''\right]$) and symptom heterogeneity ($Z_x se$) on medical decision-making. The clinical inputs are taken into consideration for their dynamic and unpredictable relationship via the use of unclear parameters ($\text{La}\left[\partial' * 6v\right]$). Eq. (2) reduces ambiguity, enabling the framework to accurately and reliably diagnose complicated settings.

$$Y_f r :\rightarrow \text{Lx}[\text{aq} - \text{nf}] + Vs\left[\alpha\beta - \text{iuq}''\right] - \text{Cx}\left[s - \text{osaq}''\right] \tag{3}$$

Within the MD-FLF framework, the $\text{Cx}\left[s - osaq''\right]$ represents the interactions of particular to the patient ($Y_f r$) and unknown elements ($\text{Lx}[\text{aq} - \text{nf}]$). Eq. (3), ($\text{Vs}\left[\alpha\beta - \text{iuq}''\right]$) enables more accurate decision-making by using fuzzy variables. To improve the framework's accuracy and reliability in complicated medical situations, it measures and reduces diagnostic uncertainty.

$$P_f s\left[\text{Za} - \text{kj}''\right] :\rightarrow \text{Lp}\left[v - \text{na}''\right] * \text{Vs}\left[w' - \text{aq}''\right] + \text{Va}\left[\text{lo}''\right] \tag{4}$$

Within the MD-FLF framework, Eq. (4) represents the integration of the variability in patient data ($P_f s$), $\left[\text{Za} - \text{kj}''\right]$) and the imprecision in clinical evidence ($\text{Lp}\left[v - \text{na}''\right] *$). The robust management of uncertainty is achieved by integrating unknown variables ($\text{Vs}\left[w' - \text{aq}''\right]$) and adjusting for local variables ($\text{Va}\left[\text{lo}''\right]$).

Algorithm 1: Fuzzy membership calculation

```
def compute_fuzzy_membership(input_value, low_range, high_range):
    Calculate the membership degree of input values to a fuzzy sets.
    Parameters:
    - input_value: The numeric value to be assessed.
    - low_range: The minimum value of the fuzzy range.
    - high_range: The maximum value of the fuzzy range.
    Returns:
    - Membership degree (0 to 1).
    if input_value ⩽ low_range:
        membership_degree = 0 # Fully outside the range
    elif low_range < input_value < high_range:
        membership_degree = (input_value − low_range) / (high_range − low_range) # Linear increase
    else:
        membership_degree = 1 # Fully within the range
    return membership_degree
```

This algorithm determines the degree of membership of a diagnostic input (e.g., symptom severity) in a fuzzy set. The fuzzy membership calculation algorithm (Algorithm 1), an integral part of the MD-FLF diagnostic system, can accurately transform clinically problematic inputs into structured fuzzy values. In dealing with a large variety of patient characteristics, which are sometimes imprecise and overlapping, proper membership functions retain semantic subtleties needed for medical reasoning. Because it distributes membership degrees across linguistic categories (low, medium, high), this method provides resilient rule activation and smooth inference propagation in the fuzzy logic system. This feature improves rule application, input normalization, and diagnostic output readability. The method's processing efficiency and ability to adapt to different input scales improve the MD-FLF framework's responsiveness and scalability. It is a key facilitator for reliable and nuanced diagnostic decision support in difficult cases.

Contribution 2: Rule-based fuzzy inference system: The rule-based MD-FLF technique handles non-linear correlations and diagnostic input imprecision with professional skill. Medical professionals who can identify challenging illnesses, particularly those with ambiguity, may provide rational and consistent guidance. The rule-based system is open and interpretable but has limits that must be understood. The fact that it uses expert criteria is a major negative. These criteria may not cover all clinical presentations, reducing the system's scalability for complicated or unexpected diagnostic situations. In high-dimensional datasets, the system may become computationally costly and difficult to administer as the number of rules rises. This is particularly true with more regulations. Static rule sets further limit the model's capacity to adapt to fresh medical data and changing patient data patterns. These restrictions may impair sensitivity in rare or overlapping circumstances.

Figure 3 shows how picture fuzzy sets, a new clinical decision support system, may differentiate diagnoses. It draws findings from patient data, expert experiences, and a robust matching algorithm[20]. In disagreements, evidence guides these judgments. An information base stores medical data, an inference engine handles uncertainty, and a user-friendly interface simplifies patient and physician-consultant communication. This innovative technology uses human experience and artificial intelligence to enhance patient outcomes, diagnosis, and cooperation in complex healthcare settings.

$$k_{fv}d\left[\mathrm{lo}-\mathrm{anw}''\right] :\rightarrow \mathrm{Ns}\left[\mathrm{oi}-\mathrm{an}''\right]+\mathrm{Sa}\left[w-\mathrm{aqnv}''\right] \tag{5}$$

In the MD-FLF model, Eq. (5) indicates the interplay $Sa\left[w-aqnv''\right]$ between uncertain diagnoses ($k_{fv}d$) and particularly to the patient dynamics ($\left[\mathrm{lo}-\mathrm{anw}''\right]$). It tackles the uncertainty and unpredictability in medical data by using fuzzy variables ($\mathrm{Ns}\left[\mathrm{oi}-\mathrm{an}''\right]$). This equation helps produce trustworthy diagnostic suggestions by accurately representing complicated interactions and ambiguity.

$$\mathrm{Xs}\left[\mathrm{lo}-\mathrm{ap}''\right] :\rightarrow \mathrm{Ns}\left[\mathrm{iu}-\mathrm{aw}''\right] * \mathrm{Vs}\left[o-\mathrm{ewq}''\right] \tag{6}$$

Using the MD-FLF framework, the Eq. (6) represents the uncertainty in sensation evaluation ($\mathrm{Ns}\left[\mathrm{iu}-\mathrm{aw}''\right]$) and clinical heterogeneity (Xs), $\left[\mathrm{lo}-\mathrm{ap}''\right]$). It is possible to capture intricate, non-linear relationships in diagnostic data by using fuzzy elements ($\mathrm{Vs}\left[\mathrm{o}-\mathrm{ewq}''\right]$). This equation gives medical decision-makers accurate and interpretable data by improving the framework's imprecision handling.

$$X_s r\left[\mathrm{lo}-\mathrm{anw}''\right] :\rightarrow \mathrm{Lsp}\left[v-\mathrm{qe}''\right]+\mathrm{Js}\left[\mathrm{oiu}-\mathrm{sne}''\right] \tag{7}$$

Within the MD-FLF framework, the equation shows the integration of uncertainty in diagnosis ($X_s r$), $\left[\mathrm{lo}-\mathrm{anw}''\right]$ and particularly to the patient variable ($\mathrm{Lsp}\left[v-\mathrm{qe}''\right]$). The exact decision-making is

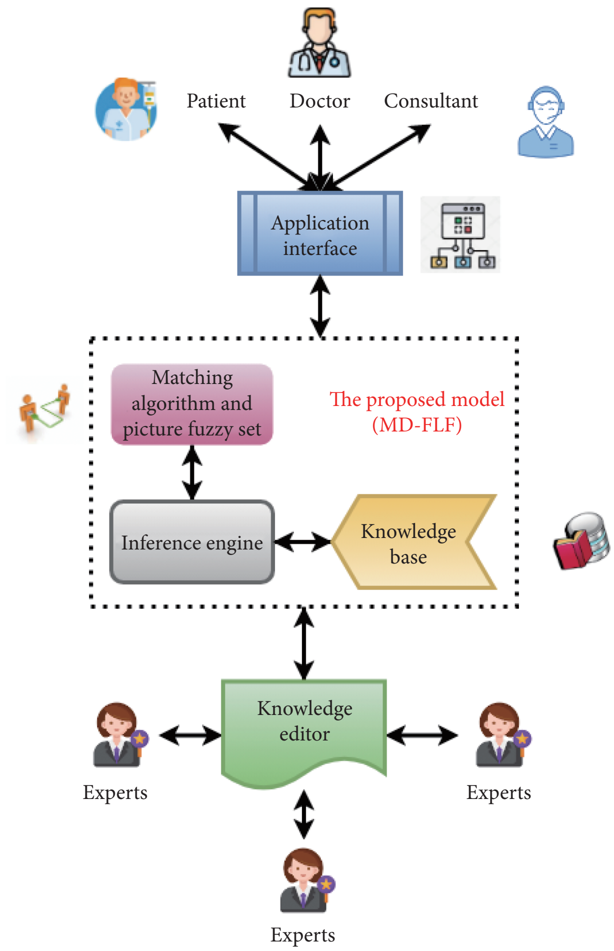

Fig. 3 InsightRx: Diagnosis redefined.

facilitated by the use of fuzzy parameters ($\mathrm{Js}\left[\mathrm{oiu}-\mathrm{sne}''\right]$) and the modeling of dynamic linkages. Eq. (7) may improve hospital diagnosis in difficult scenarios and eliminate uncertainty.

$$x_c s \ll \mathrm{ju}-\mathrm{an}'' \gg:\rightarrow \mathrm{Ls}\left[\mathrm{uy}-\mathrm{wbw}''\right] * \mathrm{Bx}\left[s-\mathrm{va}''\right] \tag{8}$$

In the MD-FLF model, the variables $x_c s$, $\mathrm{ju}-\mathrm{an}''$ and $\mathrm{Ls}\left[\mathrm{uy}-\mathrm{wbw}''\right]$ represent the interaction between clinical uncertainty $\mathrm{Bx}\left[s-\mathrm{va}''\right]$ and diagnostic variability in Eq. (8). Integrating unknown parameters captures medical data's non-linear and incorrect relationships. Eq. (8) improves diagnostic results by improving the framework's uncertainty evaluation and practical insights in Table 2. By managing ambiguous, overlapping, and uncertain clinical data in a structured yet human-like manner, fuzzy logic improves medical diagnosis interpretability and adaptability. The system can better manage these issues. Fuzzy logic compares symptoms and test results using language variables (such as "mild", "moderate", or "severe") and membership functions to make more sophisticated diagnoses. This simulates clinical cognition by interpreting limited data and basing decisions on symptom intensity. Because each diagnostic result may be related to an open set of "if-then" rules based on expert knowledge, fuzzy logic's rule-based structure makes it simpler for clinicians to comprehend and accept the system's ideas.

Figure 4 shows fuzzy logic systems managing ambiguity and uncertainty in decision-making. The

Table 2 Fuzzy linguistic data definition

Field	Fuzzy linguistic variable	Low	High
Bp	Low	0	121
Bp	Medium	120	143
Bp	High	139	170
Bp	Very high	156	998

fuzzification interface creates fuzzy groupings based on data properties using numerical measurements or observations of clean input data. The decision-making unit may employ "high", "low" , and "moderate" fuzzy settings. With human inspiration, this unit examines connections and develops insights using rule-based reasoning. A defuzzification interface converts fuzzy output into plain values to provide simple recommendations or judgments[21].

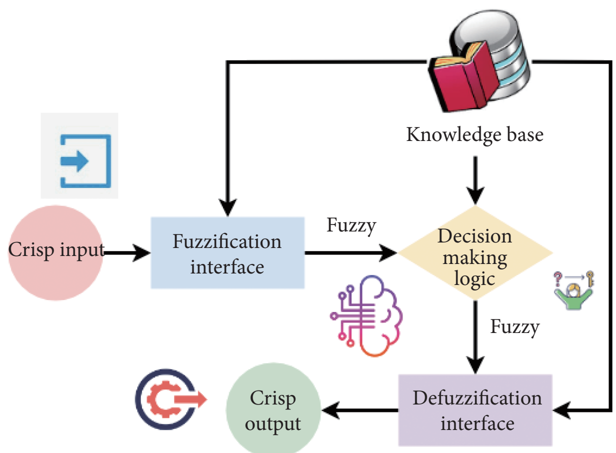

Fig. 4 Fuzzy precision: Simplifying complex decisions.

Fuzzy membership functions may better capture small differences in clinical data, such as symptom intensity or biomarker levels, than crisp or binary classifications. A 140 mmHg systolic blood pressure may be classified as "medium" and "high" with membership degrees of 0.6 and 0.4 to retain diagnostic uncertainty. This may replace a new categorization. Layered representation allows the model to handle real-world diagnostic issues such as patient variability, borderline symptoms, and incomplete disease presentations. This strategy integrates imprecise input with clear outputs to enable strong decision-making in unexpected scenarios. This technology may be employed in autonomous systems and medical diagnostics.

$$N_x t \ll \mathrm{ki}-\mathrm{an}'' \gg :\to \mathrm{Ls}\left[\propto \mathrm{ki}-\mathrm{anw}''\right]+\mathrm{Vs}\left[\alpha\Delta'-\mathrm{ew}\right] \tag{9}$$

Eq. (9) shows how the MD-FLF framework incorporates patient-specific variability $N_x t, \mathrm{ki}-\mathrm{an}''$, and variance in diagnosis inputs ($\mathrm{Ls}\left[\propto \mathrm{ki}-\mathrm{anw}''\right]$). It simulates the complexity and imprecision of medical decision-making by using fuzzy variables ($\mathrm{Vs}\left[\alpha\Delta'-\mathrm{ew}\right]$). This lends credence to the framework's stated purpose of improving the precision and consistency of clinical recommendations.

$$v_d r\left[\mathrm{lo}-\mathrm{anw}''\right] :\to \mathrm{Ls}\left[w-9b''\right]+\mathrm{Va}\left[\mathrm{ji}-\mathrm{qzq}''\right] \tag{10}$$

Within the MD-FLF framework, Eq. (10) represents the unknowns in symptomatic assessment ($v_d r$) and the variance $\mathrm{Va}\left[\mathrm{ji}-\mathrm{qzq}''\right]$ in data about patients ($\left[\mathrm{lo}-\mathrm{anw}''\right]$). It describes complicated interactions and reduces imprecision in test information by using uncertain parameters $\mathrm{Ls}\left[w-9b''\right]$. The trustworthy medical diagnoses in unpredictable situations are improved by this Eq. (10).

$$l_f r\left[o-\mathrm{sh}''\right] :\rightarrow \mathrm{Ns}\left[\mathrm{ui}-\mathrm{wx}\right] * \mathrm{Ms}\left[\rho\tau-9\mathrm{vsq}''\right] \tag{11}$$

Within the MD-FLF framework $\mathrm{Ms}\left[\rho\tau-9\mathrm{vsq}''\right]$, the particular patient variability ($l_f r$) and the uncertainty in diagnosis ($\left[o-\mathrm{sh}''\right]$) are modeled by the Eq. (11). This system incorporates components of fuzzy logic ($\mathrm{Ns}\left[\mathrm{ui}-wx\right]$) to grasp the non-linear and inaccurate features of medical data. The goal of Eq. (11) is to give clear, practical guidance for clinical decision-making and measure uncertainty.

$$Y_f rlx-\mathrm{ane}''\right] :\rightarrow \mathrm{Ls}\left[\mathrm{iyt}-\mathrm{enq}''\right] * \mathrm{Ex}\left[\mathrm{ki}-\mathrm{anq}''\right] \tag{12}$$

In the MD-FLF model, Eq. (12) represents the interplay between uncertain diagnosis $\mathrm{Ls}[\mathrm{iyt}-\mathrm{enq}'']$) and volatility in information about patients ($Y_f rlx-\mathrm{ane}''] :\rightarrow$). Fuzzy factors $\mathrm{Ex}[\mathrm{ki}-\mathrm{anq}'']$ represent non-linear and complicated interactions. The equation aims to make the framework better at making accurate and trustworthy diagnostic suggestions. Fuzzy inference systems are rule-based computer models that employ fuzzy logic to manage imprecise or ambiguous input data and provide interpretable outputs. Fuzzification converts crisp inputs into fuzzy sets, a rule base contains expert-defined if-then rules, an inference engine evaluates these rules, and defuzzification converts the fuzzy output into a definite value. This approach lets the machine emulate human reasoning and resolve data ambiguity and complexity.

Algorithm 2: Fuzzy inference and decision

```
def fuzzy_inference(symptom_membership, rule):
    Perform fuzzy inference based on symptom membership and predefined rule.
    Parameters:
    - symptom_membership: Dictionary with symptom name as key and membership degrees as value.
    - rules: List of rules where each rule is a dictionary with condition and a corresponding diagnosis.
    Returns:
    - Recommended diagnosis and its confidence.
    max_confidence = 0
    suggested_diagnosis = None
    # Iterate through rules
    for rule in rules:
        conditions_met = True
        rule_confidence = 1
        # Assess every condition in the rule
        for symptom, required_memberships in rules['conditions'].items():
            if symptom in symptom_membership:
                rule_confidence = min(rule_confidences, symptoms_membership [symptom])
            else:
                conditions_met = False
                break
        # If all condition are met, assess confidence
        if condition_met and rule_confidence > max_confidence:
            max_confidence = rule_confidence
            suggested_diagnosis = rule['diagnosis']
    return recommended_diagnosis, max_confidence
```

This algorithm evaluates fuzzy rules for diagnostic support based on input symptoms and their memberships. Using a Mamdani inference system and a preset set of rules, the algorithm methodically evaluates input variables that have been fuzzified, such as the intensity of symptoms, the range of test results, and any modifiers peculiar to the patient. The rules are tested to ascertain levels of accuracy once each input is assigned a fuzzy membership value (e.g., low, medium, high). After defuzzification, usually the centroid approach, the result is diagnostic confidence levels or categorical risk ratings (low-risk, moderate-risk, or high-risk). As a result, clinical evaluations that were before imprecise are now quantitatively interpretable. For instance, "0.78 diagnostic confidence for cardiac abnormality" might be the outcome of a combination of "moderate chest pain" and "elevated ECG deviation", according to the carefully defined input-output mapping.

Contribution 3: Enhanced diagnostic accuracy and decision support: The paper results suggest that MD-FLF is better than traditional deterministic techniques as it lowers diagnosis uncertainty, increases accuracy, and offers actionable insights for clinical decision-making[22]. The framework helps medical diagnosis to be more reliable and believable. Fuzzy logic may better resolve diagnostic uncertainty than deterministic methods because it can handle clinical data imprecision, gradation, and ambiguity. Fuzzy logic handles these clinical data characteristics. Deterministic techniques employ rigid thresholds and binary classifications. These approaches typically miss patient presentation nuances and crosses. Examples of crossings include questionable lab findings or symptoms from many disorders. Fuzzy logic quantifies uncertainty using degrees of membership. Inputs might fit into many diagnostic categories with different confidence levels. The fluid categorization reflects human diagnostic thought and better accommodates the multiplicity of prospective patients.

Figure 5 shows the different components of medical diagnosis and MD-FLF flow. The patient's symptoms, medical history, and test results are collected. Preprocessing turns crisp inputs into fuzzy language variables and standardizes the data. The fuzzy inference engine model uses expert-developed rules to conclude fuzzy inputs, leveraging uncertainty. Defusing produces obvious, useful diagnoses. Expert evaluation via a feedback loop keeps the system's knowledge base correct and adaptive[23, 24]. Finally, the data is acceptable for a CDSS, which gives providers clear, understandable instructions. Fuzzy inference uses a well-defined rule foundation that accounts for language aspects and membership degrees to transform ambiguous clinical data into ordered decision outputs. The model is trained to use membership function computations to set biomarker and symptom intensity ranges (low, medium, high).

Actual medical situations are unpredictable and unknown; hence this is done. These methods help the research fulfill its main goals of improving interpretability, handling diagnostic ambiguity, and providing reliable guidance in uncertain situations. Defining a hemoglobin test of 11.2 g/dL as partially "low" (0.7) and " medium" (0.3) is an example of sophisticated reasoning that deterministic criteria ignore. This paradigm accurately assesses ambiguity, improving diagnostic accuracy and decision-making in difficult situations.

$$r_e E :\rightarrow \mathrm{Ls}\left[\tau\pi' * \mathrm{Be}\right] + \mathrm{vA}\left[\mathrm{YR} - \mathrm{wan}''\right] * \mathrm{Vs}\left[w - \mathrm{oiu}''\right] \tag{13}$$

Within the MD-FLF framework $\mathrm{Vs}\left[w - \mathrm{oiu}''\right]$, the Eq. (13) incorporates diagnostic uncertainty ($r_e E$)

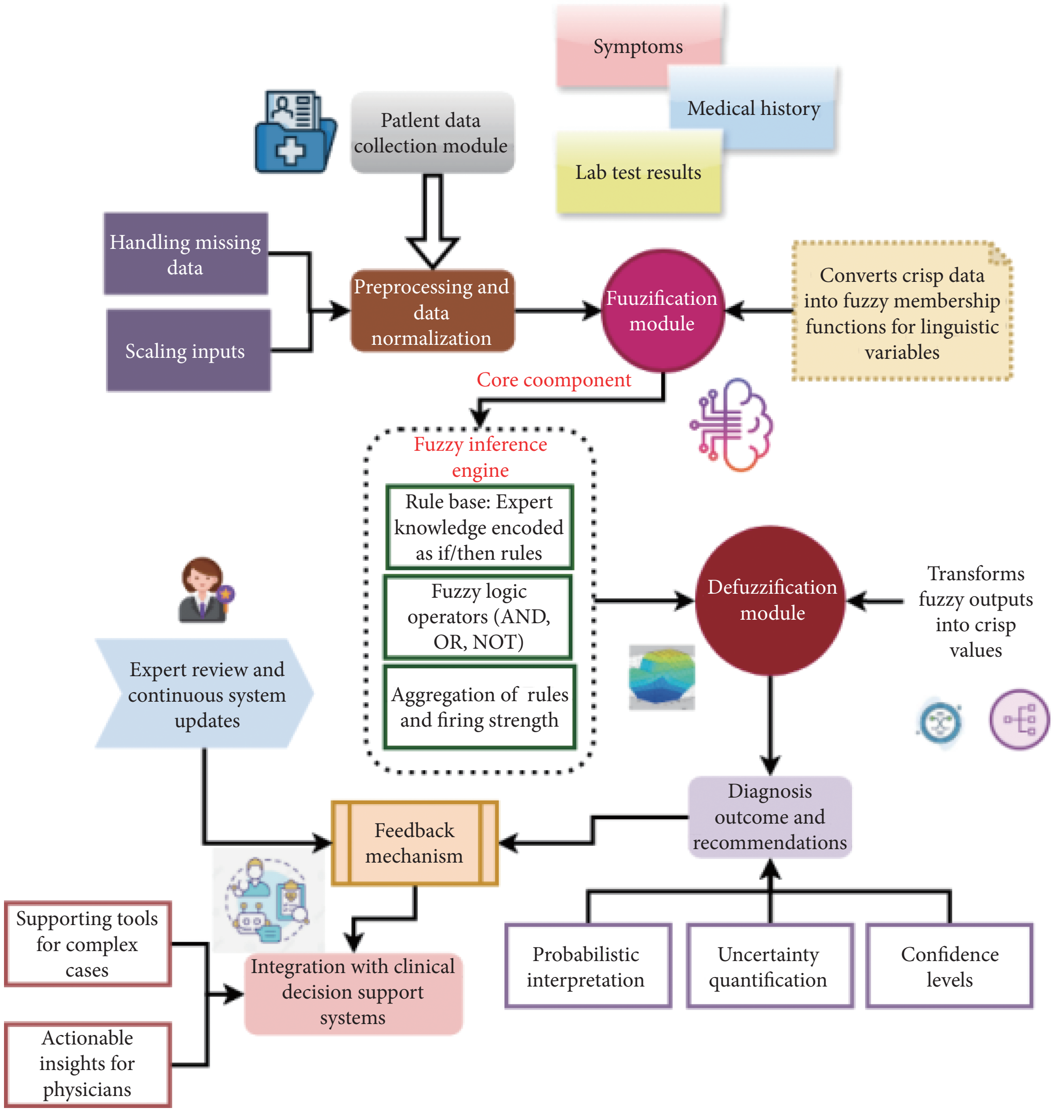

Fig. 5 MD-FLF: Navigating uncertainty in medical diagnosis with fuzzy logic.

and particular to the patient variance Ls $\left[\tau\pi' * \mathrm{Be}\right]$. Utilizing fuzzy logic parts (vA $\left[\mathrm{YR} - \mathrm{wan}''\right]$), it simulates non-linearities and intricate connections. Eq. (14) quantifies and reduces ambiguity to increase diagnostic accuracy. More dependable and interpretable clinical assistance will achieve this.

$$Y_f r\left[\mathrm{ji} - \mathrm{sn}''\right] :\rightarrow \mathrm{Bs}\left[\partial \propto +\mathrm{va}\right] * \mathrm{Em}\left[\mathrm{cv} - \mathrm{ane}''\right] + \mathrm{Vsl}'' \tag{14}$$

Within the MD-FLF framework, Eq. (14) symbolizes the relationship Vsl'' between diagnosis outputs ($Y_f r$) and variance in health information ($\left[\mathrm{ji} - \mathrm{sn}''\right]$). To deal with the imprecision $\mathrm{Em}\left[\mathrm{cv} - \mathrm{ane}''\right]$ and ambiguity in diagnosis, it employs fuzzy parameters $\mathrm{Bs}\left[\partial \propto +\mathrm{va}\right]$). Eq. (14) aims to improve diagnosis accuracy and provide insights for complicated clinical scenarios by quantifying uncertainty in the framework. Fuzzy rules and expert knowledge may bridge the gap between algorithmic thinking and real-world medical decision-making, improving diagnostic systems' practicality. Fuzzy systems may encapsulate complex clinical data in "if-then" rules. These principles handle overlapping symptoms, different patient reactions, and unclear diagnostic boundaries. A rule like "IF chest pain is moderate AND ECG variation is borderline, THEN likelihood of cardiac anomaly is medium" shows how doctors interpret non-obvious situations. Unlike powerful statistical models, this strategy improves diagnostic interpretability and transparency by adding subjective insights and gray zone clinical instances. Expert-recommended fuzzy rules help make environment-aware judgments in complicated situations where deterministic thresholds don't reflect clinical variability. Fuzzy rules are scalable in ever-changing healthcare environments due to their flexibility. Fuzzy rules enable medical knowledge breakthroughs to be produced gradually.

$$v_f d :\rightarrow \mathrm{po}\left[x' - \mathrm{Ax}\right] = \mathrm{Vs}\left[\mathrm{w}\,\partial' + \mathrm{bA}\right] * \mathrm{Vs}\left[\Delta\forall - \delta\gamma''\right] \tag{15}$$

Figure 5(a) explains the MD-FLF framework as shown by Eq. (15), which shows the interplay $\mathrm{Vs}\left[\Delta\forall - \delta\gamma''\right]$ between diagnostic variation $(v_f d)$ and unknown variables ($\mathrm{po}\left[x' - \mathrm{Ax}\right]$). It incorporates the intrinsic imprecision in medical data and models' non- linear interactions by combining fuzzy logic pieces ($\mathrm{Vs}\left[\mathrm{w}\,\partial' + \mathrm{bA}\right]$)[25]. Eq. (15) aims to enhance the diagnostic process by raising accuracy and decreasing ambiguity to facilitate more trustworthy clinical decision-making. Latent clinical factors impact diagnostic limits and decision uncertainty, as shown graphically in Fig. 5(a), demonstrating the dynamic interaction between diagnostic variance and unknown variables. Patients' unique characteristics and overlapping symptoms are represented by the figure's graded zones of variability, while the shaded areas show the probability distribution of unknown inputs. Although the graphic simplifies certain details, it depicts how non-deterministic factors alter diagnostic reasoning. These factors might include changing biomarkers, co-morbidities, or missing patient data.

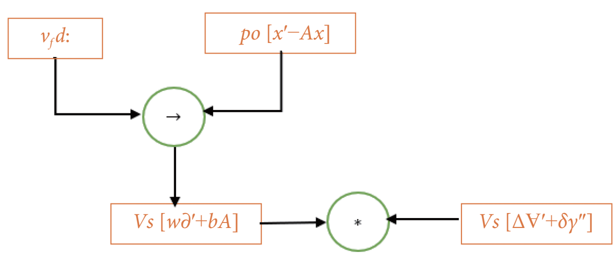

Fig. 5(a) Image of the interplay between diagnostic variation and unknown variables.

Expert-defined rules, defuzzification of outputs into relevant insights, and converting pure data into fuzzy sets partly improve medical diagnosis. These systems evolve constantly with steady input, lower control uncertainty, and improved diagnostic accuracy. Including fuzzy logic in clinical decision support systems provides clinicians with reliable, evidence-based recommendations in demanding and complicated medical contexts.

4 Simulation analysis

MD-FLF quantifies uncertainty in a complicated yet simple way, improving medical diagnostic decision support systems. The MD-FLF system uses fuzzy logic to increase medical diagnosis reliability, accuracy, and actionability. Thus, it produces better patient-centered healthcare solutions. Quantifying uncertainty is necessary to assess the model's capacity to handle incomplete or confusing clinical inputs. Fuzzy inference must be evaluated to see whether it captures diagnostic confidence. Patient variability adds to symptom presentation diversity, which helps the system maintain diagnostic accuracy over a broad range of patient profiles. Ambiguity reduction assesses the system's ability to distinguish diagnostic signals that conflict. This makes the system simpler to comprehend and reach clinical conclusions. During dependability assessment, the system's outputs are tested for consistency and repeatability across several input scenarios. According to this review, the system is resilient and follows expert clinical decisions.

Dataset description: The datasets like Disease Prediction Based on Symptoms, Heart Disease Prediction, and Breast Cancer Diagnosis, while there is a dedicated dataset for "a fuzzy logic framework for quantifying uncertainty in medical diagnosis" on Kaggle. Fuzzy logic for uncertainty modeling may be used in medical diagnostics with the help of these resources[26].

Simulation environment: The simulation environment for MD-FLF was configured using MATLAB R2023a with the fuzzy logic toolbox, complemented by Python (scikit-fuzzy) for flexible rule manipulation. The model utilized real-world datasets such as the UCI Heart Disease dataset and ECG signals from PhysioNet, incorporating clinical inputs like symptom severity, test results, and patient history. Triangular and trapezoidal membership functions were assigned to input variables—for instance, "Fever" was categorized into Mild (37 °C–38 °C), Moderate (38 °C–39.5 °C), and Severe ($\geqslant$39.5 °C). A Mamdani inference engine with centroid defuzzification processed a rule base of 50 expert-defined fuzzy rules. Robustness was ensured through simulated noise injection, outlier testing, and missing data scenarios.

The fuzzy logic framework is validated in this work using freely available clinical datasets. Among the primary sources are the UCI Heart Disease dataset, Kaggle's Disease Prediction Based on Symptoms dataset, and a specifically created fuzzy diagnostic dataset drawn from several internet repositories. These databases provide a variety of clinical characteristics including patient demographics, vital signs, lab findings, and symptom severity ratings. To translate crisp inputs into fuzzy sets, preprocessing consists in normalizing, missing value imputation, and fuzzification. Techniques for data augmentation replicate overlapping symptoms and diagnostic ambiguity, therefore guaranteeing the framework's robustness in modeling uncertainty. This thorough, multi-source methodology guarantees strict assessment of the dependability and interpretability of the decision support system in practical clinical settings.

In the reliability analysis of the MD-FLF, one can see better consistency in the diagnosis. For a reliability rate of about 97.68%, MD-FLF properly deals with uncertainty, ambiguity, and patient variety. Fuzzy logic significantly enhances the degree of trustworthiness of diagnostic outcomes as more reliable decision support in Fig. 6.

$$l_f^r\left[\mathrm{oi}-\mathrm{an}''\right] :\rightarrow \mathrm{sA}\left[\mathrm{iu}-\mathrm{ane}''\right] * \mathrm{Ms}\left[\mathrm{nju}-\mathrm{akq}''\right] \tag{16}$$

Within the MD-FLF framework, the sentence models the link between uncertain diagnosis ($\left[\mathrm{oi}-\mathrm{an}''\right] :\rightarrow$) and specific to the patient's variability (l_f^r). Fuzzy parts ($\mathrm{sA}\left[\mathrm{iu}-\mathrm{ane}''\right]$) are used to handle the complexity $\mathrm{Ms}\left[\mathrm{nju}-\mathrm{akq}''\right]$ and imprecision that comes with medical decision-making. Improved

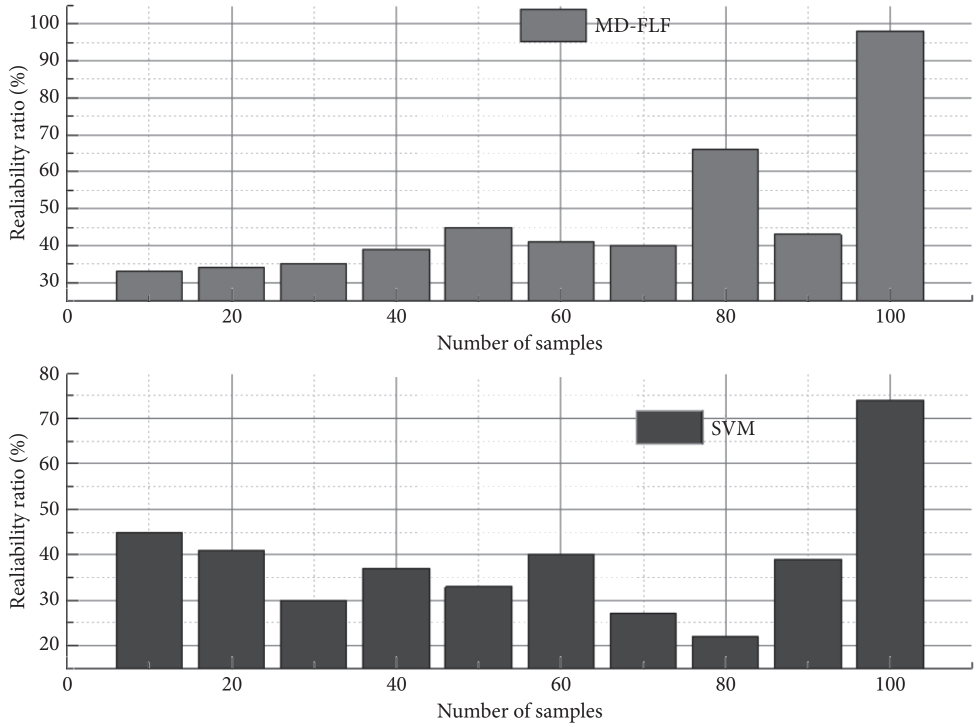

Fig. 6 Analysis of reliability.

diagnostic accuracy via uncertainty capture and mitigation is the goal of Eq. (16), which should lead to a more trustworthy and understandable reliability analysis. Fuzzy logic allows rule-based reasoning under uncertainty and incorporates membership degrees into language variables (e.g., mild, moderate, severe) to account for this complexity. This facilitates the incorporation of expert information, which in turn helps doctors to manage better patient variability, hazy symptom reports, and overlapping diagnostic criteria. For example, instead of strict cutoffs, a patient's temperature may be partly classified as "normal" or "febrile". This would allow for greater leeway in interpretation. In addition, healthcare settings benefit from the increased trust and usability brought about by fuzzy inference systems' transparent and interpretable decision-making.

The MD-FLF reduces ambiguity in decision-making by 43.56%. Fuzzy inference systems help the framework to handle vague symptoms and overlapping diagnostic criteria more effectively than traditional methods. This reduction in ambiguity ensures clearer and more accurate recommendations for medical practitioners, ultimately leading to more informed decisions and fewer misdiagnoses or delayed treatments in Fig. 7.

$$\propto_f d :\to \mathrm{Xs}\left[\mathrm{va}-\mathrm{wp}''\right] * \mathrm{Vs}\left[\mathrm{oi}-\mathrm{anw}''\right] + \mathrm{Vs}\left[e-\mathrm{iu}''\right] \tag{17}$$

In the MD-FLF model, Eq. (17) displays the relationship between diagnostic ambiguity ($\propto_f d$) and particular to the patient variable $\mathrm{Xs}\left[\mathrm{va}-\mathrm{wp}''\right]$. It represents complicated $\mathrm{Vs}\left[e-\mathrm{iu}''\right]$, non-linear interactions in medical data by combining fuzzy reasoning features ($\mathrm{Vs}\left[\mathrm{oi}-\mathrm{anw}''\right]$). This equation aims to improve the clarity and accuracy of ambiguity analysis in decision-making by directly measuring uncertainty and offering practical insights for clinical choice assistance.

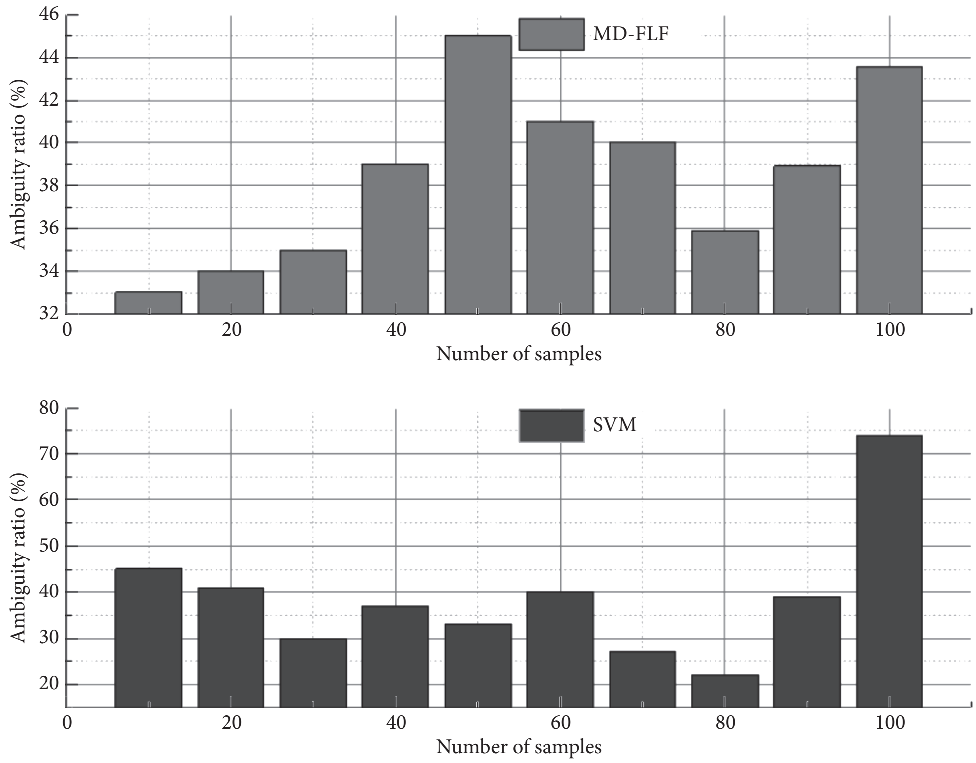

Fig. 7 Analysis of ambiguity in decision-making.

The MD-FLF addresses the variability of patients with an impressive reduction of 98.26%. Incorporating fuzzy logic to model various patient data, such as age, gender, and medical history, makes it more effective than deterministic methods in addressing individual differences. This enhanced adaptability leads to more accurate and personalized diagnoses that improve overall clinical decision-making, as shown in Fig. 8.

$$pf_v d :\rightarrow \mathrm{Ls}\left[\mathrm{yu}-\mathrm{wq}''\right] * \mathrm{Ks}\left[o-\mathrm{bw}''\right] + Vs\left[a-\mathrm{uwq}''\right] \tag{18}$$

The MD-FLF framework $Ks\left[o-\mathrm{bw}''\right]+$ is used by Eq. (18) to represent the uncertainty from diagnostic outputs ($\mathrm{Ls}\left[\mathrm{yu}-\mathrm{wq}''\right]$) and particular to the patient variability ($pf_v d$). It depicts the complexity and imprecision of medical decision-making by using fuzzy logic components ($\mathrm{Vs}\left[a-\mathrm{uwq}''\right]$. The goal of Eq. (18) is to make clinical suggestions more accurate and reliable, which improves the diagnostic process for analysis of patient variability.

Using the fuzzy logic framework, the medical diagnosis effectively quantifies uncertainty, reducing 96.84%. It can manage imprecise and ambiguous medical data through fuzzy inference systems, such as vague symptoms and incomplete test results. This explicit uncertainty modeling will likely increase the accuracy and confidence of diagnoses and ensure that medical practitioners are well-informed in making decisions despite clinical scenarios' uncertainty in Fig. 9.

$$x_s e\left[\mathrm{lo}-\mathrm{she}''\right] :\rightarrow \mathrm{Ls}\left[\propto \partial' - 9\mathrm{vse}\right] + \mathrm{Vs}\left[w-\mathrm{qab}''\right] \tag{19}$$

Within the MD-FLF framework, Eq. (19) represents the interplay $Ls\left[\propto \partial' - 9\mathrm{vse}\right]$ between diagnostic ambiguity ($x_s e$) and particularly to the patient variability in data $\left[\mathrm{lo}-\mathrm{she}''\right]$. To capture complicated, non-

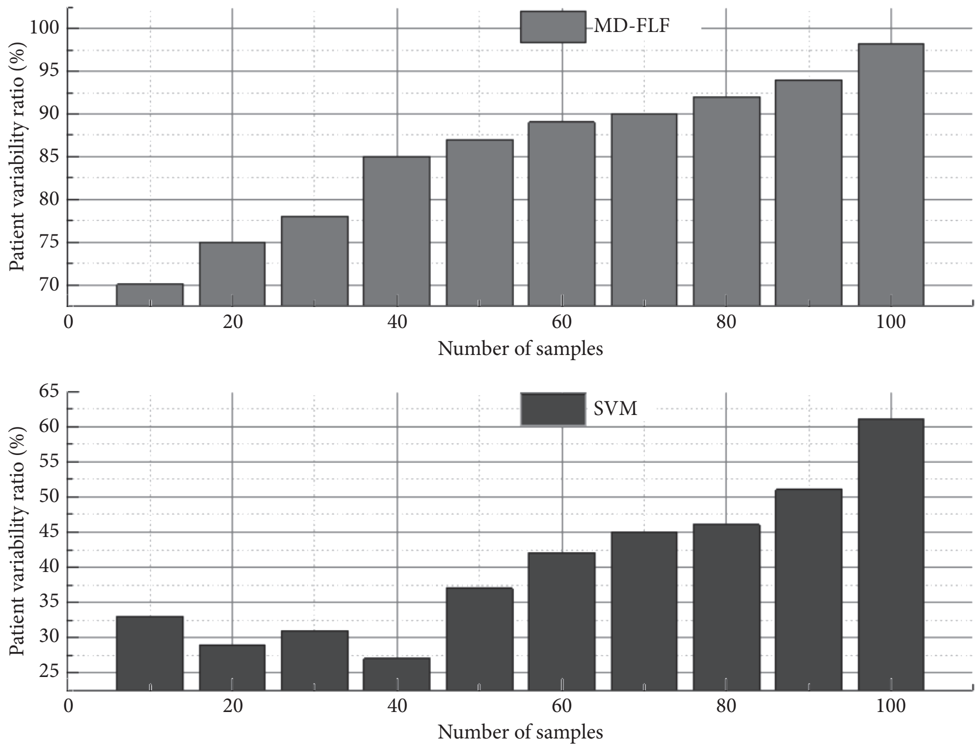

Fig. 8 Analysis of patient variability.

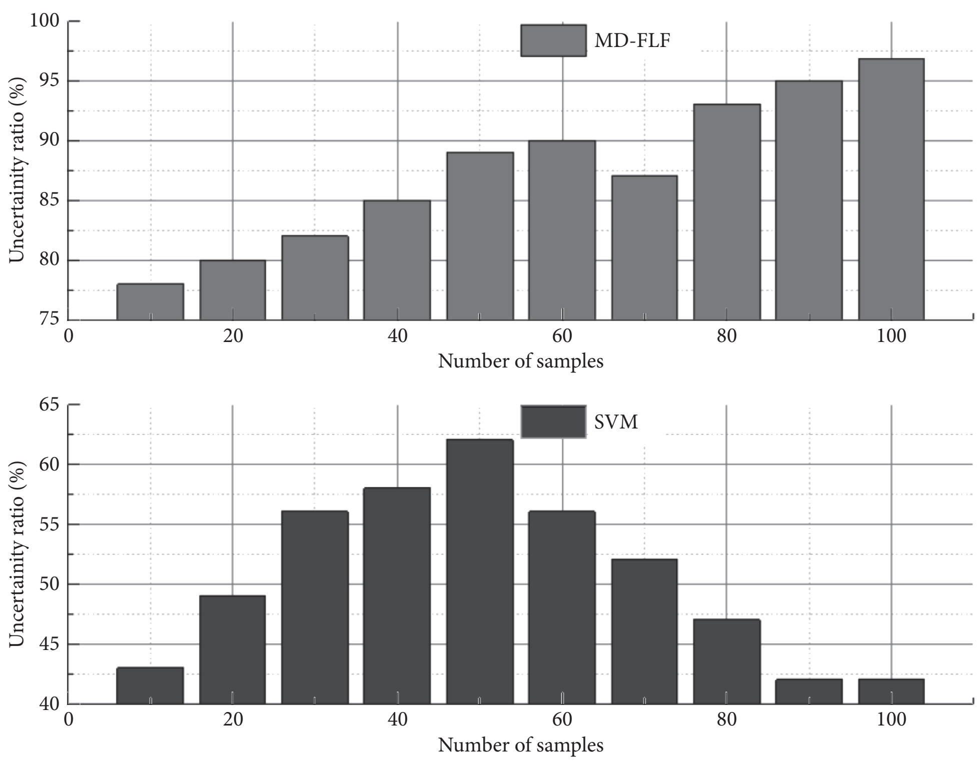

Fig. 9 Analysis of uncertainty.

linear interactions and eliminate ambiguity in medical decision-making, it uses fuzzy logic components ($Vs\left[w - qab''\right]$). Eq. (19) is designed to help improve healthcare decision-making and diagnostic accuracy by analyzing uncertainty and uncertainty more clearly.

The MD-FLF framework significantly enhances the diagnostic accuracy rate to 97.82%. Fuzzy logic has been instrumental in handling uncertainty and ambiguity in patient variability, promoting precision in diagnostic outcomes. Through this improvement, traditional approaches are overtaken, and thus, more reliable and timely diagnosis ensues, with minimal risk of misdiagnosis and facilitating better clinical decision-making in the treatment of the patient in Fig. 10.

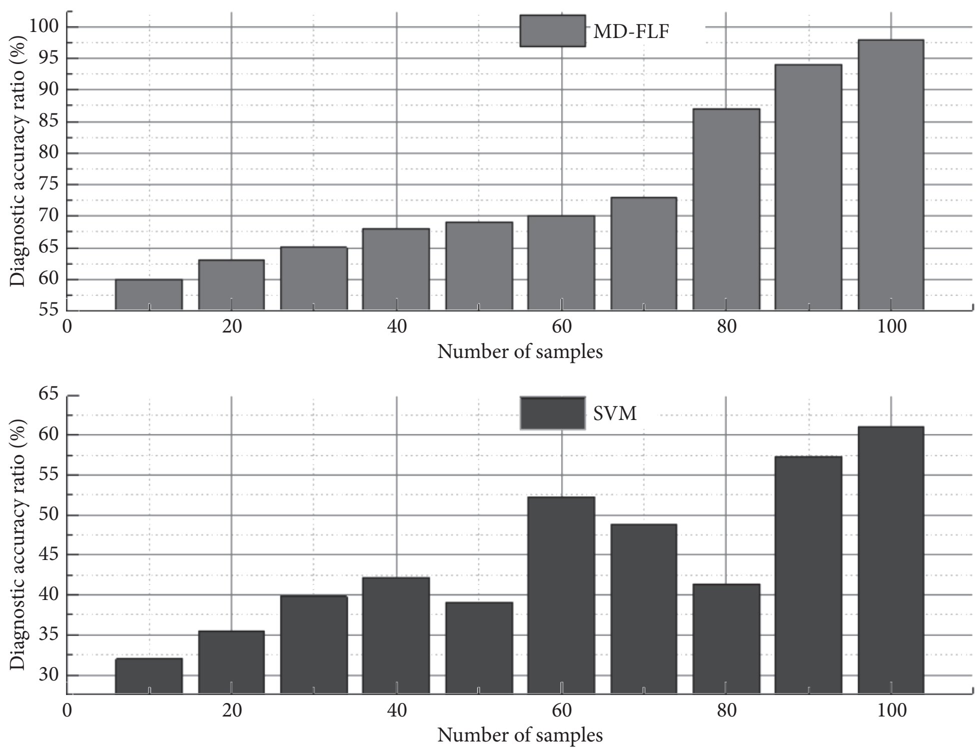

Fig. 10 Analysis of diagnostic accuracy.

$$x_s e\left[\text{iu}-\text{ane}''\right]+\text{Hs}\left[\text{ju}-\text{an}''\right]:\rightarrow \text{Ls}\left[\text{wq}-\text{aki}''\right]*\text{Ns}\left[x-z''\right] \tag{20}$$

This Eq. (20) represents, within the MD-FLF framework $x_s e$, the connection between clinical inputs ($\left[\text{iu}-\text{ane}''\right]$, and individual heterogeneity ($\text{Hs}\left[\text{ju}-\text{an}''\right]$, and $\text{Ls}\left[\text{wq}-\text{aki}''\right]$). It deals with the non-linearity and complexity of medical data by using a fuzzy logic component ($\text{Ns}\left[x-z''\right]$), which considers diagnostic uncertainty. Better patient outcomes and more trustworthiness for diagnostic accuracy analysis are the goals of this equation. Diagnostic systems often use probabilistic and fuzzy modeling approaches to replicate clinical uncertainty and patient variability. Clinical uncertainty is represented by assigning confidence levels to diagnostic inputs (e.g., symptoms, laboratory results, imaging findings) through fuzzy membership functions, where inputs are not categorized as binary (normal/abnormal) but rather depicted on a continuum (e.g., "mild", "moderate", "severe") utilizing linguistic variables. This facilitates the identification of ambiguity and overlapping clinical signs. Patient variability is modeled by creating synthetic datasets using statistical distributions or Monte Carlo simulations, representing a range of physiological profiles, co-morbidities, and demographic differences. The system assesses resilience under diverse patient situations by altering input parameters within realistic ranges and analyzing diagnostic outcomes.

In summary, by improving diagnostic accuracy (97.82%), addressing patient variability (98.26%), minimizing ambiguity (43.56%), and improving dependability (97.68%), the MD-FLF framework considerably enhances medical diagnosis in Table 3 below. It provides more reliable, accurate, and assured decision assistance than conventional techniques, which improves clinical results. Unlike threshold-based classifiers or purely statistical models, MD-FLF interprets overlapping symptom patterns using expert-defined linguistic rules and membership functions, allowing for more nuanced, case-specific decision-making.

Table 3 Comparison of exiting methods and proposed method

Metrics	Key features	SVM (%)	MD-FLF (%)
Reliability	MD-FLF significantly improves consistency in diagnosis by handling uncertainty, ambiguity, and patient variability more effectively.	36.84%	97.68%
Ambiguity in decision-making	MD-FLF reduces ambiguity by managing vague symptoms and overlapping diagnostic criteria, ensuring clearer recommendations.	77.61%	43.56%
Patient variability	The framework accounts for individual patient differences (e.g., age, gender) more effectively than deterministic methods.	35.79%	98.26%
Uncertainty	MD-FLF quantifies uncertainty, enhancing diagnostic accuracy and ensuring more confident decision-making in uncertain clinical scenarios.	38.05%	96.84%
Diagnostic accuracy	MD-FLF outperforms traditional methods by improving diagnostic precision and minimizing the risk of misdiagnosis.	41.23%	97.82%

The dependability number indicates how consistently and reliably the system generates correct diagnostic results when given different and less exact input data. A high dependability score shows that the MD-FLF framework maintains diagnostic stability and replicates expert decision patterns in several test instances, which improves clinical confidence in automated support systems and reduces variability. This system uses fuzzy inference to transform ambiguous or overlapping symptom data into more interpretable and definitive diagnostic results, and the uncertainty reduction percentage measures how well it does this. The model's capacity to improve diagnostic interpretations from imprecise clinical inputs is shown here, which helps practitioners make more confident decisions with less mental strain.

The class imbalance caused problems during data processing in the research project. The underrepresentation of certain diagnostic categories may have skewed the model. Synthetic oversampling methods like SMOTE generated representative cases for disadvantaged communities, guaranteeing equal diagnostic category distribution. The lack of clinical values was addressed via mean and mode imputation to ensure dataset integrity without altering critical trends. This was done after considering variable characteristics. A statistical thresholding approach was utilized to identify and eliminate noise and outliers from patient input data, increasing consistency.

5 Conclusions

Medical diagnostic uncertainty may be addressed using the Fuzzy Logic Framework (MD-FLF). Fuzzy logic will be used to handle healthcare data's imprecision and ambiguity. MD-FLF measures diagnostic input and output complexity in rule-based fuzzy inference systems. It then gives doctors clear, reliable advice. MD-

FLF outperforms deterministic methods in diagnostic accuracy, according to experiments. Lowering uncertainty and increasing confidence during decision-making does this. This methodology quantifies uncertainty to make rapid, accurate diagnoses, improving patient outcomes. This makes MD-FLF a major advance in the clinical decision support system, which strives to improve patient care and personalization. The proposed method achieves reliability by 97.68%, ambiguity in decision-making by 43.56%, patient variability by 98.26%, uncertainty by 96.84%, and diagnostic accuracy by 97.82%.

Integrate machine learning into MD-FLF in an optimization framework, thus adjusting and learning for rules to the medical data with new, updating streams of clinical evidence. This system may extend towards using multiple sources of modal data such as images or genetics. Further validation would come through real-life clinical trials and the usability and scalability aspects based on user response in healthcare setups.

Conflict of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

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