Vol.9 Issue 4 Oct 2026

Multimedia Research

Received 24 September, Revised 28 September, Accepted 10 October



Early Acute Respiratory Disease Identification From Confusing Symptom Sets Using A Fuzzy C-Means-Based Soft Computing Model

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Abstract: Acute Respiratory Diseases (ARDs) frequently present with overlapping symptoms, creating diagnostic ambiguity during early clinical assessment. This study developed a Fuzzy C-Means (FCM)-based soft computing decision-support model for early detection and classification of confusable ARDs from structured symptom information. A dataset of 20,373 instances was assembled from clinical records, published datasets and medical literature, and domain-expert input. After data collection and preprocessing, FCM was applied to represent soft membership across disease clusters, while a Random Forest classifier was used for supervised disease classification. The developed Python–MySQL application operationalized data entry, processing and result presentation. Reported clustering results were PC=0.82, PE=0.19, Dunn Index=0.24, DBI=0.31, ARI=0.78 and NMI=0.81. For the supervised classifier, the manuscript reports 90.3% accuracy, 0.92 precision/sensitivity, 91.7% specificity, 0.90 F1-score and 0.95 AUC. Separately, the comparative diagnostic-system table reports 50% accuracy, 39% precision, 49% recall and 39% F1-score for the FCM-based system, compared with 5%, 30%, 28% and 27% for RCCD and 5%, 30%, 26% and 27% for SCCD. These values are therefore treated as results from different evaluation stages rather than as interchangeable measures. The model is intended to support, not replace, professional clinical diagnosis by making symptom overlap and diagnostic uncertainty explicit.

Keywords: Fuzzy C-Means; Acute Respiratory Diseases; Soft Computing; Clinical Decision Support; Symptom Classification

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
ARD	Acute Respiratory Disease
ARI	Adjusted Rand Index
AUC	Area Under the Receiver Operating Characteristic Curve
DBI	Davies–Bouldin Index
FCM	Fuzzy C-Means
MCDM	Multi-Criteria Decision Making
NMI	Normalized Mutual Information
PC	Partition Coefficient
PE	Partition Entropy
RCCD	Rule-Based Conventional Clinical Diagnosis
RF	Random Forest
SCCD	Symptom-Based Conventional Clinical Diagnosis

1. Introduction

ARDs, including pneumonia, influenza, COVID-19, Severe Acute Respiratory Syndrome (SARS) and Acute Respiratory Distress Syndrome (ARDS) [2], can present with similar clinical manifestations such as fever, cough, dyspnea, chest discomfort and hypoxemia. The source manuscript identifies this symptom overlap as a central cause of diagnostic uncertainty, particularly at the early stage of illness. Distinguishing overlapping symptom patterns is important for clinical decision support because a decision-support tool is most useful when it can preserve uncertainty rather than force an early binary choice.

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Conventional diagnosis remains essential and may include laboratory investigation and imaging, but these approaches can be resource-intensive and are not always available at the first point of assessment. Recent AI research has demonstrated the value of machine learning for respiratory surveillance and diagnosis using symptoms, laboratory measurements, imaging and other clinical data [9][14][15]. For example, symptom-based ML has been evaluated for RSV and pertussis surveillance [14], while other studies have used deep learning and imaging for pneumonia and ARDS [10][12]. These approaches demonstrate the potential of computational decision support [5], but they do not remove the specific methodological challenge addressed here: representing overlapping symptoms among multiple confusable respiratory conditions.

The proposed work therefore uses FCM, a soft clustering method in which an observation can have different membership degrees in multiple clusters, followed by RF classification. The approach is designed around structured symptom information and is implemented as a Python–MySQL application. Unlike a hard assignment procedure, the FCM stage can expose partial membership and thereby provide an explicit representation of uncertainty.

The major contributions of this study are:

- Development of an FCM-based soft computing framework for structured symptom-based analysis of confusable ARDs.
- Construction and preprocessing of a 20,373-instance symptom dataset for the experimental study.
- Integration of FCM clustering with RF classification in a Python–MySQL decision-support application.
- Evaluation using internal and external clustering indices, together with supervised classification metrics.
- Comparative evaluation against the RCCD and SCCD systems reported in the study.

The experimental results reported in the manuscript show FCM clustering indices of PC=0.82, PE=0.19, Dunn=0.24, DBI=0.31, ARI=0.78 and NMI=0.81. The supervised RF stage is reported at 90.3% accuracy and 0.95 AUC, whereas the separate comparative diagnostic-system table reports 50% accuracy for the FCM-based system. This revised manuscript explicitly distinguishes these evaluation stages to prevent an apparent contradiction.

The remainder of the paper is organized as follows. Section 2 reviews previous research and identifies the research gap. Section 3 presents the research methodology, data preparation and FCM formulation. Section 4 describes the existing and proposed systems. Section 5 reports the experimental results. Section 6 discusses the findings, including comparison with related approaches, advantages and limitations. Section 7 concludes the study and outlines future work.

2. Summary of Related Works

Existing research relevant to this study can be grouped into four broad strands: fuzzy/soft clustering for diagnosis, fuzzy expert systems for uncertain clinical reasoning [18][4], symptom-based machine learning [8][17][19][22], and imaging/deep-learning approaches. James et al. (2022) [11] investigated FCM for confusable disease diagnosis, while Faith-Michael et al. (2021) [6] used a fuzzy cognitive map for differential diagnosis of tropical confusable diseases. Shahzaib et al. (2023) [16] proposed a probabilistic hesitant fuzzy N-soft approach for infectious disease identification. Other work has demonstrated symptom-based ML for respiratory infections, including pertussis and RSV, and machine-learning triage of respiratory symptoms [19][20]. Imaging-based studies, such as pneumonia detection from chest X-rays and ARDS models combining clinical data with radiographs, demonstrate strong potential but typically depend on imaging infrastructure.

2.1 Comparative Review

Table 1 summarizes the methodologies, advantages, and limitations of existing fuzzy, soft-clustering, and machine-learning approaches to disease diagnosis, highlighting the research gap addressed by the proposed framework.

Table 1. *Comparative Analysis of Existing Disease Diagnosis Approaches*

Study / Approach	Methodology	Advantages	Limitations / Relevance to Gap
James et al. (2022) [11]	FCM for confusable diseases	Represents overlapping disease membership	Does not provide the present ARD dataset/application workflow
Faith-Michael et al. (2021) [6]	Fuzzy Cognitive Map	Supports differential reasoning	Different reasoning architecture; not the same FCM–RF pipeline
Shahzaib et al. (2023) [16]	Probabilistic hesitant fuzzy N-soft information	Handles uncertainty in infectious disease identification	More complex representation; different experimental setting
Haris et al. (2023) [7]	Fuzzy clustering using age and early symptoms	Uses early symptom indicators	Focused on COVID-19 patient classification rather than a broader confusable ARD set
Mc Cord-De Iaco et al. (2023) [14]	LightGBM using symptoms and laboratory variables	Demonstrates symptom-based respiratory decision support	Targets pertussis/RSV and uses a different population and outcome
Jaiswal et al. (2019) [10]	Deep learning on chest X-rays	Automated pneumonia image classification	Requires imaging data and infrastructure
Kai-Chih et al. (2022) [12]	AI using clinical data and chest radiographs	Combines clinical and imaging information	Not primarily a symptom-only confusability model
Heyman et al. (2024) [15]	Interpretable deep learning for dyspnoea	Uses complete healthcare-system data	Targets dyspnoea differential diagnosis rather than the present ARD symptom-clustering problem
Krasnov et al. (2023) [13]	Review of FCM applications	Shows broad utility and adaptations of FCM	Focuses on breast-cancer image segmentation rather than respiratory diagnosis
El-Ibrahimi et al. (2024) [4]	Fuzzy-logic expert system	Demonstrates fuzzy reasoning for clinical prediction	Different disease domain and methodology
Aniobi et al. (2020) [1]	Neutrosophic-AHP expert system	Supports diagnosis of confusable diseases under uncertainty	Does not provide the present FCM–RF pipeline
Haruna et al. (2020) [8]	Bibliometric survey of machine-learning approaches	Reviews ML approaches for coronavirus control	Does not present the proposed integrated diagnostic workflow
Theyazn et al. (2021) [17]	Soft clustering with machine-learning algorithms	Explores soft clustering for chronic disease diagnosis	Focuses on chronic diseases rather than confusable ARDs
Remote diagnosis study (2024) [19]	Neural network using few symptom words	Supports remote diagnosis of upper respiratory tract infections	Uses a different diagnostic approach from FCM–RF
ARDS systematic review (2024) [20]	Review of machine-learning algorithms	Summarizes ML applications in ARDS	Does not implement the proposed symptom-clustering pipeline
Smart healthcare diagnosis study (2024) [21]	Fuzzy clustering with battle royale optimization	Combines clustering and optimization for disease diagnosis	Uses a different optimization framework
RSV detection study (2024) [22]	ML using patient-reported symptoms	Supports symptom-based RSV detection	Focuses on RSV in pediatric patients rather than multiple confusable ARDs
Artificial intelligence in respiratory disease diagnosis (2024) [23]	Review of AI applications in respiratory diagnosis	Highlights the potential of AI for respiratory disease diagnosis	Does not specifically establish the proposed FCM–RF application workflow

2.2 Research Gap

The reviewed studies indicate that symptom-based and fuzzy approaches can support clinical decision-making, while imaging and deep-learning methods can achieve strong performance when suitable images are available. However, the source study addresses a narrower gap: an operational soft-computing pipeline

that uses structured symptoms to model overlapping membership among multiple confusable ARDs and then applies supervised classification. The proposed framework addresses this gap by combining FCM's soft membership representation with RF classification and a deployable Python-MySQL application.

3. Methodology

This study adopts an Analytical and Empirical Research Methodology (AERM) to evaluate the effectiveness of the proposed diagnostic framework. The methodology involves analyzing symptom data, applying FCM clustering to represent overlapping disease characteristics, and using RF classification for disease prediction. The proposed framework aims to support the differentiation of confusable acute respiratory diseases (ARDs) and improve diagnostic decision-making. Fig. 1 illustrates the proposed FCM-based soft-computing workflow.

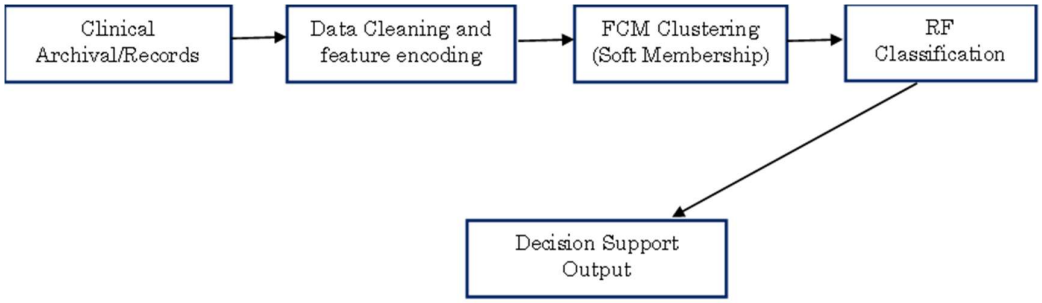


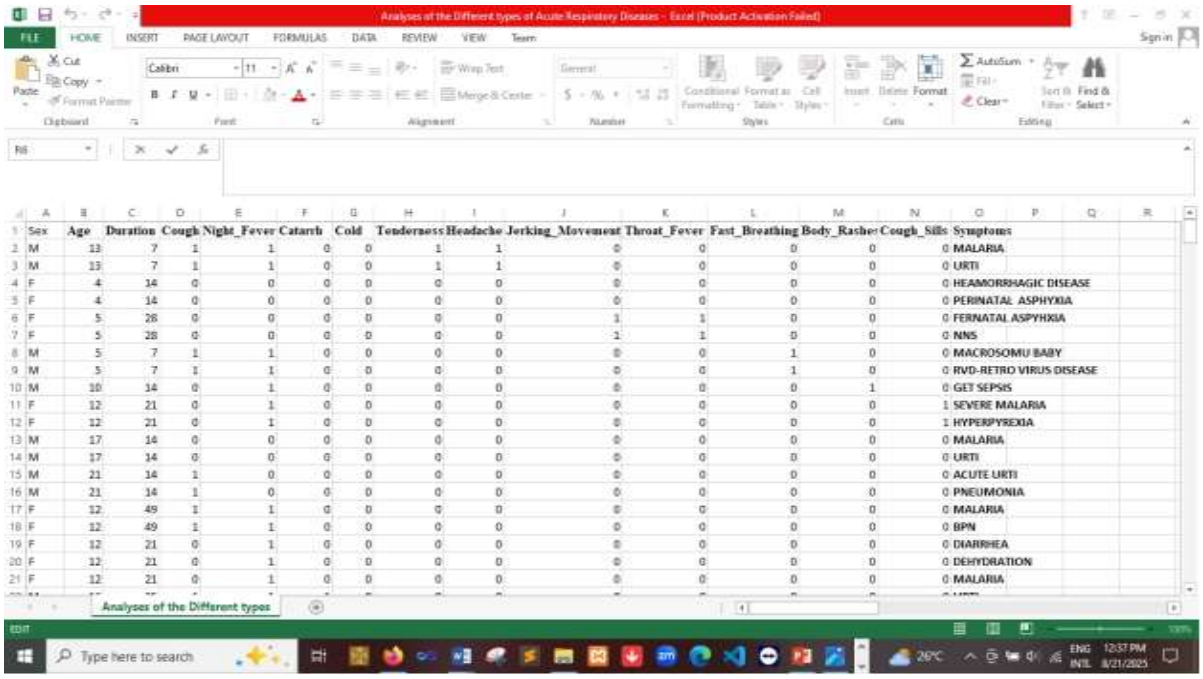
Fig. 1. *Proposed FCM-Based Soft Computing Workflow*

Evaluation: PC, PE, Dunn Index, DBI, ARI, NMI, Accuracy, Precision, Recall, F1-Score and AOC

3.1 Data Collection and Preprocessing

The dataset contains 20,373 instances and five attributes as reported in the original abstract. Data sources described in the manuscript include clinical symptom records, published datasets and medical literature, and domain experts. The recorded information includes symptoms and contextual variables such as age, gender, duration of illness and binary symptom indicators. The revised workflow treats data preprocessing as a distinct stage comprising record review, feature encoding, consistency checking, handling of incomplete entries where identified, and preparation of numerical feature vectors for FCM.

Because the submitted manuscript does not provide a numerical audit of the number or percentage of missing observations, this revision does not invent a missing-value rate or imputation statistic. Instead, missing entries should be reported in the final dataset description if the authors' preprocessing log contains those counts. For reproducibility, categorical variables should be encoded consistently, binary symptoms represented as 0/1 indicators, and numerical variables normalized when their scales differ materially before distance-based FCM clustering. Fig. 2 depicts the sample data collected.



Sex	Age	Duration	Cough	Night_Fever	Catarrh	Cold	Tenderness	Headache	Jerking_Movement	Throat_Fever	Fast_Breathing	Body_Rashes	Cough_Sills	Symptoms
M	13	7	1	1	0	0	1	1	0	0	0	0	0	MALARIA
M	13	7	1	1	0	0	1	1	0	0	0	0	0	URTI
F	4	14	0	0	0	0	0	0	0	0	0	0	0	HEAMORRHAGIC DISEASE
F	4	14	0	0	0	0	0	0	0	0	0	0	0	PERINATAL ASPHYXIA
F	5	28	0	0	0	0	0	0	1	1	0	0	0	FERNATAL ASPYHXIA
F	5	28	0	0	0	0	0	0	1	1	0	0	0	NNS
M	5	7	1	1	0	0	0	0	0	0	1	0	0	MACROSOMU BABY
M	5	7	1	1	0	0	0	0	0	0	1	0	0	RVD-RETRO VIRUS DISEASE
M	10	14	0	1	0	0	0	0	0	0	0	1	0	GET SEPSIS
F	12	21	0	1	0	0	0	0	0	0	0	0	1	SEVERE MALARIA
F	12	21	0	1	0	0	0	0	0	0	0	0	1	HYPERPYREXIA
M	17	14	0	0	0	0	0	0	0	0	0	0	0	MALARIA
M	17	14	0	0	0	0	0	0	0	0	0	0	0	URTI
M	21	14	1	0	0	0	0	0	0	0	0	0	0	ACUTE URTI
M	21	14	1	0	0	0	0	0	0	0	0	0	0	PNEUMONIA
F	12	49	1	1	0	0	0	0	0	0	0	0	0	MALARIA
F	12	49	1	1	0	0	0	0	0	0	0	0	0	BPN
F	12	21	0	1	0	0	0	0	0	0	0	0	0	DIARRHEA
F	12	21	0	1	0	0	0	0	0	0	0	0	0	DEHYDRATION
F	12	21	0	1	0	0	0	0	0	0	0	0	0	MALARIA

Fig. 2. *Sample Data Collected*

3.2 FCM Mathematical Formulation

Let $X=\{x_1,x_2,\ldots,x_n\}$ denote the set of n feature vectors and let c denote the number of clusters. FCM estimates a membership matrix $U=[u_{ij}]$, where $u_{ij}\in[0,1]$ represents the degree to which observation x_i belongs to cluster j and $\Sigma_j u_{ij}=1$ for every i. The fuzzification parameter m controls the degree of fuzziness and is constrained by $m>1$ [3].

$$J_m(U,V) = \Sigma_{i=1}^{n} \Sigma_{j=1}^{c} (u_{ij})^m \|x_i - v_j\|^2 \quad (1)$$

$$v_j = [\Sigma_{i=1}^{n} (u_{ij})^m x_i] / [\Sigma_{i=1}^{n} (u_{ij})^m] \quad (2)$$

$$u_{ij} = 1 / \Sigma_{k=1}^{c} (\|x_i - v_j\| / \|x_i - v_k\|)^{(2/(m-1))} \quad (3)$$

$$\Sigma_{j=1}^{c} u_{ij} = 1, \quad 0 \le u_{ij} \le 1 \quad (4)$$

Equation (1) is the FCM objective function minimized during clustering. Equation (2) updates the cluster centroids using membership-weighted observations, while Equation (3) updates the membership degrees from the relative distances to the centroids. Equation (4) states the membership constraints. Iteration continues until the objective function or centroid changes satisfy the selected stopping criterion.

4. Analysis of Existing and Proposed Systems

4.1 Existing System

The existing diagnostic process described in the manuscript is primarily manual and sequential: patient information is obtained, the physician performs clinical assessment, laboratory tests are requested where available, and a diagnostic output is produced. The limitations include symptom overlap, dependence on clinical judgment and potential resource constraints. Fig. 3 depicts the architecture of the existing system.

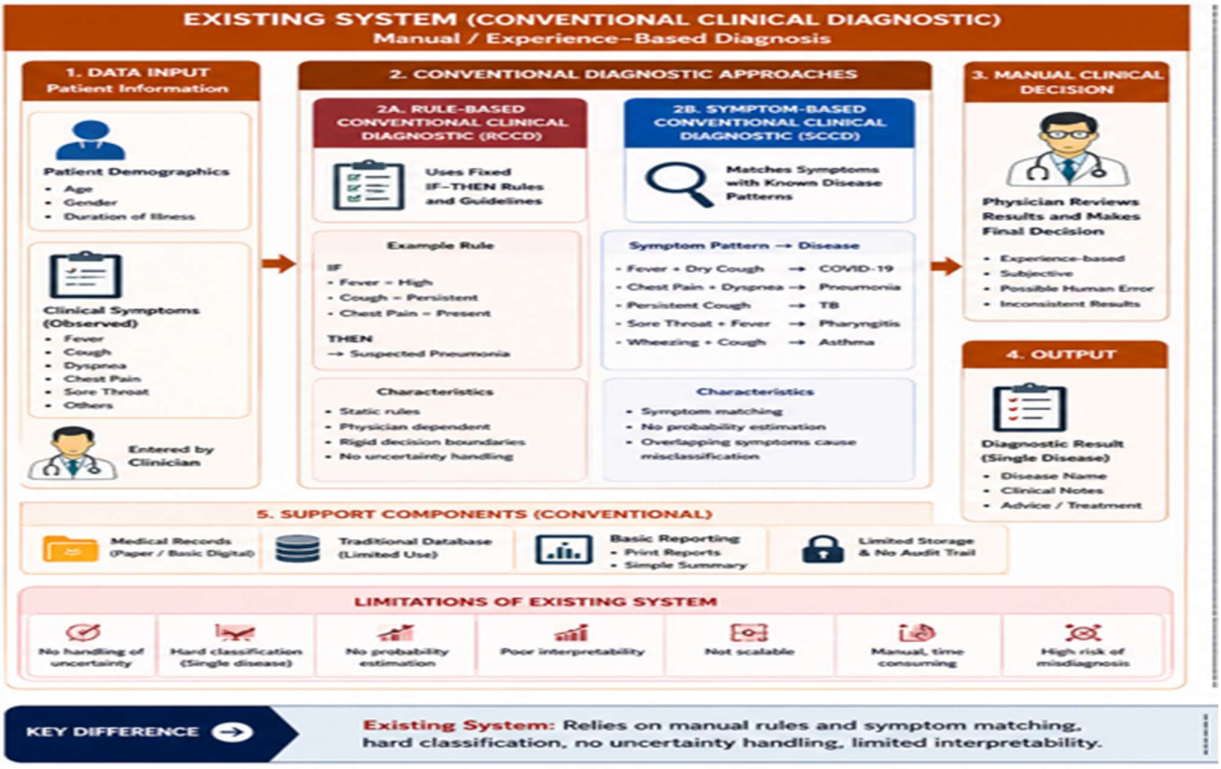


Fig. 3. *The Architecture of the Existing System*

4.2 Proposed System Architecture

The architecture consists of a user/clinician layer, input and data layer, process layer, decision layer and output layer. The process layer contains preprocessing, FCM clustering and RF classification. The decision layer exposes membership scores and predicted disease class, while the output layer provides an interpretable early decision-support result. Fig. 4 depicts the architecture of the proposed system.

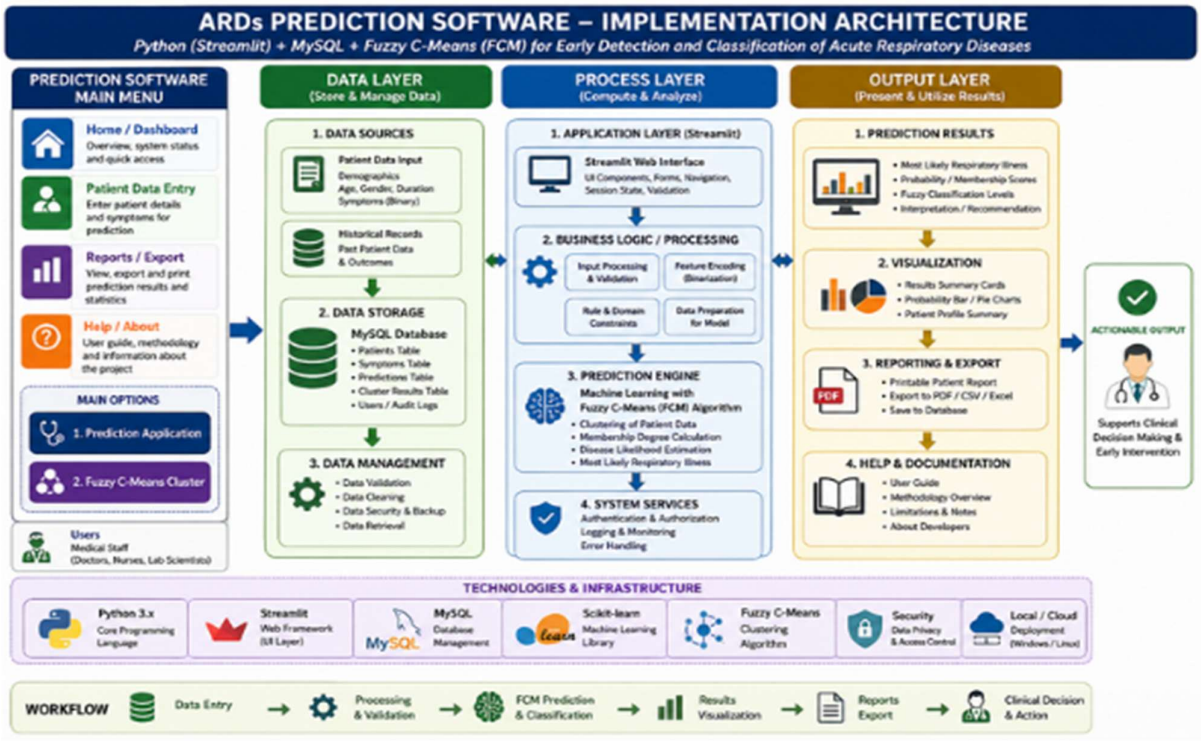


Fig. 4. *The Architecture of the Proposed System (ARDs Prediction Software System)*

4.3 FCM Clustering Engine

The Fuzzy C-Means (FCM) clustering engine forms the core of the proposed soft-computing methodology. It groups symptom data according to different acute respiratory diseases (ARDs) while allowing each patient to belong to multiple clusters with varying membership degrees (μ-values). This soft membership representation captures symptom overlap and diagnostic uncertainty, reflecting the ambiguity often encountered in respiratory disease diagnosis. Unlike hard clustering, FCM accommodates partial membership in multiple disease clusters, supporting differential diagnosis in cases where symptoms do not clearly indicate a single disease.

4.4 Analysis of the Proposed System

The goal of the suggested Fuzzy Cluster Means-Based Soft Computing System with Fuzzy Cognitive Map is to facilitate the early identification and differentiation of ARDs from their confusing counterparts. The design incorporates a number of linked modules, each of which is in charge of handling, processing, making decisions, and interpreting the results. Fig. 4 provides comprehensive details regarding the system and it is of the following components: Prediction Software Main Menu where the user selects what operation to carry on, Data Layer used to store and manage data, Process Layer used to compute and analyses data, and Output Layer which is used to present and utilize result.

5. Results & Evaluation

This section presents and evaluates the results of the proposed Fuzzy C-Means (FCM) clustering and Random Forest (RF) classification framework for diagnosing confusable acute respiratory diseases (ARDs). The evaluation examines clustering quality, classification performance, and comparative results to assess the effectiveness of the proposed approach in distinguishing diseases with overlapping symptoms.

5.1 FCM Clustering Results

The table 2 presents the evaluation metrics and reported values for the Fuzzy C-Means (FCM) clustering process.

Table 2. *FCM Clustering Performance Metrics*

Metric	Reported value
PC	0.82
PE	0.19
Dunn Index	0.24
DBI	0.31
ARI	0.78
NMI	0.81

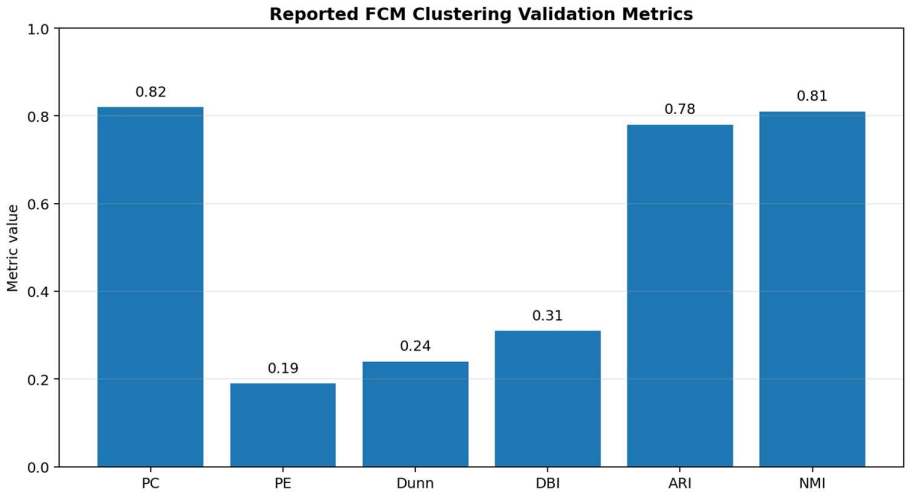


Fig. 5. *Reported FCM clustering-validation metrics: PC=0.82, PE=0.19, Dunn=0.24, DBI=0.31, ARI=0.78 and NMI=0.81.*

The chart in fig. 5 visualizes the reported numerical values; the metrics have different definitions and should not be interpreted as directly comparable scales.

5.2 Supervised Classification Results

The table 3 presents the performance metrics of the Random Forest (RF) classifier for diagnostic disease classification.

Table 3. *Random Forest Classification Performance Metrics*

Metric	RF result reported in manuscript
Accuracy	90.3%
Precision	0.92
Sensitivity / Recall	0.92
Specificity	91.7%
F1-score	0.90
AUC-ROC	0.95

The reported performance metrics correspond to the Random Forest (RF) supervised classifier and not directly to the Fuzzy C-Means (FCM) clustering process. The RF classifier achieved an accuracy of 90.3%, whereas the comparative evaluation reports 50% accuracy for the FCM-Based System. These results are presented separately because they correspond to different evaluation contexts.

5.3 Evaluation Metrics

FCM was evaluated using the following standard classification metrics: PC for assessing the degree of fuzziness in a fuzzy clustering result, PE for assessing fuzzy cluster assignment uncertainty, The Dunn Index (DI) for considering both cluster separation and compactness when assessing the quality of clustering, DBI for evaluating the degree of cluster separation and compactness, The ARI as an external validation parameter that assesses the degree of agreement between the predicted cluster labels and the actual class labels and NMI for assessing the degree of agreement between the actual class labels and the anticipated cluster labels. The table 4 compares the accuracy, precision, recall, F1-score, and support of the FCM-Based, RCCD, and SCCD diagnostic systems.

Table 4. *Comparative Results Evaluation*

Performance Metric	FCM-Based System	RCCD System	SCCD System
Accuracy	**50%**	5%	5%
Precision	**39%**	30%	30%
Recall	**49%**	28%	26%
F1-Score	**39%**	27%	27%
Support	61%	61%	61%

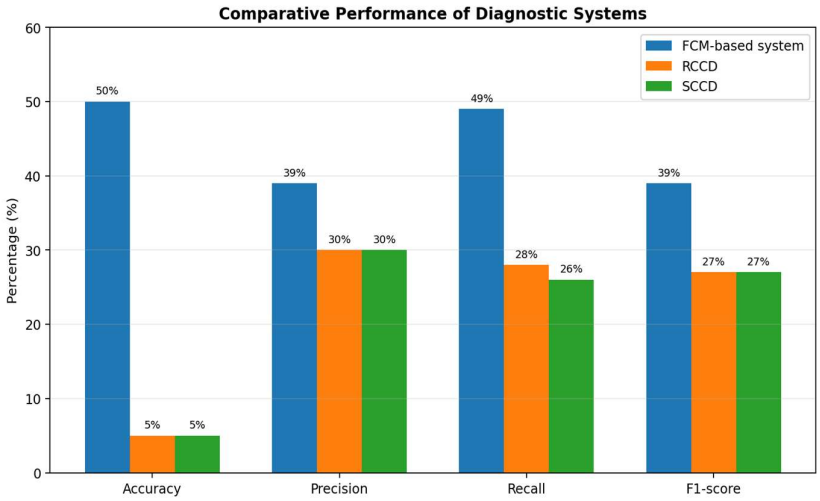


Fig. 6. *Comparative performance values reported for the FCM-based, RCCD and SCCD diagnostic systems.*

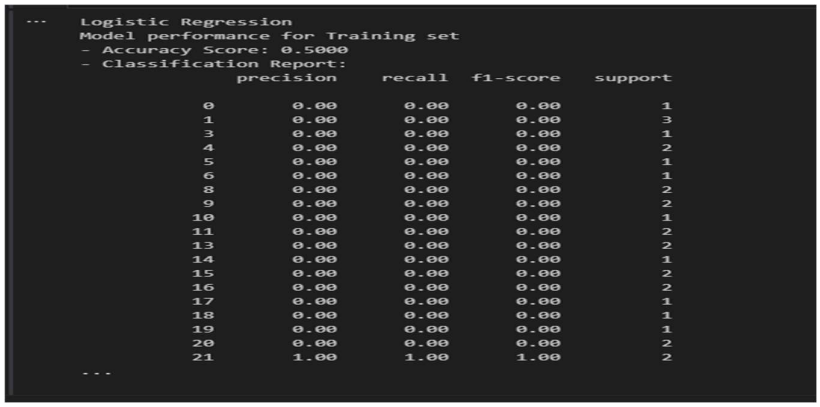
The FCM-based system is shown in fig. 6 with 50% accuracy, 39% precision, 49% recall and 39% F1-score; RCCD and SCCD values are reproduced from the submitted comparative table.

5.4 Graphical Evaluation

The comparative bar chart in Fig. 6 visualizes the reported system-level metrics. A true confusion matrix and empirical ROC curve require the individual test-set predictions and ground-truth labels. Those raw observations are not included in the submitted manuscript; therefore, the final publication version should generate these two plots directly from the saved test predictions rather than from reconstructed or assumed counts

5.5 Overall Comparative Performance Ranking of the Diagnostic Systems

Fig. 7 depicts the model performance of the existing diagnostic system on the training set.

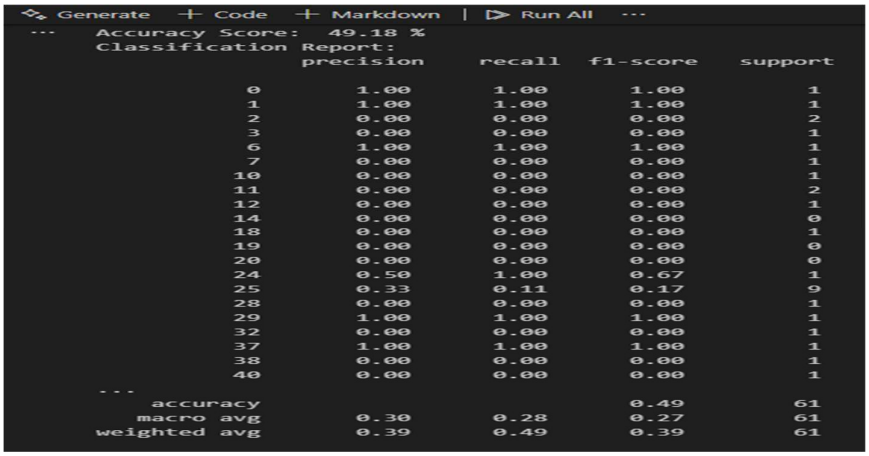


```
Logistic Regression
Model performance for Training set
- Accuracy Score: 0.5000
- Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         3
           3       0.00      0.00      0.00         1
           4       0.00      0.00      0.00         2
           5       0.00      0.00      0.00         1
           6       0.00      0.00      0.00         1
           8       0.00      0.00      0.00         2
           9       0.00      0.00      0.00         2
          10       0.00      0.00      0.00         1
          11       0.00      0.00      0.00         2
          13       0.00      0.00      0.00         2
          14       0.00      0.00      0.00         1
          15       0.00      0.00      0.00         2
          16       0.00      0.00      0.00         2
          17       0.00      0.00      0.00         1
          18       0.00      0.00      0.00         1
          19       0.00      0.00      0.00         1
          20       0.00      0.00      0.00         2
          21       1.00      1.00      1.00         2
...
```

Fig. 7. *Model Performance for Training Set of the Existing System*

Fig. 8 depicts the model performance of the proposed diagnostic system on the training set.



```
Generate  + Code  + Markdown  |  Run All  ...
Accuracy Score:  49.18 %
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           1       1.00      1.00      1.00         1
           2       0.00      0.00      0.00         2
           3       0.00      0.00      0.00         1
           6       1.00      1.00      1.00         1
           7       0.00      0.00      0.00         1
          10       0.00      0.00      0.00         1
          11       0.00      0.00      0.00         2
          12       0.00      0.00      0.00         1
          14       0.00      0.00      0.00         0
          18       0.00      0.00      0.00         1
          19       0.00      0.00      0.00         0
          20       0.00      0.00      0.00         0
          24       0.50      1.00      0.67         1
          25       0.33      0.11      0.17         9
          28       0.00      0.00      0.00         1
          29       1.00      1.00      1.00         1
          32       0.00      0.00      0.00         1
          37       1.00      1.00      1.00         1
          38       0.00      0.00      0.00         1
          40       0.00      0.00      0.00         1
...
    accuracy                           0.49        61
   macro avg       0.30      0.28      0.27        61
weighted avg       0.39      0.49      0.39        61
```

Fig. 8. *Model Performance for Training Set of the New System*

6. Discussion

The results indicate that the FCM stage provides a soft representation of symptom membership, while the RF stage provides a supervised classification result. This distinction is important because clustering quality and classification accuracy answer different questions. FCM evaluates the structure and overlap of the symptom space, whereas RF evaluates predictive classification against labelled outcomes.

The reported comparative table shows that the FCM-based diagnostic system has higher reported accuracy, recall and F1-score than the RCCD and SCCD systems in that particular evaluation. A plausible methodological explanation is that FCM does not force every symptom profile into a single hard cluster at the clustering stage; instead, membership degrees can represent overlap. RCCD uses rule-based clinical logic, while SCCD uses symptom-based conventional decision rules. Their lower reported comparative values may therefore reflect the difficulty of representing overlapping symptom patterns with hard or conventional rules. These are interpretations of the reported experimental pattern rather than claims that FCM is universally superior.

The findings are consistent with the broader literature showing that symptom-based machine learning can support respiratory clinical decision-making and that fuzzy clustering is useful when observations do not belong naturally to a single crisp group [3]. Recent respiratory decision-support studies have used clinical symptoms and routine laboratory variables to distinguish infections [14], while other work has focused on imaging or multimodal data [10][12]. The present contribution is specifically the integration of soft clustering with supervised classification for confusable ARD symptom patterns.

6.1 Advantages

- Represents overlapping symptom patterns using fuzzy membership rather than only hard cluster assignment.
- Uses structured clinical information that can be collected without requiring an imaging study at the initial computational stage.
- Separates unsupervised symptom-space modelling from supervised classification.
- Provides multiple clustering-validity and classification measures for evaluation.
- Is implemented as an operational Python–MySQL application architecture.

6.2 Limitations

- The submitted manuscript does not provide sufficient raw-data detail to independently reproduce every preprocessing decision.
- The missing-value counts and exact imputation procedure are not quantified in the supplied manuscript.
- The manuscript contains two accuracy values associated with different evaluation stages; the underlying experiment logs should be audited before final publication.
- Raw test predictions are not supplied, preventing independent reconstruction of a confusion matrix and empirical ROC curve from the manuscript alone.
- Clinical decision support should not be interpreted as replacement for laboratory confirmation, imaging or professional diagnosis.

6.3 Future Research

- Release an anonymized, reproducible dataset description and preprocessing protocol.
- Evaluate the model prospectively across multiple hospitals and patient populations.
- Add calibration analysis, external validation and subgroup performance analysis.
- Generate confusion matrices and ROC/precision–recall curves from held-out patient-level predictions.
- Investigate explainable AI methods that show which symptoms contribute to disease membership and classification.
- Compare FCM with alternative soft-clustering and hybrid neuro-fuzzy approaches under identical experimental conditions.

Above all, the FCM-based system greatly outperforms RCCD and SCCD systems across all main performance measures, as confirmed by the experimental comparison using Scikit-learn 1.1.1.

7. Conclusion

This study developed and evaluated a FCM-based soft computing framework for early decision support in the classification of confusable ARDs. The central methodological contribution is the use of fuzzy membership to represent overlapping symptom patterns, followed by supervised RF classification in an integrated Python–MySQL application. The reported FCM clustering results were PC=0.82, PE=0.19, Dunn=0.24, DBI=0.31, ARI=0.78 and NMI=0.81. The manuscript also reports 90.3% RF accuracy with 0.92 precision/sensitivity, 91.7% specificity, 0.90 F1-score and 0.95 AUC, while the separate diagnostic-system comparison reports 50% accuracy, 39% precision, 49% recall and 39% F1-score for the FCM-based system. Explicit separation of these evaluation stages resolves the principal reporting ambiguity identified during review, although the underlying experimental records should be checked before final submission. Practically, the system can serve as an early clinical decision-support aid for organizing symptom information and exposing uncertainty, but it should complement rather than replace professional diagnosis and confirmatory clinical investigation.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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