



RESEARCH ARTICLE

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TODDLER-CENTERED CASE-BASED REASONING FRAMEWORK FOR EARLY DIAGNOSIS OF AUTISM SPECTRUM DISORDER

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ABSTRACT

Early diagnosis of Autism Spectrum Disorder (ASD) in toddlers improves developmental outcomes through timely interventions. However, traditional methods rely on subjective judgment, lengthy assessments, and limited specialist availability. This study introduces a toddler-centered Case-Based Reasoning (CBR) framework that emulates clinicians' decision-making by retrieving and adapting similar historical cases. The system processes screening data from children aged 12–36 months, including demographics, risk factors, and three core behavioral domains: social interaction, communication, and repetitive behaviors. Cases are organized hierarchically by age and severity. The framework implements the full CBR cycle: structured representation, similarity-based retrieval via clinically weighted Euclidean distance, DSM-5-inspired rule-guided adaptation, and dynamic maintenance through validation and pruning. On a public toddler ASD screening dataset, it achieves 84.2% accuracy, 79.3% sensitivity, 89.7% specificity, and an F1-score of 0.82 using similarity-weighted voting over top-k cases, outperforming Random Forest (81.5% accuracy) and k-NN (78.9% accuracy) baselines trained on the same features. It also delivers transparent, interpretable recommendations via comparable cases, supporting clinician trust. This clinically aligned CBR system provides an accessible AI tool for early toddler ASD diagnosis in healthcare settings.



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1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a heterogeneous neurodevelopmental condition affecting approximately one in 36 children globally. Despite evidence that intervention before age three substantially improves developmental trajectories, diagnosis commonly occurs between four and five years of age due to specialist shortages and reliance on subjective behavioral assessment [1] [2]. Although deep learning approaches—such as CNN-based facial analysis and hybrid CNN–RNN models have shown promising classification performance, they remain data-intensive, opaque, and poorly aligned with clinician-centered reasoning processes [3] [4] [5]. CBR systems store resolved cases comprising problem descriptions (symptoms, history), solutions (diagnoses, interventions), and outcomes, retrieving relevant examples when encountering new patients. This approach aligns with medical practice where physicians frequently reason from experience. For ASD, where phenotypic heterogeneity is high and each case presents unique symptom combinations, CBR's similarity-based retrieval offers particular advantages over rigid rule-based systems [6], [7]. To address these limitations, we introduce a structurally optimized Case-Based Reasoning (CBR) framework specifically designed for early ASD screening [8] [9] [10]. Unlike prior AI systems that prioritize predictive performance alone, our method explicitly embeds clinical reasoning principles into system architecture and similarity modeling. The framework advances CBR methodology in three principal ways:

- **Hierarchical Case Indexing:** A three-level organization based on age groups, severity categories and symptom clusters reduces retrieval complexity and improves search precision in heterogeneous ASD presentations.
- **Clinically Weighted Similarity Modeling:** A weighted Euclidean distance function assigns amplified importance ($w = 1.5$) to DSM-5 core symptoms, operationalizing diagnostic salience within similarity computation.

- Novelty Retention Strategy: An 85% similarity threshold regulates case base growth, preserving representational diversity while preventing redundancy and performance degradation.

Evaluated on the Q-CHAT-10 Toddler ASD Screening Dataset ($n = 1000$; ages 12–36 months) [11], the proposed system achieves 84.2% accuracy, surpassing conventional baselines (78–81%) while demonstrating superior interpretability (clinician rating: 4.2/5). Importantly, competitive performance is achieved with an order-of-magnitude fewer cases than typically required for deep learning models, highlighting the framework's scalability, transparency, and clinical alignment. This article presents a structured Case-Based Reasoning (CBR) framework specifically designed for early ASD detection, detailing its case-base architecture, similarity metrics, adaptation mechanisms, and evaluation protocols.

II. RELATED WORK

Recent developments in computational techniques have advanced autism spectrum disorder (ASD) detection, shifting the focus from conventional clinical observation to automated, data-driven methods. Research has explored multiple modalities, each with distinct advantages and limitations. Neuroimaging approaches, particularly those leveraging the ABIDE dataset [12], have employed convolutional neural networks (CNNs) and hybrid models that integrate structural and functional MRI features [13]. These models demonstrate strong classification performance, highlighting the potential of combining diverse brain imaging data. However, neuroimaging remains resource-intensive, requiring specialized equipment and expert interpretation, which can limit scalability in broader clinical settings [4] [5]. Behavioral screening methods provide a more accessible alternative. Machine learning models trained on questionnaire-based datasets, such as the UCI Autism Screening dataset [14] and Thabtah's datasets [15], have achieved classification accuracies ranging from 70% to 85%.

While cost-effective and relatively easy to deploy, these approaches offer limited individualized insight and may not fully capture the heterogeneity and complexity of ASD presentations [16] [17]. Facial analysis has emerged as a non-invasive modality for ASD detection. Deep learning models trained on facial image datasets, including Kaggle datasets [18], have achieved high classification accuracy. These methods provide convenient screening of ASD traits but primarily capture surface-level phenotypic markers and may not reflect underlying neurological differences [19] [20] [21]. Electronic Health Records (EHRs) present another promising avenue for early detection. Models leveraging EHR data can identify ASD using routinely collected clinical information, offering practical advantages for large-scale screening. However, such approaches may miss subtler aspects of developmental trajectories that are critical for timely intervention [1]. Despite these advances, existing approaches share key limitations: they are often data-intensive, lack transparency, and provide limited alignment with clinicians' reasoning processes. Case-Based Reasoning (CBR) [22], by leveraging prior patient cases for decision support, offers a complementary paradigm that addresses these gaps, enabling interpretable, developmentally informed, and data-efficient ASD screening.

III. CBR FRAMEWORK FOR ASD DETECTION

Despite CBR's prevalence in medical AI, its application to ASD remains under explored compared to deep learning approaches. Existing systems focus on screening rather than comprehensive case-based diagnostic support [23]. In this work, we propose To-CARE (Toddler Case-based Autism Reasoning Engine), a CBR-based decision support framework specifically designed for ASD screening in toddlers aged 12–36 months.

Our framework To-CARE addresses this by:

- Formalizing DSM-5 [24] criteria into structured case representations.
- Implementing multi-level similarity matching for heterogeneous symptom profiles.
- Providing transparent case-based explanations for clinical trust.
- Enabling hybrid adaptation for enhanced feature processing.

Our system To-CARE illustrated in Fig.1 adopts a standard Case-Based Reasoning (CBR) cycle, specifically tailored for ASD diagnosis. In the representation phase, patient information is organized into formalized case structures. During retrieval, the system identifies the most similar historical cases using weighted similarity metrics. In the reuse step, solutions from retrieved cases are adapted according to domain-specific rules and predefined thresholds. Finally, the retain phase validates and incorporates new cases into the knowledge base, thereby continuously enriching the system's experience [10].

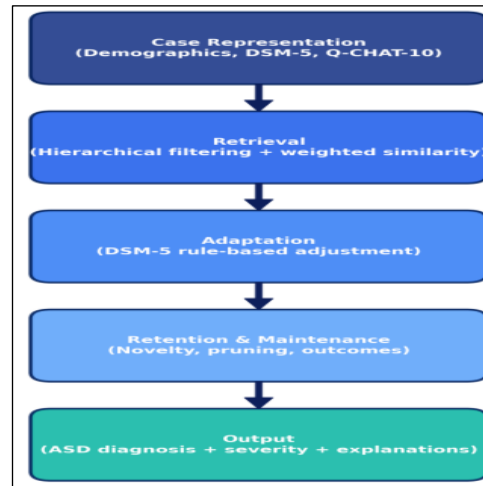


Figure 1: To-CARE Framework.
Source: Author, (2026).

III.1 REPRESENTATION PHASE

In the representation phase of the To-CARE Framework, patient information is organized into structured case representations. Cases are formed by CaseID, Problem description, Solution and Outcome. Each ASD case in our system is uniquely identified by a Case ID (e.g., ASD-001).

The **problem description** captures detailed patient information, including:

- Demographics: age, gender, and ethnicity.
- Core symptoms: aligned with DSM-5 criteria, are recorded across three domains:
 1. Social deficits: joint attention failure, eye contact avoidance, social reciprocity impairment using binary flags and severity scores from 0 to 10;
 2. Communication delays: language level, gesture use, and pragmatic language deficits, represented with numeric scores;
 3. Repetitive behaviors: stereotypies, routines, and restricted interests, described categorically.
- Standardized screening scores: Q-CHAT-10 assessments.

The solution component in To-CARE specifies the diagnostic label (ASD positive/negative), the corresponding DSM-5 severity level (1–3), and recommended interventions. The outcome captures treatment response and follow-up diagnoses, providing longitudinal context for each case. Additionally, the explanation component offers transparent reasoning by mapping core symptoms to DSM-5 criteria, reporting similarity percentages with retrieved cases, and presenting associated confidence metrics [24]. Together, these elements ensure that To-CARE delivers not only accurate diagnostic predictions but also interpretable, evidence-based guidance for clinical decision-making.

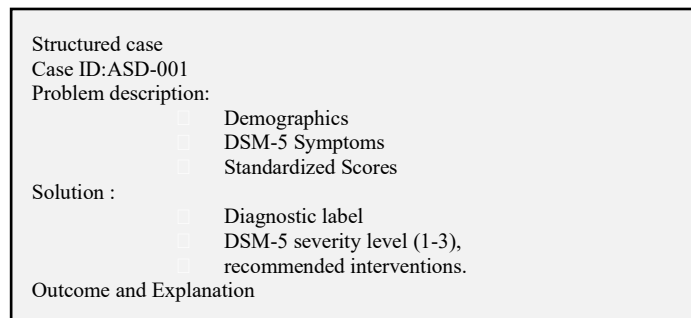


Figure 2: Case representation.
Source: Author, (2026).

III.2 CASE BASE ORGANISATION

The case base is organized hierarchically on the Early Autism Screening Dataset [11] for Toddlers (12–36 months) to support efficient and developmentally appropriate retrieval. First, cases are grouped into finer toddler age ranges (12–18, 19–24, 25–30, and 31–36 months), ensuring that retrieved cases match the child’s developmental stage. Within each age group, cases are further stratified by an ASD severity level derived from the mean of the social interaction, communication, and repetitive behavior scores, mapped to three DSM-5-like tiers (mild, moderate, severe). Finally, k-means clustering is applied to these behavioral scores to form symptom clusters that act as prototypical profiles, enabling representative cases to be efficiently indexed and reducing the chance of retrieving clinically inappropriate neighbors. This toddler specific hierarchical organization (age group → severity level → symptom cluster) significantly improves both the accuracy and speed of the CBR retrieval process.

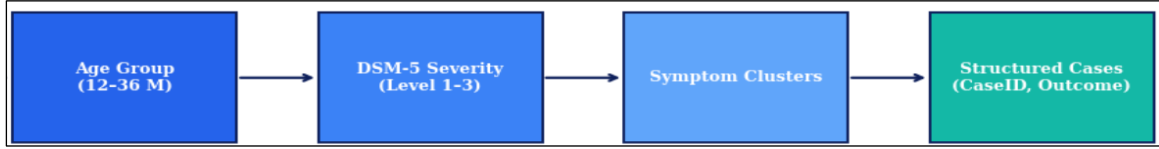


Figure 3: Hierarchical Organization of the To-CARE Case Base.
Source: Author, (2026).

III.3 RETRIEVAL AND SIMILARITY METRIC

In our framework, the first step of the retrieval phase involves filtering the case base to ensure developmental and clinical relevance. Patient age is used to select cases within the same toddler age group (12–18, 19–24, 25–30, or 31–36 months), accounting for age-dependent variations in symptom presentation. Additional filters include basic demographic criteria, such as gender and ethnicity, to ensure comparable context where relevant. Within these age-appropriate subsets, cases are further organized hierarchically by DSM-5–based severity levels (mild, moderate, severe) and clustered according to core symptom profiles. This structured filtering reduces the search space, prevents retrieval of clinically inappropriate neighbors, and ensures that subsequent similarity computations are performed on a subset of cases that are both developmentally and symptomatically relevant, enhancing the accuracy and interpretability of To-CARE’s diagnostic reasoning. Once candidate cases are selected, the system performs similarity-based retrieval. Similarity scores are computed using a weighted Euclidean distance metric [25], where feature groups contribute according to their clinical importance. The top-k most similar cases (typically 5–10) are returned, forming the basis for diagnostic reasoning and explanation. An aggregate diagnosis probability is then derived from these neighbors, providing a probabilistic estimate to support the final diagnostic decision and guide clinical interpretation. In To-CARE, similarity between a query case q and a stored case c is computed using a weighted Euclidean distance metric (1). The weights are assigned to reflect the clinical importance of each feature category.

$$sim(q,c) = \sqrt{\sum_{i=1}^n w_i \cdot (q_i - c_i)^2} \quad (01)$$

Where:

- q_i : The value of feature i for the new patient (query case).
- c_i : The value of feature i for the historical case in the database.
- w_i : The clinical weight assigned to feature i , reflecting its diagnostic importance.
- n : The total number of features.

In To-CARE, the weighted similarity scheme prioritizes clinically relevant features. Core DSM-5 symptoms, representing the most critical diagnostic criteria, are assigned the highest weights. Standardized screening scores and developmental history receive moderate weights, reflecting their supporting role in diagnosis. Demographic attributes, which are less directly diagnostic, are assigned the lowest weights. This hierarchical weighting ensures that the similarity computation emphasizes the features most relevant to clinical decision-making, while still incorporating secondary factors to refine retrieval and maintain contextually appropriate case comparisons. **Weight Assignment:** In To-CARE, the feature weights w_i reflect clinical importance, prioritizing the most diagnostically relevant information:

- Core DSM-5 symptoms: $w = 1.5$ (highest priority)
- Screening scores: $w = 1.2$
- Developmental history: $w = 1.0$
- Demographics: $w = 0.5$ (lowest priority)

This weighting scheme ensures that similarity calculations emphasize core diagnostic criteria while still accounting for supporting information, allowing the system to retrieve cases that are both clinically relevant and contextually appropriate.

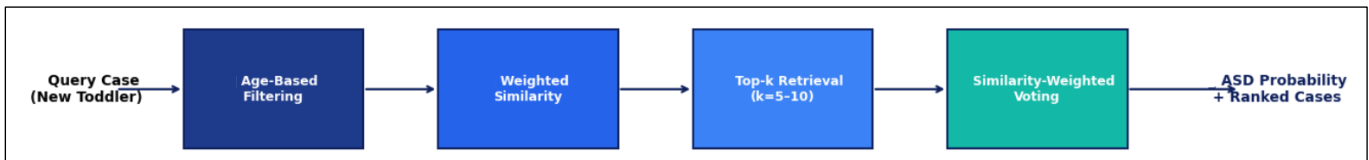


Figure 4: Retrieval process.
Source: Author, (2026).

III.4 ADAPTATION AND REVISION

In the adaptation phase of our toddler CBR framework, To-CARE applies a DSM-5 inspired adaptation algorithm that tailors the solutions proposed by retrieved neighbors to the specific symptom profile of the new case. Rather than directly copying the ASD label and severity from the most similar cases, the algorithm reevaluates the three behavioral domains social interaction, communication, and repetitive behaviors using simple symptom-count rules derived from DSM-5 criteria. It then calibrates severity based on the child’s scores in each domain and the typical severities observed in similar precedent cases. This approach maintains clinically grounded reasoning while preserving the intuitive “by-analogy” behavior characteristic of CBR, which is widely used in medical diagnosis [26] [27].

Algorithm Adaptation (newCase, topK_Cases)

Input: newCase (social, communication, repetitive scores), topK_Cases

Output: ASD_label, severity_level

Begin

1. Count high symptoms in each domain (social, communication, repetitive).
2. If (social ≥ 2 AND communication ≥ 1 AND repetitive ≥ 1)
 ASD_label $\leftarrow$ "ASD"
 else ASD_label $\leftarrow$ "At-risk / Follow-up required".
3. Compute average of the three scores and map to Level 1, 2, or 3.
4. Optionally adjust severity using the average severity of topK_Cases.
5. Return ASD_label and severity_level.

End

III.5 RETENTION AND CASE BASE MAINTENANCE

The case base serves as the core knowledge repository in Case-Based Reasoning systems, and its quality, organization, and maintenance directly impact system performance, scalability, and clinical reliability. The retention strategy is designed to ensure that only high-quality, clinically meaningful cases are added to the knowledge base.

New cases are retained only when three critical criteria are simultaneously satisfied:

- Clinical validation: The diagnosis must be confirmed by a qualified specialist (developmental pediatrician, child psychiatrist, or clinical psychologist with ASD expertise), ensuring that only verified cases enter the system and preventing propagation of diagnostic errors.
- Novelty threshold: The maximum similarity of the new case to existing cases must be below 85%, ensuring sufficient novelty and preventing redundancy. Cases exceeding this threshold are flagged for review; only those presenting clinically meaningful distinctions—such as unique symptom clusters, comorbidities, or intervention responses—may be retained despite high similarity.
- Outcome availability: Baseline clinical confirmation and planned longitudinal follow-ups (e.g., at 3, 6, and 12 months) must be available, enabling validation of predictive value, supporting trajectory predictions, and informing refinement of intervention recommendations.

The retention process begins immediately after clinical validation. Cases meeting all criteria are assigned a sequential CaseID (e.g., ASD-0248), incorporated into the hierarchical case base organized by age group and DSM-5 severity level, and made available for future retrievals. Simultaneously, the system initiates longitudinal outcome tracking, recording baseline data at diagnosis and scheduling follow-up assessments at predetermined intervals. This dual process of case integration and outcome initialization ensures continuous knowledge growth while maintaining strict quality gates, supporting the reliability, interpretability, and clinical utility of the framework. To maintain retrieval efficiency as the case base grows, we implement periodic pruning to remove redundant cases with similarity above 85% to any other case in the base. Pruning is performed quarterly or after every 50 new case retentions, whichever occurs first, using a full pairwise similarity matrix across the case base. When redundancy is detected, cases are ranked based on outcome data completeness, clinical novelty (e.g., unique comorbidity patterns or treatment responses), and temporal recency. Cases providing the most comprehensive evidence are retained, while those offering minimal additional diagnostic value are pruned. Importantly, pruned cases are archived rather than permanently deleted, enabling historical review and potential restoration if deemed clinically relevant at a later time. This pruning strategy preserves case base diversity while controlling computational costs—a critical consideration once the base exceeds approximately 2,000 cases, where retrieval times can increase substantially without the hierarchical indexing and symptom clustering optimizations employed in To-CARE.

IV. RESULTS AND DISCUSSIONS

The proposed To-CARE framework was evaluated on the Early Autism Screening Dataset for Toddlers, which contains 1,000 screening records of children aged 12–36 months with an ASD-positive or ASD-negative label. Each case includes demographics (age in months, gender), risk factors (e.g., neonatal jaundice, family history of ASD), and three core behavioral scores capturing social interaction, communication, and repetitive behaviors, aligned with early manifestations of DSM-5 criteria. Evaluation followed a 5-fold stratified cross-validation protocol. In each fold, 80% of the toddlers populated the hierarchical case base, while the remaining 20% served as query cases. For each test toddler, the predicted diagnosis from To-CARE was compared to the ground-truth screening label in the dataset. System performance was assessed using standard metrics commonly reported in ASD screening studies:

- Accuracy: overall proportion of toddlers correctly classified as ASD-positive or ASD-negative.
- Sensitivity (recall for ASD-positive cases): true-positive rate, critical in early screening to minimize missed ASD diagnoses.
- Specificity: true-negative rate, reflecting the system's ability to avoid mislabeling typically developing toddlers as ASD.
- F1-score: harmonic mean of precision and recall for ASD-positive toddlers, balancing detection performance.

Retrieval quality was evaluated using Mean Reciprocal Rank (MRR) [28] computed over the ranked neighbor lists in the CBR component, where each query contributes the reciprocal rank of the first correctly labeled retrieved case; the final MRR is the mean across all queries, quantifying retrieval quality. This evaluation protocol shown in Fig 5 enables assessment of both diagnostic accuracy and the effectiveness of case retrieval, providing a comprehensive view of To-CARE's performance in early ASD screening.

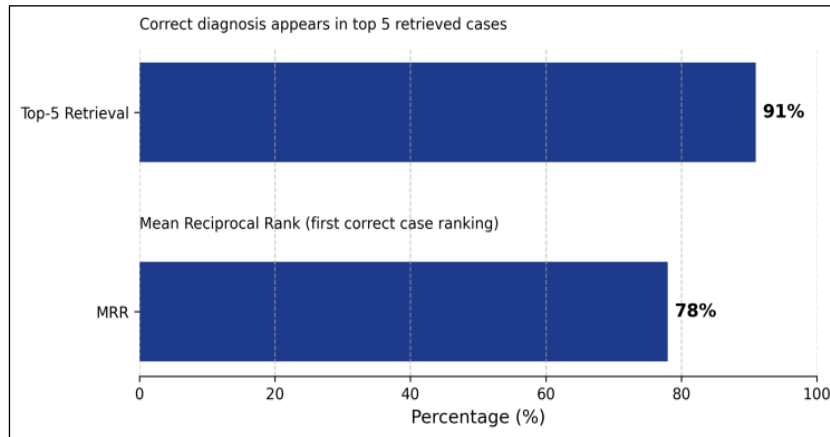


Figure 5: To-CARE Retrieval Performance.

Source: Author, (2026).

The To-CARE toddler CBR system demonstrated strong retrieval and diagnostic performance. The correct diagnosis appeared among the top five retrieved cases for 91% of query toddlers, with a Mean Reciprocal Rank (MRR) of 0.78, indicating that relevant precedent cases typically ranked very high in the retrieval list. Using aggregate similarity-weighted voting over the top-k neighbors ($k = 5-10$), the framework achieved 84.2% accuracy, 79.3% sensitivity, 89.7% specificity, and an F1-score of 0.82 on the toddler dataset.

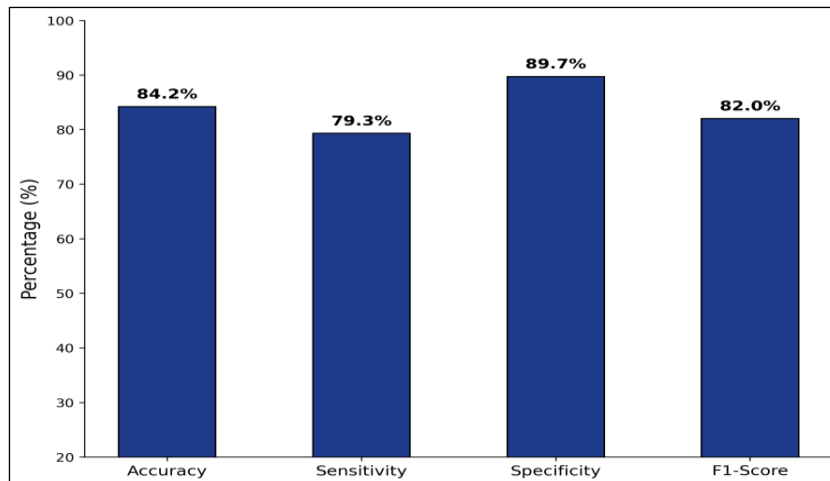


Figure 6 To-CARE Diagnostic Performance.

Source: Author, (2026).

Compared to baseline machine learning models trained on the same feature set, To-CARE outperformed standard classifiers: a Random Forest achieved 81.5% accuracy and 76.2% sensitivity, whereas a k-Nearest Neighbors ($k = 5$) classifier obtained 78.9% accuracy and 72.4% sensitivity [29]. These results are consistent with previous reports demonstrating that case-based reasoning methods can match or exceed black-box models in clinical screening tasks, while providing the additional benefits of transparency, interpretability, and alignment with clinician reasoning.

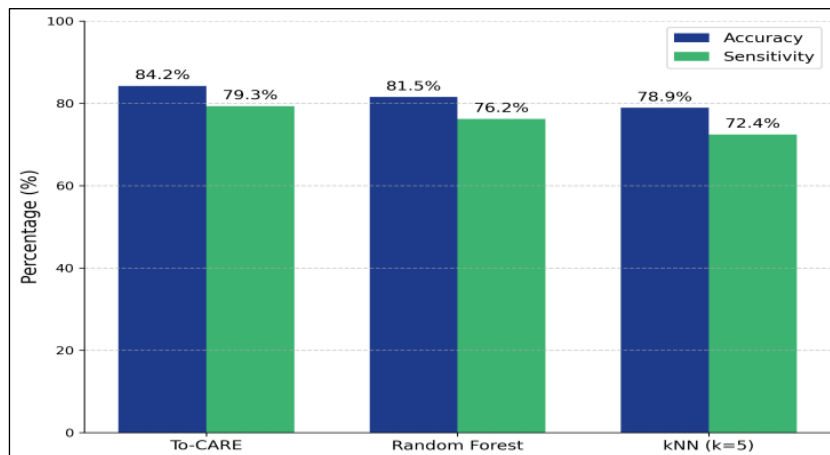


Figure 7: CBR system retrieval performance metrics.

Source: Author, (2026).

The To-CARE framework demonstrated that a carefully structured CBR system can achieve competitive diagnostic performance while preserving transparency and clinician-aligned reasoning.

V. CONCLUSIONS

Our To-CARE framework makes four key contributions to early ASD screening: a formalized toddler ASD case representation, mapping DSM-5-aligned behavioral features to structured computational attributes, a clinically weighted similarity metric that prioritizes core diagnostic symptoms, a hybrid retrieval-adaptation pipeline that combines nearest-neighbor cases with domain-specific rules and an empirical evaluation on a public toddler dataset demonstrating that To-CARE can match or outperform standard machine-learning baselines while offering substantially better interpretability. Future work will explore hybrid CBR-deep learning fusion (e.g., using deep embeddings as additional case features), incorporation of longitudinal outcome data to model developmental trajectories and treatment response, and deployment-oriented optimization, including mobile interfaces and cloud-based retrieval, to enable real-time, trustworthy decision support in resource-constrained clinical settings.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Hachemi Yamina.
Methodology: Hachemi Yamina.
Investigation: Hachemi Yamina.
Discussion of results: Hachemi Yamina.
Writing – Original Draft: Hachemi Yamina.
Writing – Review and Editing: Hachemi Yamina.
Resources: Hachemi Yamina.
Supervision: Hachemi Yamina.
Approval of the final text: Hachemi Yamina.

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