

Mini Project



**Virtual AI Clinician – Generative AI for
Accurate Medical Diagnosis**

SDG:GOAL-3:Ensure healthy lives and promote well-being for all at all ages



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Project Overview:

A scalable, AI-powered virtual clinician that leverages Large Language Models (LLMs) to simulate real doctor-patient interactions, diagnose over 9000+ common conditions, and provide accurate triage recommendations with 98% accuracy. It is designed to assist patients with non-emergency symptoms through a human-like AI avatar interface.

Problem Statement

- Overloaded healthcare systems with rising outpatient traffic
- Limited access to doctors in rural and low-resource areas
- Inconsistent triaging due to human error and time constraints
- High costs for primary-level consultations
- Existing tools lack real-time, personalized, and clinically sound interactions



Solution

A Virtual AI Clinician that:

- Listens to symptoms and asks follow-up questions
- Uses LLMs for clinical reasoning
- Provides evidence-based advice instantly
- Delivers safe, empathetic interaction via a human-like avatar

Uniqueness of the Solution:

- Avatar interface for trust and engagement
- Clinical safety layer to prevent unsafe advice
- Counterfactual logic to minimize errors
- Trained on medical literature for high accuracy



Target Customers:

- Hospitals & Clinics (AI triage assistant)
- Public Health Agencies (mass healthcare deployment)
- Telemedicine Platforms (integrated AI consult module)
- Insurance Companies (preliminary claims triage)
- Health Startups (chatbot-based care delivery)
- Pharmacies (walk-in advisory kiosks)



Tech Stack:

- Frontend: React.js with Unity3D/WebGL for interactive avatar and patient UI.
- Backend: Node.js or Python (Flask/FastAPI) for API, logic, and routing.
- Deployment: AWS/GCP, Docker, and PostgreSQL/MongoDB for scalable hosting and data.



Approach

Requirement Analysis with healthcare experts

Architecture Design based on 4-layer AI pipeline

LLM Integration with clinical fine-tuning

Iterative Testing with clinical reviewers

Avatar & UI Design for empathetic user experience

Launch & Feedback Loop for continuous refinement

Key Features

Diagnosis of 918+ conditions

Clinical safety and compliance checks

Natural conversation flow with clarifying questions

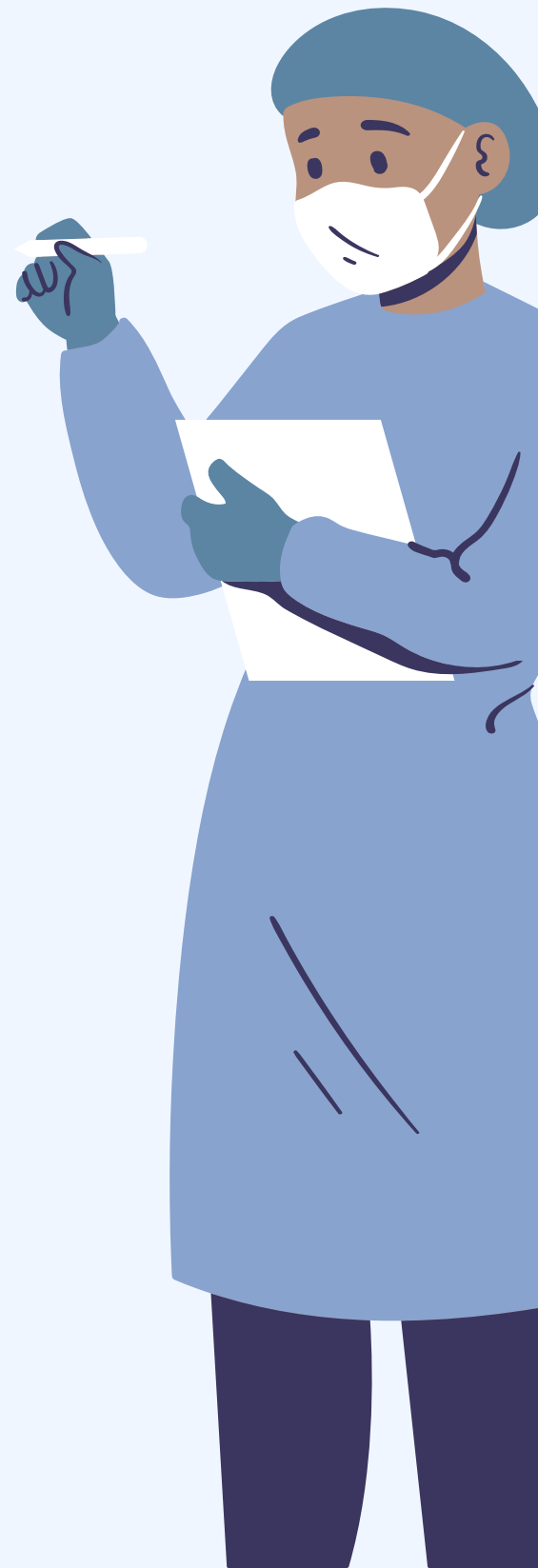
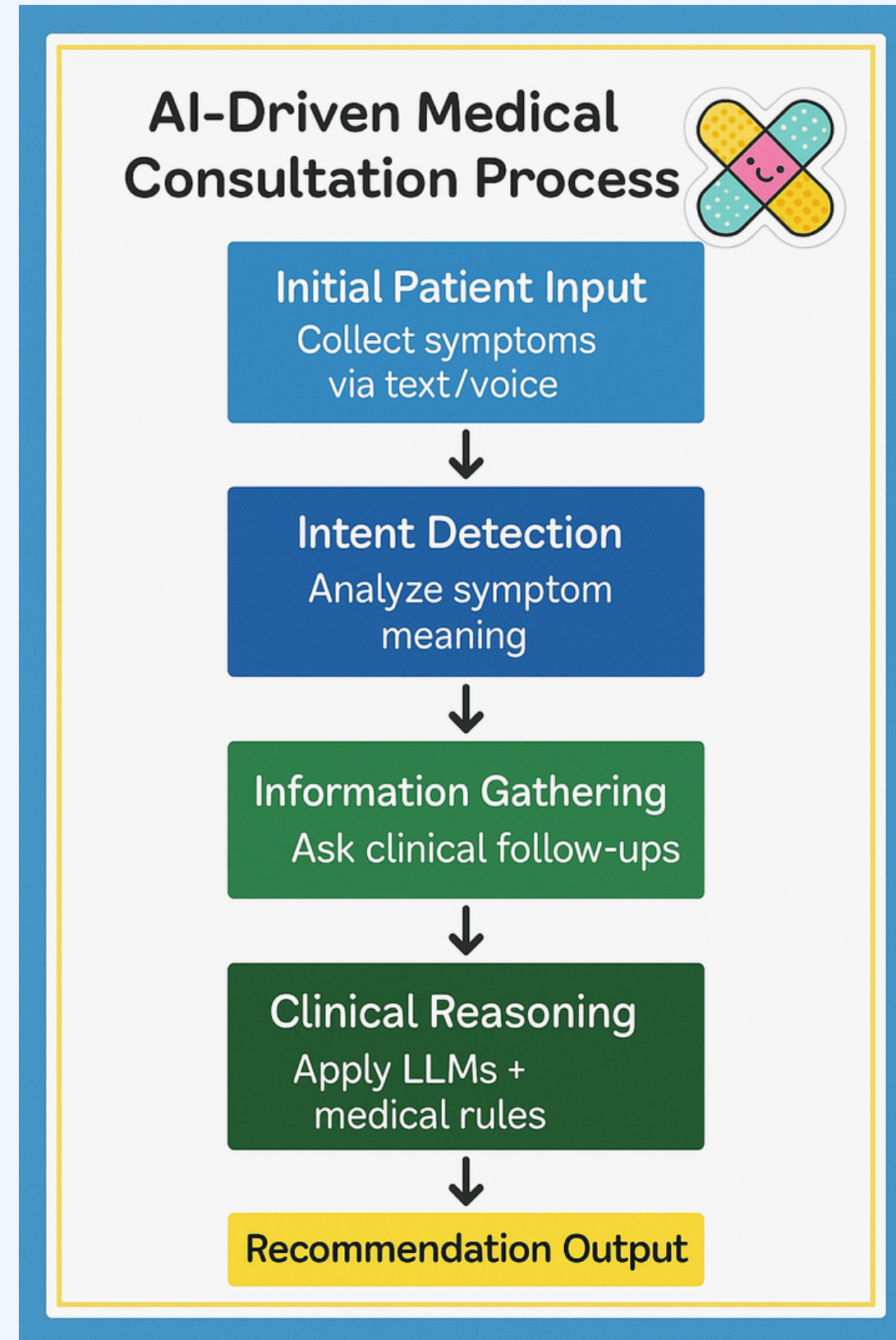
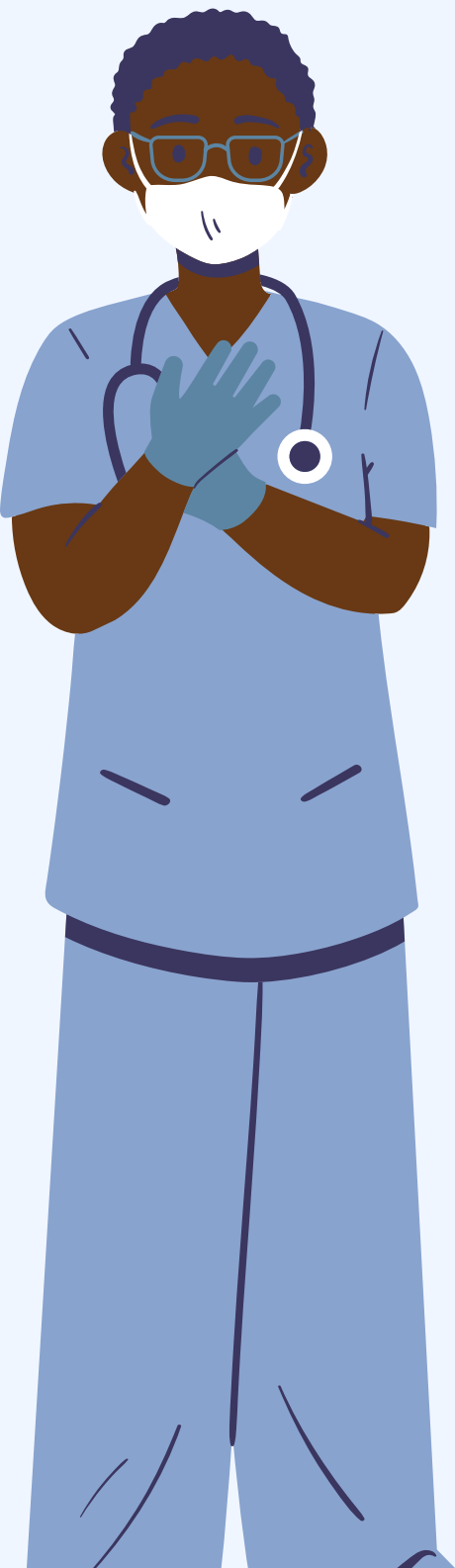
Multilingual and scalable across regions

Humanized avatar interface

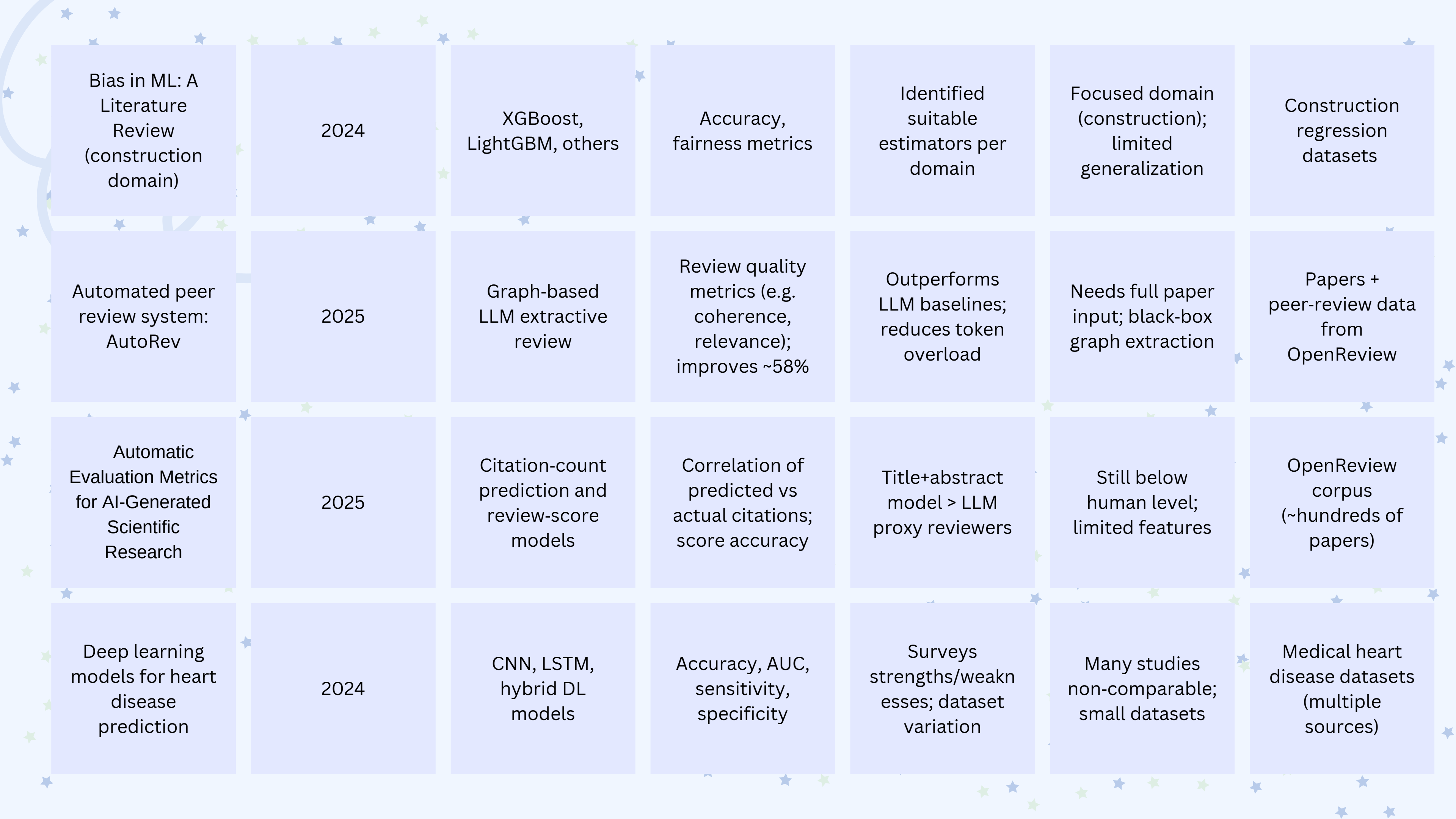
Data logging for continuous improvement



Architecture Diagram:



Title	Year	Algorithm /Model	Metrices	Merits	Demerits	Dataset
ADDAEIL: Anomaly Detection with Drift-Aware Ensemble-Based Incremental Learning	2025	Ensemble incremental learner with drift awareness	AUROC, F1, detection latency	Adapts to concept drift; unsupervised streaming	Computational overhead; needs tuning	3 synthetic + 2 real world time-series streams
From Variability to Stability: Advancing RecSys Benchmarking Practices	2024	Collaborative filtering (11 CF methods compared)	Precision@k, Recall@k, NDCG, HR, MRR, coverage, diversity	Evaluated across 30 datasets; robust benchmarking	CF only; no neural methods tested	30 public recommendation datasets (incl. two new ones)
Systematic review of ML methods in software testing	2024	Supervised, unsupervised, RL, hybrid ML methods	Accuracy, precision, recall, F1, MSE	Comprehensive taxonomy; discusses merits/de-merits	Not empirical experiments; summarizes others	40 studies from 2018–2024 databases



Bias in ML: A Literature Review (construction domain)

2024

XGBoost, LightGBM, others

Accuracy, fairness metrics

Identified suitable estimators per domain

Focused domain (construction); limited generalization

Construction regression datasets

Automated peer review system: AutoRev

2025

Graph-based LLM extractive review

Review quality metrics (e.g. coherence, relevance); improves ~58%

Outperforms LLM baselines; reduces token overload

Needs full paper input; black-box graph extraction

Papers + peer-review data from OpenReview

Automatic Evaluation Metrics for AI-Generated Scientific Research

2025

Citation-count prediction and review-score models

Correlation of predicted vs actual citations; score accuracy

Title+abstract model > LLM proxy reviewers

Still below human level; limited features

OpenReview corpus (~hundreds of papers)

Deep learning models for heart disease prediction

2024

CNN, LSTM, hybrid DL models

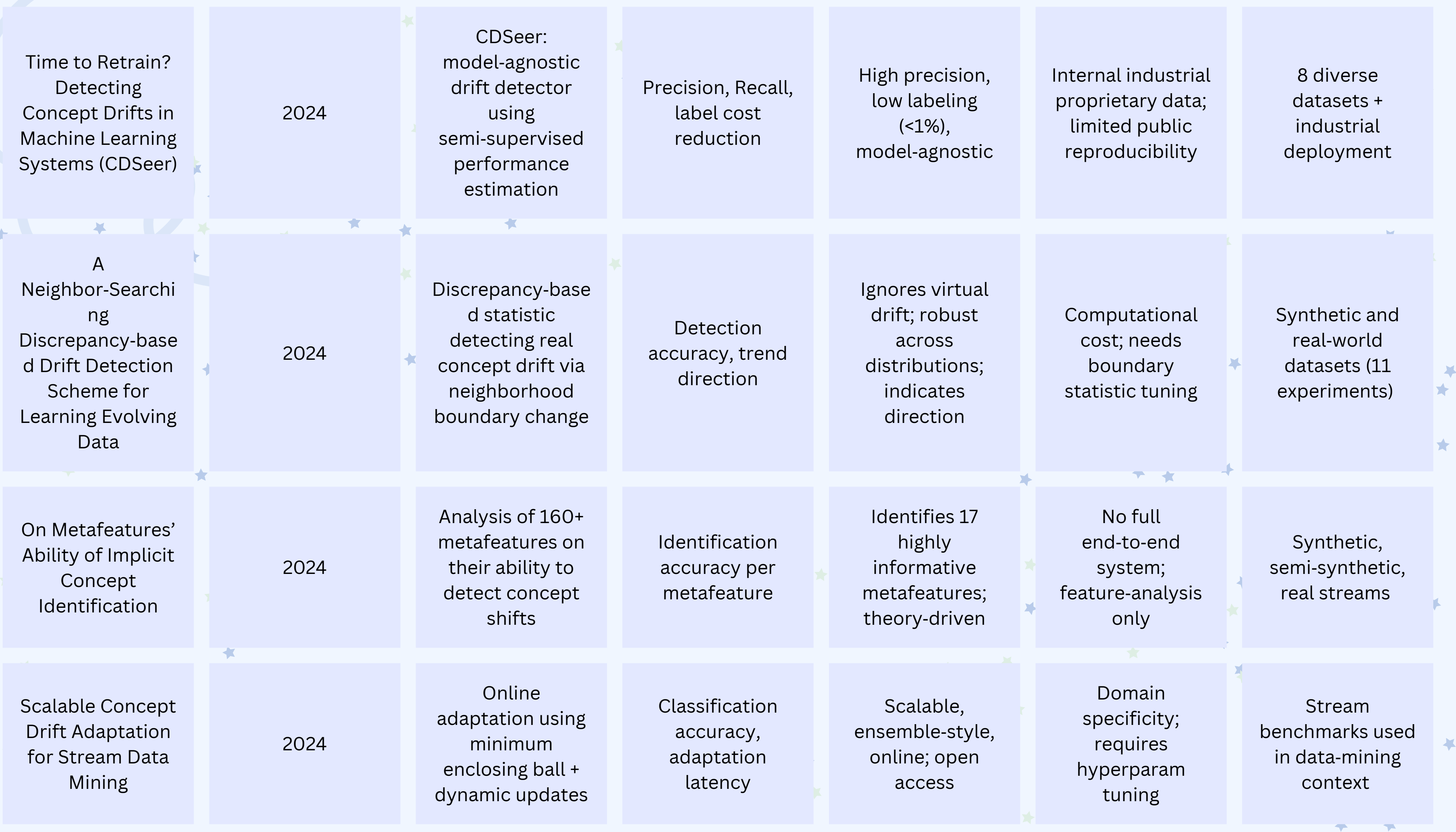
Accuracy, AUC, sensitivity, specificity

Surveys strengths/weaknesses; dataset variation

Many studies non-comparable; small datasets

Medical heart disease datasets (multiple sources)

Systematic review ML & student performance prediction	2020	SVM, RF, ensemble, ANN, GA-based DT	Accuracy, precision, recall, F1, ROC AUC, MSE	Highlights algorithm comparative performance; key gaps	Older (2020); limited newer methods	Multiple student datasets (academic, VLE log data)
METRIC-framework for assessing data quality for trustworthy AI	2024	Meta-analysis of data issues in ML	Quality dimensions (accuracy, completeness, balance)	Identifies key data-quality threats; tool-agnostic	Not algorithm-specific; no performance metrics	Studies across non-life science datasets
Literature review of ML methods in building performance evaluation	2024	Machine learning vs statistical models (e.g. RF, SVR vs linear models)	RMSE, MAE, R ²	ML outperforms statistical models in many cases; benchmarking framework	Domain-specific; fewer deep models	Building performance datasets (energy use, HVAC logs)
A Systematic Literature Review of Novelty Detection in Data Streams: Challenges and Opportunities	2024	Survey of novelty/concept drift methods: unsupervised, ensembles, clustering, GNN	Not applicable (survey)	Comprehensive taxonomy; up-to-date on online novelty detection	No experiments / no metrics	Reviewed many real & synthetic streams



References:

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- Höpner et al., “Automatic Evaluation Metrics for Artificially Generated Scientific Research”, arXiv, Feb 2025. [arXiv](#)
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- Comparative ML/statistical methods for building performance evaluation, ScienceDirect, 2024.
- “A Systematic Literature Review of Novelty Detection in Data Streams: Challenges and Opportunities”, ACM Computing Surveys, May 2024.
- Pham et al., “Time to Retrain? Detecting Concept Drifts in Machine Learning Systems (CDSeer)”, arXiv, Oct 11 2024.
- Gu et al., “A Neighbor-Searching Discrepancy-based Drift Detection Scheme for Learning Evolving Data”, arXiv, May 23 2024.
- “On Metafeatures’ Ability of Implicit Concept Identification”, Machine Learning, Sept 2024.

The background is a light blue gradient. It is decorated with numerous small, five-pointed stars in two colors: a muted green and a darker blue. The stars are scattered across the entire background, with a higher density towards the left and right edges. At the top, there are two sets of three short, thick, dark blue lines arranged in a fan-like shape, resembling stylized fireworks or confetti. At the bottom, there is a large, solid blue shape that resembles a stylized wave or a cloud. Overlaid on this blue shape are two dark blue, hand-drawn style loops or swirls, one on the left and one on the right, adding a decorative touch.

Thank you