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Heart Disease Diagnosis Using Agentic Ai

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Abstract- Every year, a significant number of deaths worldwide are caused by heart disease. This study proposed an independent multi-agent system for early diagnosis that can work efficiently even when patient data arrive slowly and are usually incomplete in real clinical setting. The proposed system does not rely at all on language learning tools, unlike traditional machine learning models which require access to all (pre-trained) data or large language model tools and their inherent trustworthiness and reproducibility issues. The system depicted diagnosis as a series of small, adaptive decisions by six specialised agents. Using a conformal prediction reliable quantification of uncertainity and an active feature selection approach based on the short term bandit framework that balanced expected uncertainty reduction vs. cost per clinical test. Agents iteratively retrieved only the missing features most relevant to the task, terminated once sufficient confidence was achieved, and produced intelligible rationales with clinical suggestions. This research tested the system on UCI Cleveland heart disease dataset. It had an AUROC of 0.979, accuracy of 90.0%, precision of 100%, recall of 83.3% and F1-score ratio of 0.909 whilst using on average far fewer features than static baselines. We demonstrated successful predictive performance, decreased the cost of diagnostics, and improved explainability. This work proposes a simple, transparent and cost-sensitive framework that is transferable for real-world healthcare deployment in low-resourced settings.

Keywords: Agentic AI, Heart Disease Diagnosis, Active Feature Acquisition, Uncertainty Quantification, Explainable AI

I. INTRODUCTION

Heart disease is still among the top killing diseases worldwide. To improve patient outcomes and reduce mortality, early and accurate diagnosis is key. The complexity of this task is further exacerbated by the assumption in most traditional machine learning models that complete clinical data is observed at prediction time and provides a single, deterministic output. This assumption makes them less useful for real-world clinics where information comes in over time and much of the needed tests may not have been completed yet. LLMs require more challenges to be addressed such as hallucination, privacy concerns and providing reproducible explanations in high-stakes decisions in medicine.

To bridge this gap, our research proposed a novel type of LLM-free multi-agent architecture. The main contribution is an uncertainty-aware active feature acquisition approach that dynamically selects next most informative clinical feature while explicitly considering its acquisition cost. The system learns to use both conformal prediction for confidence calibration and a bandit-based decision strategy in the setting of collaborative six-agent framework.

II. LITERATURE REVIEW

Promising accuracy has been achieved through the application of numerous machine learning algorithms such as decision trees, support vector machines and ensemble methods like Random Forest to heart disease prediction. State-of-the-art methods included conformal prediction for uncertainty quantification, active feature acquisition that sought informative variables and multi-agent systems to empower healthcare decision making.] Most previous works, however, focused on these components in isolation or assumed static input.

Only a few unified uncertainty quantification, cost awareness, sequential decision making and explainability into a single LLM-free agentic system. This work bridges that gap by integrating all these elements into a broadly applicable and deployable framework.

III. METHODOLOGY

The implementation of the system in this study was in the form of a modular multi-agent architecture and comprised of six agents which acted in a sense-think-act loop. The Data Ingestion Agent received the patient information as it was being received, cleaned, and validated the information and detected missing characteristics. Statistical imputation and normalizing were done by the preprocessing agent. Risk Assessment agent generated risk probability and confidence score with a calibrated Random Forest classifier with conformal prediction.

When the confidence level was low, the Active Feature Acquisition Agent selected the next feature based on a bandit-based policy that optimized expected uncertainty reduction per dollar. The Explainability Agent produced global and patient specific explanations with justification of each of the captured features. The Planning and Recommendation Agent mapped the collective risk to low/medium/high grades, and even generated rule-based medical advice. The loop was repeated until the confidence threshold was achieved or no additional features were found.

System Architecture

A collaboration among the agents was depicted in Fig. 1. Patient data initially went through ingestion and preprocess. The current feature set was tested by the risk assessment. The active acquisition agent made the next move based on the uncertainty reduction and cost consideration in case it was required. Explanations were created during the process and the recommendation agent generated the final output at the end of the termination when the confidence threshold was reached or no more features could be generated.

Fig. 1. Flow of Agents in the Proposed System

IV. EXPERIMENTAL SETUP

This study deployed the system in Python with scikit-learn, NumPy and Pandas. Tests were performed with a regular CPU with no GPUs or other external services. The UCI Cleveland heart disease data was separated into training, calibration, and test data. The model was then trained using the training data, calibrated to be uncertain, and tested on unseen test data that models the incremental availability of features.

V. RESULTS AND ANALYSIS

Performance results of the proposed system: AUROC = 0.979, accuracy = 90.0%, precision = 100%, recall = 83.3% and F1-score = 0.909 However, still retaining its efficiency in using the feature set to get these results. Such high precision is of great clinical value as it reduces unnecessary follow-up procedures.

The agentic system performed equally (or more) well on discrimination with fewer features on average and lower estimated diagnostic costs compared to state-based baselines. The sequential acquisition strategy was able to trade-off the uncertainty reduction requirement with the cost and a special explainability agent enhanced interpretability.

Table 1. Comparative Performance of the Proposed System.

Method	AUROC	Accuracy	Avg. Features Used	Cost Efficiency	Explainability	Adaptivity to Partial Data
Static Random Forest	0.96	88%	All	Low	Limited	None
Uncertainty-aware Ensemble	0.97	89%	All	Medium	Medium	Limited

Active Feature Acquisition	0.965	87%	Reduced	High	Low	Partial
Proposed Agentic System	0.979	90%	Fewer	High	High	High

VI. CONCLUSION

The first study proposed a novel policy-free agentic AI heart disease diagnostic model that quantifies uncertainty with uncertainty-sensitive feature acquisition (via active features and explainability) in the form of a six-agent network. The system was more predictive with fewer expenditures and higher transparency. It effectively tackled the major issues of missing data and scarcity of resources seen in clinical practice. Limitations Examination on a publicly available benchmark dataset; validation in the real-world hospital setting is the next step that is planned to be conducted during future work. Future research directions: Constant evaluation of peripheral neuropathy due to chemotherapy and incorporation of wearable sensor data.

Declarations Study Limitation:
Because we tested things with a dataset that anyone can get, the results might be different when used with the actual, and often quite varied, data you find in hospitals. We definitely need to test it in real hospital settings.

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