Course: Artificial Intelligence

Date: 11.01.2026

Term Project

Clinical Deterioration Risk Prediction and Intelligent Patient Visit Prioritization Using Random Forest and Greedy A* Planning

1. Agent Design and Task Environment Analysis

1.1 Agent Classification

The proposed system is designed as a learning, model-based intelligent agent.

- Learning agent:
  The agent incorporates a Random Forest classifier trained on historical clinical data to learn patterns associated with short-term patient deterioration. Through supervised learning, the agent improves its ability to estimate medical risk based on physiological and demographic inputs, rather than relying on fixed rules or handcrafted thresholds.
- Model-based agent:
  The agent maintains an internal representation of the environment, including:
  - Predicted deterioration risk for each patient
  - Patient ward locations
  - Patient age and vulnerability
  - The current location of the nurse
    This internal model allows the agent to reason about future states and outcomes when selecting actions.
- Decision-support agent (not autonomous):
  The agent does not act independently on patients; instead, it supports clinical staff by recommending a prioritized visit sequence. Final decisions remain under human control, ensuring safe and ethical use in a healthcare context.

This combination allows the agent to adapt to new patient data while making informed, rational decisions based on both learned knowledge and environmental constraints.

1.2 Task Environment Analysis

The task environment of the intelligent agent can be characterized using standard AI environment properties:

Observability

- Partially observable
  While the agent receives structured patient data (vital signs, age, lab values), it does not have access to the complete internal physiological state of patients or all external clinical factors. Medical uncertainty and latent health conditions make full observability impossible.

Determinism

- Stochastic
  Even with identical observed vital signs, patient outcomes may differ due to unobserved biological and environmental factors. The Random Forest model therefore outputs probabilistic risk estimates rather than deterministic predictions.

Dynamics

- Dynamic
  The environment changes over time:
  - Patient conditions may deteriorate or stabilize
  - The nurse's location updates after each visit
  - The set of remaining patients changes as visits occur
    The agent re-executes the A* search dynamically after each action to adapt to these changes.

Episodic vs. Sequential

- Sequential
  Each action (visiting a patient) affects future states of the environment, including the nurse's position and the remaining visit options. Decisions must therefore consider long-term consequences, not just immediate outcomes.

Discrete vs. Continuous

- Mixed
  - Discrete elements: ward locations, visit actions, patient selection
  - Continuous elements: predicted deterioration risk (probability between 0 and 1), physiological measurements

This mixture reflects the real-world nature of hospital decision-making, where continuous medical signals inform discrete operational actions.

Known vs. Unknown

- Partially known
  The agent has knowledge of:
  - The structure of the environment (wards, distance approximation)
  - The decision-making algorithm (A*)
    However, the true patient deterioration process is unknown and approximated through statistical learning.

1.3 Rationality of the Agent

The agent is considered rational within its defined performance measure, which aims to:

- Prioritize patients with higher predicted medical risk
- Reduce response time by accounting for ward distances
- Adapt dynamically as visits are completed

The agent is considered rational because, at each decision point, it selects the action that maximizes its expected performance measure based on available information. By combining probabilistic deterioration risk estimates with operational constraints such as ward distance, the agent reasons under uncertainty and selects patient visits that offer the highest expected clinical utility. Although outcomes are stochastic and not fully predictable, the agent's decisions are rational with respect to its defined objectives and knowledge at the time of action.

2. Model Selection and Algorithm Justification

2.1 Statistical Learning Model Selection

The clinical deterioration prediction task is formulated as a binary classification problem with the objective of estimating the probability that a patient will deteriorate within the next 12 hours. Among several statistical learning models studied in the course, a Random Forest (RF) classifier was selected for this task.

Why Random Forest?

Random Forest is well suited to this problem for several reasons:

1. Modeling Non-Linear Relationships
   Clinical deterioration arises from complex interactions between vital signs (e.g., heart rate, respiratory rate, SpO_2, blood pressure) and patient-specific factors such as age. Random Forests effectively capture non-linear relationships and feature interactions without requiring explicit feature engineering.
2. Robustness to Noise and Correlated Features
   Medical datasets often contain correlated measurements and noisy observations. By aggregating multiple decision trees trained on different bootstrap samples, Random Forest reduces variance and improves generalization compared to a single decision tree.
3. Probabilistic Output for Decision Support
   Unlike hard rule-based models, Random Forest provides probability estimates via class probabilities. These continuous risk scores are critical for downstream planning, as they are directly incorporated into the heuristic function of the search component.
4. Handling Class Imbalance
   Patient deterioration events are relatively rare. The use of class weighting in the Random Forest helps mitigate class imbalance, improving sensitivity to high-risk patients without excessive false positives.

Comparison with Alternative Models

- Decision Trees (DT)
  While decision trees are interpretable, a single tree is prone to overfitting and unstable decision

boundaries. Random Forest improves upon this by ensemble averaging, offering better predictive performance while maintaining reasonable interpretability.

- Support Vector Machines (SVM)
  SVMs can perform well in high-dimensional spaces but require careful kernel selection and parameter tuning. Additionally, probability estimation in SVMs is less direct and computationally more expensive, making them less suitable for real-time risk scoring.
- XGBoost / Gradient Boosting
  Gradient boosting methods can achieve strong performance but are more sensitive to hyperparameters and may overfit in noisy clinical data if not carefully tuned. Given the project's focus on interpretability, robustness, and integration with a planning module, Random Forest provides a better balance between performance and stability.

2.2 Search and Planning Method Selection

To determine the order in which a nurse should visit patients, the system employs a *greedy best-first planning strategy using A-style cost principles**, rather than classical exhaustive A* search.

Rationale for Greedy A*-Style Planning

In this problem, the state space of all possible patient visit permutations grows factorially with the number of patients. Performing a full A* search over this space would be computationally infeasible and unsuitable for real-time hospital environments.

Instead, the system adopts a step-by-step greedy planning approach:

- Initial state: Nurse's current ward location
- Goal state: All patients have been visited
- Action: Select the next patient to visit

At each decision step, the agent evaluates all remaining patients using an A*-inspired cost function:
f(n)=g(n)+h(n)

Where:

- $g(n)$ represents the estimated response time based on ward distance
- $h(n)$ represents medical urgency derived from predicted deterioration risk and patient age

The patient with the lowest f(n) $f(n)$ value is selected as the next visit target.

Why Not Classical A*?

Classical A* guarantees optimality and completeness when searching a fully defined state space. However:

- The environment is dynamic
- Patient risk estimates may change
- Real-time decisions are required after each visit

Recomputing a full A* plan after every state change would be inefficient and unnecessary. The greedy A*-style approach enables fast re-planning, making it more suitable for interactive and time-sensitive clinical decision support. Although the cost function follows the structure of A* search, the system does not perform classical A* over a fully defined state space. Instead, it adopts a greedy best-first strategy that selects the next patient with the lowest estimated cost at each step and replans dynamically as the environment changes. This approach is more suitable for real-time clinical decision support.

2.3 Integration Between Learning and Planning

A key strength of the proposed system is the tight integration between statistical learning and planning:

- The Random Forest model produces probabilistic deterioration risk scores
- These scores directly inform the heuristic function of the planning algorithm
- The planner dynamically adapts as the nurse moves between wards

This integration ensures that medical risk assessment and operational efficiency are jointly optimized, demonstrating a coherent application of multiple AI paradigms.

3. Correctness and Efficiency Analysis

3.1 Completeness

Completeness refers to whether a planning algorithm is guaranteed to find a solution if one exists.
The proposed planning approach is complete at the decision-step level. At each step, the agent evaluates all remaining patients and selects the next patient based on the minimum cost value. Since one patient is removed after each visit and the patient set is finite, the algorithm is guaranteed to eventually visit all patients and reach the goal state. However, the algorithm is not globally complete in the classical A* sense, as it does not explore the full state space of all possible visit sequences. Instead, it uses greedy best-first decision-making with dynamic re-planning, a design choice that prioritizes real-time responsiveness over exhaustive search.

3.2 Optimality

Optimality refers to whether an algorithm is guaranteed to find the best possible solution according to a defined cost function. Classical A* search guarantees global optimality when it explores the full state space using an admissible heuristic. The planning strategy used in this project is not globally optimal, because it applies a greedy A*-style approach that selects the locally best patient at each step without evaluating all possible visit sequences. As a result, it does not guarantee the minimum total cost over the entire plan.

Despite this, the algorithm is locally rational:

- It prioritizes patients with higher predicted medical risk
- It accounts for ward distance to reduce response time
- It dynamically adapts after each visit

Given the stochastic and dynamic nature of clinical environments, global optimality is neither realistic nor required. The primary objective is to support timely and medically reasonable decision-making.

3.3 Time Complexity

Let n denote the number of patients.
At each step, all remaining patients are evaluated and organized in a priority queue, resulting in a time complexity of: $O(n \log n)$.

Since this process is repeated for each patient, the total time complexity is: $O(n^2 \log n)$.

This polynomial complexity is suitable for real-time hospital settings.

3.4 Space Complexity

The algorithm stores patient data and a priority queue containing at most n patients, resulting in a space complexity of: $O(n)$

This is significantly more efficient than classical A*, which may require exponential space.

3.5 Practical Trade-offs

The greedy A*-style planning approach represents a deliberate trade-off:

- Avoids exponential state-space explosion
- Enables rapid re-planning in dynamic environments
- Scales efficiently with patient volume

This makes it well suited for real-world clinical decision-support systems, where timely and adaptive responses are more valuable than globally optimal but computationally expensive solutions.

4. Performance Measure and Quantitative Evaluation

4.1 PEAS Framework for the Intelligent Agent

The task environment of the proposed intelligent agent is formally described using the **PEAS framework (Performance Measure, Environment, Actuators, Sensors)**, which provides a structured representation of the agent's objectives and its interaction with the environment.

P — Performance Measure

The performance of the intelligent agent is evaluated based on its ability to accurately identify patients at risk of short-term clinical deterioration while supporting efficient and safe patient monitoring.

Specifically, the performance measure is defined as:

- Maximizing correct identification of patients who will deteriorate within the next 12 hours
- Minimizing false negatives, where high-risk patients are incorrectly classified as low-risk
- Producing reliable **probabilistic risk estimates** that can be used for prioritization and planning
- Supporting timely and efficient nurse movement by balancing **medical urgency** and **response time**

Because missing a deteriorating patient may lead to delayed intervention and serious clinical consequences, **recall and F1-score for the positive (deterioration) class** are prioritized over overall accuracy alone.

E — Environment

The environment is a **hospital ward setting** in which multiple patients are monitored simultaneously by a limited number of medical staff.

Key characteristics of the environment include:

- Multiple patients distributed across different wards
- Time-sensitive clinical conditions that may deteriorate
- Operational constraints such as ward distance and limited staff availability
- Uncertainty in patient outcomes due to incomplete observability

The environment is **dynamic**, **partially observable**, **stochastic**, and **sequential**, reflecting the complexity and uncertainty of real-world hospital conditions.

A — Actuators

The agent's actuators correspond to the **decision-support actions** it can perform. These include:

- Recommending the next patient to be visited
- Producing an ordered sequence of patient visits
- Updating the planned visit order dynamically after each completed visit

The agent does not directly perform physical actions. Instead, it influences human decision-making by providing **prioritized recommendations** to clinical staff, who retain full control over patient care.

S — Sensors

The agent perceives the environment through **structured patient data**, which serve as its sensors. These include:

- Physiological measurements (e.g., heart rate, respiratory rate, SpO_2, systolic blood pressure, temperature)
- Patient demographic information (e.g., age)
- Patient ward location
- Historical clinical data used during model training

These inputs allow the agent to estimate deterioration risk and reason about patient prioritization, even though the **full internal medical state** of each patient is not directly observable

4.2 Classification Performance Metrics

The Random Forest classifier was evaluated on a held-out test set using standard classification metrics. The results are summarized below:

Class	Precision	Recall	F1-score	Support
No deterioration (0)	0.98	0.96	0.97	79,056
Deterioration (1)	0.51	0.72	0.60	4,518

Overall Accuracy: 0.95
Macro-average F1-score: 0.78
Weighted-average F1-score: 0.95
ROC-AUC: 0.956

4.3 Interpretation of Results

Accuracy

The model achieves a high accuracy of 95%. However, due to the strong class imbalance in the dataset (deterioration events are relatively rare), accuracy alone is not a sufficient indicator of performance.

Precision and Recall

For the deterioration class (1):

- Recall = 0.72
  → The model correctly identifies 72% of patients who will deteriorate. This is critical in a clinical setting, where missing high-risk patients can have severe consequences.
- Precision = 0.51
  → Approximately half of the patients flagged as high-risk actually deteriorate. While this introduces some false positives, it is an acceptable trade-off in healthcare decision support, where sensitivity is prioritized over specificity.

F1-score

The F1-score of 0.60 for the deterioration class reflects a balanced trade-off between precision and recall. This metric is particularly appropriate for imbalanced datasets and provides a more meaningful measure than accuracy alone.

ROC-AUC

The ROC-AUC score of 0.956 indicates excellent discriminatory ability. This means the model is highly effective at ranking patients by risk, even when classification thresholds vary. This property is especially important because the system does not rely solely on binary predictions; instead, continuous risk probabilities are passed to the planning component to inform patient prioritization.

4.4 Evaluation of the Planning Component

While the planning module does not produce traditional classification metrics, its performance is evaluated indirectly through:

- Effective prioritization of high-risk patients
- Reduced estimated response time by incorporating ward distance
- Dynamic re-planning after each visit

By combining probabilistic risk estimates with heuristic search, the agent demonstrates coherent decision-making that aligns with the defined performance objectives.

5. Ethical and Societal Considerations

The proposed system is designed as a clinical decision-support tool, and its use in healthcare raises important ethical and societal considerations. While it aims to improve patient safety and workflow efficiency, careful oversight is required to ensure responsible use.

5.1 Algorithmic Bias

The model is trained on historical clinical data, which may contain biases related to patient demographics or clinical practices. Such biases could lead to unequal risk predictions and prioritization. To mitigate this, the system relies on probabilistic outputs and should be continuously monitored and retrained with diverse data.

5.2 Patient Safety and False Negatives

False negatives, where deteriorating patients are classified as low risk, pose a serious safety concern. To address this, the system prioritizes recall for high-risk patients, accepting more false positives to reduce the chance of missing critical cases.

5.3 Over-Reliance on Automation

There is a risk that clinicians may over-trust algorithmic recommendations. To prevent automation bias, the system is explicitly designed as a support tool, with final decisions remaining under human clinical judgment.

5.4 Transparency and Responsible Deployment

The system uses interpretable clinical inputs and provides risk scores rather than opaque decisions, allowing clinicians to contextualize recommendations. Responsible deployment requires clear guidelines, clinical oversight, and ethical awareness.