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Project Report

On

Predicting Cancer Presence Using Tumor Features

By

Amrutha Paalathara
23122004
MSc Data Science

Jyosna Philip
23122019
MSc Data Science

Under the guidance of

Asst. Prof. Salve Margaret Joseph

Department Of Data Science
Christ (Deemed to be University), Lavasa

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1. Introduction

1.1 Background and Motivation

A cancer diagnosis often relies on analysing tumor features such as size, texture, and shape. These features provide critical insights into the nature of a tumor, aiding clinicians in determining whether it is benign or malignant. Manual analysis or reliance on singular predictive models can result in limitations, such as reduced accuracy or inability to adapt to new patient profiles.

Early and accurate prediction of tumor malignancy is essential to ensure effective treatment and improve patient outcomes, reducing the burden on healthcare systems and saving lives. Lately, data-driven approaches have demonstrated remarkable potential to enhance medical diagnoses and improve outcomes. While Decision Trees (DT) offer a straightforward and interpretable method for initial classification, their static nature may not account for incoming data. Reinforcement learning stands out for its ability to adapt to dynamic environments and learn through iterative feedback.

By integrating a DT with reinforcement learning, the hybrid model uses the strengths of both approaches. The DT serves as a robust baseline for initial predictions, while the reinforcement learning component refines these predictions based on new patient data and evolving patterns. This combination enables dynamic and adaptive decision-making, enhancing prediction accuracy and reliability.

1.2 Problem Statement and Objective

This project aims to accurately predict whether a tumor is malignant or benign by analysing its features, such as size, shape, and texture. This is achieved through a hybrid model integrating a DT for initial classification and reinforcement learning to refine predictions. The DT serves as a baseline by leveraging historical patterns in the data. Reinforcement learning adapts dynamically, refining forecasts as new data arrives, which boosts the model's accuracy and responsiveness to evolving conditions.

2. Methodology

The dataset is split into training and testing sets, and a Decision Tree model is trained first. Then, an environment is created where each row is treated as a state, then a Reinforcement Learning model is built and trained. The hybrid model combines predictions from both models, where the RL model's predictions overwrite the DT's if they differ. Finally, the models are evaluated using accuracy, F1-score, precision, and recall metrics. The steps are sequential and align well with the code (Fig. 1)

Machine Learning Model:

Training the dataset using the DT, an ML model, helps predict tumors. The model is trained using labelled data, where it learns to make predictions based on input features.

Reinforcement Learning Model:

Developing an RL environment that simulates interactions with the trained ML model. The environment allows the RL agent to take actions (such as overriding the ML model's prediction) and receive feedback. It uses the ML model's predictions as part of the decision-making process. The agent learns through trial and error, using feedback from the environment. By repeated action of this, the agent learns a policy that maximises its cumulative reward.

Hybrid Model:

Integrating a trained ML model with an RL agent creates a hybrid system that uses the best of both approaches. The RL agent decides whether to trust the ML model's prediction or override it based on the agent's learned policy, creating a dynamic decision-making system.

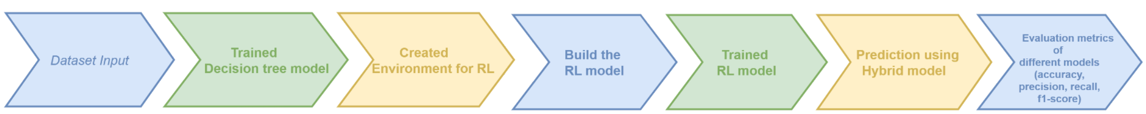

Fig 1: Methodology

2.1 Machine Learning Phase

Model Used: Decision Tree

Based on the provided dataset, a DT Classifier is used to classify breast cancer cases. The features represent tumor characteristics, and the target variable, diagnosis, indicates whether the tumor is malignant or benign. Here, we have selected all the features for prediction, and the model (70% of the data) is trained using the sklearn.tree.DecisionTreeClassifier and evaluated for accuracy. Also, the notebook integrates this DT model into a hybrid framework involving reinforcement learning for dynamic decision adjustments. The DT is the core classifier, providing predictions that can be overridden or maintained based on reinforcement learning actions.

Dataset description:

This dataset is related to breast cancer analysis, consisting of 569 samples with 31 features each. It includes measurements such as radius, texture, perimeter, area, and their corresponding variations (e.g., radius1, radius2), along with features like concavity, symmetry, and fractal dimension. The target variable, diagnosis, indicates whether a tumor is malignant (1) or benign (0). Each row represents a tumor sample characterised by its physical and morphological attributes. This dataset is ideal for classification tasks, particularly in predicting cancer diagnoses based on tumor characteristics.

1. ***Data Features:***
   a. *Tumor size:* Captures the overall dimensions of the tumor, providing a key indicator of growth.
   b. *Shape:* Describes the geometric properties of the tumor, such as roundness or irregularity, which can correlate with malignancy.
   c. *Texture:* Evaluates the pixel intensity variations within the tumor area, offering insights into internal structural irregularities.
   d. *Perimeter:* Measures the boundary length of the tumor, reflecting its spread.
   e. *Smoothness:* Quantifies variations in surface smoothness, which can distinguish between benign and malignant growths.

   Other relevant features include additional parameters such as compactness, concavity, and symmetry.

2. ***Data Preprocessing:***
   - Normalise continuous variables to ensure consistent scaling across features.
   - Handle missing data through imputation or removal of incomplete records.
   - Encode categorical variables in categorical columns.
3. ***Training:***
   - Train a DT model on historically labelled data containing tumor characteristics and their corresponding diagnoses.
   - Use a split dataset for training and validation to fine-tune the tree depth and avoid overfitting.
   - Evaluate the model on the validation set to assess its performance metrics, such as accuracy, precision, recall, and F1-score.
   - Output: The DT generates an initial classification for each tumor, identifying it as malignant or benign based on learned patterns.

2.2 Reinforcement Learning Phase

1. ***State Space:***
   - The state space includes detailed tumor features such as size, texture, shape, perimeter, smoothness, and compactness, alongside the initial prediction generated by the DT. Each state is a vector representation of these features.
   - States also incorporate auxiliary patient data, such as age or previous health history, to provide contextual insights.

- Including dynamic information (e.g., follow-up results or treatment responses) enables the RL model to adapt to temporal patterns in diagnostic data.

2. ***Action Space:***
   - The action space defines the set of decisions the agent can make:
     - **Action 0:** Maintain the DT's prediction.
     - **Action 1:** Override the DT's prediction, flipping it from malignant to benign or vice versa.
     - **Action 2:** Mark the prediction as uncertain, prompting further investigation or additional data collection.
3. ***Reward Structure:***
   - The reward function incentivises correct predictions and penalises errors:
     - **Correct prediction:** A high reward of +10 to reinforce accurate decisions.
     - **Incorrect prediction:** A penalty of -10 to discourage misclassifications.
     - **Uncertainty action:** A moderate reward of +2 when the agent opts for caution, fostering a balanced approach in ambiguous cases.
   - The reward system balances precision and recall, ensuring that the agent optimises for accuracy and cautious decision-making in sensitive scenarios.
4. ***Environment Dynamics:***
   - The environment simulates a diagnostic workflow where each episode corresponds to a single patient's data. At each step:
     - The agent observes the state (patient's tumor features and DT output).
     - Based on the selected action, the environment provides a reward and transitions to the next state.
   - The environment can introduce noise or uncertainty in features to simulate real-world diagnostic challenges, ensuring robustness.
   - Episodes are designed to end after one step, reflecting the binary nature of prediction tasks, or after a fixed sequence of related patient cases.

2.3 RL Algorithm and Parameters

- **Algorithm:**
  - Q-learning with a neural network as the function approximator.
  - The algorithm learns the optimal policy by iteratively updating Q-values using the Bellman equation.
- **Parameters:**
  - **Learning Rate (α):** 0.1, controlling the speed of policy updates.
  - **Discount Factor (γ):** 0.9, prioritising long-term rewards.
  - **Exploration-Exploitation Tradeoff (ε):** Starts at 1.0 and decays to 0.01 to gradually reduce random exploration as the agent learns.
- **Policy Optimization:**

    - The RL model uses experience replay, where past state-action-reward transitions are stored in a replay buffer. This allows the agent to learn from diverse experiences and break correlations in data.
    - The Q-network is trained using stochastic gradient descent on mini-batches sampled from the buffer, improving convergence stability.

2.4 Interaction Between ML and RL Components

- **Initial Prediction:** The DT generates a baseline classification for each patient.
- **Refinement by RL Agent:** The RL agent evaluates this prediction against additional features and patterns observed in real-time data.
- **Feedback Loop:** The agent's actions and outcomes are recorded to refine the policy, enabling it to learn from its mistakes and improve future decisions.
- **Real-Time Adaptability:** The hybrid system adapts to changing diagnostic trends, such as variations in tumor characteristics or evolving clinical guidelines.

3. Result

3.1 Implementation

Initially, a DT, an ML model, is used to train the model with the historical dataset to predict the presence of cancer. With the help of evaluation metrics, as shown in Fig 1. The accuracy of DT was validated. Then, with the help of the OpenAI Gym framework, designed an RL environment (CancerEnv) which simulates decision-making by defining states (input features), actions (maintaining or overriding ML predictions), rewards, and termination conditions. It is trained using episode episodes to refine this decision-making process. Lastly, the hybrid model, where the agent adjusts the DT's predictions based on its learned policy, improves predictive accuracy.

Fig. 2 shows the evaluation metrics of the Decision Tree (DT) model with an accuracy of 93% and a precision of 89%. Fig. 3 shows the RL model's metrics, revealing poor performance with 13% accuracy and 6% precision. Fig. 4 presents the hybrid model's metrics, with 56% accuracy and 30% precision, indicating it is less efficient than the DT model for cancer detection. Therefore, the DT model is more suitable for predicting cancer.

```
Decision Tree Evaluation Metrics:
Accuracy: 0.93
Precision: 0.89
Recall: 0.92
F1-Score: 0.91
Confusion Matrix:
[[101   7]
 [  5  58]]

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.94      0.94       108
           1       0.89      0.92      0.91        63

    accuracy                           0.93       171
   macro avg       0.92      0.93      0.93       171
weighted avg       0.93      0.93      0.93       171
```

Fig. 2 Classification Report of Decision Tree

```
Reinforcement Learning Model Evaluation Metrics:
Accuracy: 0.13
Precision: 0.06
Recall: 0.10
F1-Score: 0.07
Confusion Matrix:
[[16 92]
 [57  6]]

Classification Report:
              precision    recall  f1-score   support

           0       0.22      0.15      0.18       108
           1       0.06      0.10      0.07        63

    accuracy                           0.13       171
   macro avg       0.14      0.12      0.13       171
weighted avg       0.16      0.13      0.14       171
```

Fig. 3 Classification Report of Reinforcement Learning Model

```
Hybrid Model Evaluation Metrics:
Accuracy: 0.56
Precision: 0.30
Recall: 0.14
F1-Score: 0.19
Confusion Matrix:
[[87 21]
 [54  9]]

Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.81      0.70       108
           1       0.30      0.14      0.19        63

    accuracy                           0.56       171
   macro avg       0.46      0.47      0.45       171
weighted avg       0.50      0.56      0.51       171
```

Fig. 4 Classification Report of Hybrid Model

Expected Outcomes:

- The hybrid model enhances prediction accuracy compared to the standalone DT model.
- It adapts to new and unseen tumor data, ensuring robust predictions.

Obtained Outcomes:

- A machine learning model that accurately predicts outcomes based on historical data.
- A simulated environment where an RL agent can interact with the ML model and take actions
- A reinforcement learning agent that learns to make optimal decisions based on the environment, maximising rewards.
- A combined system where the RL agent decides whether to use the ML model's prediction or override it based on learned policies.

Strengths:

- Combines the interpretability of a DT with the adaptability of reinforcement learning.
- Handles dynamic environments effectively, particularly when new data becomes available.

Limitations:

- Requires substantial computational resources for RL training.
- Performance depends on the diversity and quality of the training dataset.

References

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