Related Works on Personalized Healthcare using Artificial Intelligence

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May 12, 2025

Abstract

This report summarizes recent research and developments in the field of AI-based personalized healthcare. It highlights the key contributions, methodologies, and challenges faced by existing systems.

1 Introduction

The use of Artificial Intelligence (AI) in healthcare has opened new avenues for personalized treatment. This report reviews existing studies and methods used in AI-driven healthcare solutions.

2 Related Works

3 Towards Realizing the Vision of Precision Medicine: AI-Based Prediction of Clinical Drug Response

Article Reference: [1]

Overview

This study uses machine learning to predict patient response to the epilepsy drug brivaracetam using integrated clinical and genomic data. The resulting model demonstrated strong performance (AUC: 0.76 training, 0.75 validation) and identified specific biomarkers associated with poor response. The research underscores the potential of ML models to support precision medicine and optimize clinical trials by targeting likely responders. This study highlights the potential of AI to personalize treatment strategies in epilepsy by predicting drug response, a key aspect of personalized medicine.

Dataset

- **Discovery dataset:** 235 adult patients from a phase III clinical trial (NCT01261325).
- **External validation dataset:** 47 patients from an independent trial (NCT00490035).

Data Processing

Clinical data included demographic and seizure-related information. Whole Genome Sequencing (WGS) data (∼20 million variants) was filtered down to 40 features through knowledge-driven extraction, focusing on epilepsy-related genes and drug mechanism (e.g., SV2A gene, eQTLs). Genetic features included mutational load scores, polygenic risk scores, and structural variant descriptors.

ML Approach

Multiple ML models were evaluated: sparse multi-block PLS-DA, multimodal neural networks, elastic net, gradient-boosted decision trees (GBDT), and stacked classifiers. The best performance was achieved using a GBDT model integrating all data types. GBDT models are well-suited for handling the complex interactions between clinical and genetic features, which is crucial for personalized drug response prediction. However, the inherent complexity of GBDT models can make it challenging to interpret the specific contributions of individual features, a limitation that future explainable AI (XAI) techniques could address.

Results

- AUC (training): 0.76
- AUC (validation): 0.75

Challenges

- Addressing high dimensionality and sparsity of genomic data. This is a common challenge in personalized medicine research, as genomic data often has many variables but few samples.
- Integrating additional data types (e.g., EEG, imaging) to improve model performance. Multimodal data integration is essential for a holistic view of the patient but increases complexity.
- Generalizing models to other anti-epileptic drugs. This is crucial for wider clinical applicability in personalized epilepsy treatment.
- Collaborating with regulatory bodies for clinical adoption. AI-driven personalized medicine tools require rigorous validation and regulatory approval for safe and effective use.
- Increasing dataset size to enhance model performance (targeting ∼350 patients for AUC = 0.9). Larger datasets are vital for building robust and generalizable predictive models in personalized healthcare.

Critique

- The sample size, while sufficient for the study, could be larger to further enhance model performance and generalizability.
- The complexity of the GBDT model, while providing good predictive power, makes it difficult to interpret the specific contributions of individual features.

4 Diabetes Prediction Using Machine Learning and Explainable AI Techniques

Article Reference: [2]

Overview

This study proposes an automated diabetes prediction system using ML and explainable AI. The system combines the public Pima Indian dataset with a private dataset collected from female workers in a Bangladeshi textile factory. The system addresses data imbalance, missing values, and is deployed for real-time prediction via web and mobile applications. The development of non-invasive AI-driven tools for diabetes detection, as presented in this paper, contributes to personalized healthcare by enabling earlier and more accessible diagnosis.

Dataset

- **Pima Indian Dataset:** 768 records, 268 diabetes-positive; includes 8 features.
- **RTML Private Dataset:** 203 female employees; features similar to Pima dataset but lacks insulin values.

Data Processing

- Zero values in the merged dataset were replaced with corresponding mean values and the dataset was separated into training and test sets using the holdout validation technique.
- Mutual information was used to measure the interdependence of variables and feature importance.
- A semi-supervised approach using the extreme gradient boosting technique (XGB regressor) was used to predict the missing insulin feature of the RTML dataset.

ML Approach

Various models were tested: decision trees, KNN, SVM, random forest, logistic regression, AdaBoost, XGBoost, bagging, and voting classifiers. Hyperparameters were tuned using GridSearchCV. The final model employed XGBoost with ADASYN for balancing. The choice of XGBoost is appropriate due to its effectiveness in handling complex datasets, but the lack of inherent explainability highlights the need for methods.

Results

- Accuracy: 81%
- F1 Score: 0.81
- AUC: 0.84

Challenges

- Missing insulin values required imputation via semi-supervised learning. This introduces a degree of uncertainty into the model.
- Class imbalance necessitated oversampling (SMOTE, ADASYN). Oversampling techniques can sometimes lead to overfitting.
- Limited private dataset size may hinder generalizability. Larger, more diverse datasets would improve the robustness of the model.

Future Directions

- Expanding dataset size for better robustness.
- Integrating fuzzy logic and optimization for improved prediction.

Critique

- The use of imputation for missing insulin values introduces some uncertainty.
- The private dataset is relatively small, which may limit the model's generalizability.

5 Integrating Machine Learning and Deep Learning Techniques for Advanced Alzheimer's Disease Detection through Gait Analysis

Article Reference: [3]

Overview

The paper aims to enhance early detection of Alzheimer's Disease (AD) by leveraging gait analysis combined with advanced machine learning (ML) and deep learning (DL) techniques. Gait abnormalities, such as reduced stride length and irregular cadence, are identified as early biomarkers for cognitive decline associated with AD. The study emphasizes the need for non-invasive, scalable diagnostic tools. This research highlights the potential of AI-driven gait analysis to contribute to personalized AD management through early detection.

Dataset

Data were collected using wearable sensors and motion capture systems in both clinical and real-world environments, providing high-resolution temporal and spatial gait metrics. The dataset includes gait features like stride length, cadence, swing time, and gait variability, with some data sourced from publicly available repositories like the UCI Machine Learning Repository.

Data Processing

- **Normalization:** Features were scaled between 0 and 1 to standardize the data, ensuring that features with larger ranges (e.g., stride length) did not dominate the model training.

- **Handling Missing Data:** Missing values were imputed using median substitution to maintain data integrity and reduce bias.
- **Class Imbalance:** The Synthetic Minority Over-sampling Technique (SMOTE) was applied to generate synthetic samples of the minority class (AD patients), addressing class imbalance issues.
- **Feature Selection:** Recursive Feature Elimination (RFE) was used to identify the most significant gait features—such as stride length, gait variability, and cadence—to improve model performance.
- **Correlation Analysis:** High correlations between key features (e.g., stride length and step length) validated their importance for prediction, informing feature selection.

ML Approach

The study employed a hybrid deep learning model comprising Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to classify individuals as healthy or at risk for AD. These models analyzed temporal-spatial gait features, capturing sequential patterns and irregularities. Traditional ML classifiers such as Random Forest and SVM were also evaluated for comparison. The use of a hybrid CNN-RNN model is a strength, as it leverages the capabilities of both CNNs for spatial feature extraction and RNNs for temporal sequence modeling, which is well-suited for gait analysis.

Results

- Hybrid CNN-RNN model accuracy: 93%
- Precision: 92%
- Recall: 91%
- F1-score: 91.5%
- AUC-ROC: 95%
- Traditional models: Random Forest (88%) and SVM (86%)

Challenges

- The reliance on controlled datasets, which may not fully reflect real-world variability, impacting model robustness.
- The complexity and interpretability of deep learning models, posing a barrier for clinical acceptance.
- The need for large, diverse datasets to ensure generalizability.
- Integration into clinical workflows and validation through real-world testing.

Future Directions

- Incorporating multimodal data sources, such as MRI, PET scans, vocal, and cognitive measures, to improve diagnostic precision.
- Expanding datasets to include diverse populations and environmental conditions, enhancing model robustness.
- Developing explainable AI frameworks to improve interpretability and clinician trust.
- Extending studies to include longitudinal gait data for monitoring disease progression and enabling earlier detection.
- Conducting clinical pilot studies and developing affordable wearable technologies for widespread, low-resource application.

Critique

- The dataset may not fully represent the variability of real-world gait patterns.
- Deep learning models are often considered "black boxes," which can hinder clinical acceptance.

6 Diabetes Detection Using Deep Learning Algorithms

Article Reference: [4]

Overview

The authors developed a non-invasive method to detect diabetes using heart rate variability (HRV) signals derived from ECG data. They designed a deep learning architecture combining convolutional neural networks (CNN) and long short-term memory (LSTM) networks to automatically extract complex features from the HRV signals. These features were then classified using a support vector machine (SVM) with an RBF kernel. The approach achieved a high accuracy of 95.7%, outperforming previous methods. This research demonstrates the potential of AI for non-invasive, personalized diabetes screening.

Dataset

- ECG recordings from 20 individuals (both diabetic and normal)
- Each participant provided a 10-minute ECG sample, from which heart rate time series data was derived
- Total datasets: 71 datasets for both groups, each containing 1000 samples

Data Processing

- Used Pan and Tompkins algorithm for QRS complex detection to extract heart rate intervals.
- Derived HRV signals directly from ECG without additional preprocessing.
- Input data fed into deep learning architectures for automatic feature learning.

ML Approach

- Built a deep learning model comprising 5 CNN layers followed by an LSTM layer to capture spatial and temporal features.
- Used dropout (0.1) for regularization.
- Extracted features automatically within the network, then classified using an SVM with RBF kernel.
- Employed 5-fold cross-validation for robust evaluation.

Results

- Maximum classification accuracy: 95.7% (CNN-LSTM with SVM)
- Various architectures tested with accuracies ranging from 68% to 95.7%
- The combination of deep learning feature extraction with SVM classification outperformed using deep learning alone
- Highest accuracy reported so far for non-invasive diabetes detection using HRV signals

Challenges

- Limited dataset size could affect generalization; larger datasets are needed.
- Variability in HRV signals due to individual differences may pose challenges.
- Ensuring model interpretability for clinical acceptance.
- Moving from controlled datasets to real-world, noisy ECG signals.

Future Directions

- Increase dataset size to improve model accuracy and robustness.
- Explore anomaly prediction techniques by analyzing dynamic characteristics in HRV data.
- Develop more advanced deep learning models for early and accurate detection.
- Investigate applicability to real-time monitoring and broader clinical validation.

Critique

- The dataset size is limited (only 20 individuals), which may affect the model's ability to generalize to larger populations
- Like other deep learning models, the interpretability of the model could be a concern for clinical use

7 Enhancing Heart Disease Prediction with Reinforcement Learning and Data Augmentation

Article Reference: [5]

Overview

This study aims to improve the prediction accuracy of heart disease by integrating reinforcement learning (RL) and data augmentation techniques. The approach addresses the complexities of cardiac data, which often hampers traditional machine learning models, by leveraging advanced methods to enhance predictive performance and early diagnosis.

Dataset

The primary dataset employed is similar to the Cleveland Heart Disease dataset, sourced from the UCI Machine Learning Repository. It contains features such as age, gender, blood pressure, cholesterol levels, ECG results, and other patient health indicators. The dataset includes a target variable indicating the presence or absence of heart disease, facilitating classification tasks. Additional datasets might come from healthcare agencies and research repositories.

Data Processing

- **Feature Selection:** Techniques such as feature importance scores and recursive feature elimination were used to identify the most impactful variables for heart disease prediction.
- **Data Augmentation:** Applied transformations like feature scaling, rotation, noise addition, and synthetic data generation to expand and diversify the training data. This helps models handle variability and reduce overfitting.
- **Model Training:** The models were trained on augmented data, using reinforcement learning strategies to iteratively improve predictions based on feedback.
- **Evaluation:** The models were assessed using metrics like accuracy, precision, recall, F1-score, and AUC-ROC scores to gauge performance and robustness.

ML Approach

- **Data Augmentation:** Applying transformations like feature scaling, rotation, noise addition, and synthetic data generation to expand and diversify the training data. This helps models handle variability and reduce overfitting.
- **Reinforcement Learning (RL):** Utilizing RL algorithms to optimize decision-making processes dynamically, allowing models to adapt to evolving patient data and improve prediction accuracy over time.

How It Functions in the Study:

- **Initialization:**
  - The RL agent starts with an initial policy, possibly based on prior knowledge or random actions.
  - The dataset is preprocessed, and the model's initial parameters are set.
- **Interaction Loop:**
  - For each episode, the agent:
    - Observes the current state (e.g., patient features).

    * Selects an action according to its policy (e.g., choosing a specific augmentation or parameter setting).
    * Executes the action, which may involve training the model further, updating parameters, or selecting data augmentation techniques.
    * Moves to the next state, reflecting the outcome of its action, such as improved data representation or better predictive performance.
    * Receives a reward based on the effectiveness of its action, such as increased accuracy or better generalization.

- **Learning:**
  - The agent updates its policy based on the feedback (rewards), aiming to improve decision-making over future episodes.
  - Techniques like Q-learning or policy gradients are often used to optimize this process.
- **Outcome:**
  - Over many iterations, the RL model learns which actions lead to higher rewards and adapts its strategy to improve heart disease prediction accuracy continually.

In summary:

- **States** represent patient data or model status.
- **Actions** correspond to decisions like data augmentation choices or model updates.
- **Rewards** are signals (e.g., accuracy improvements) guiding the learning process.
- The RL agent learns the best policy to update the model continuously, maximizing prediction performance.

Results

- Achieved an accuracy rate of approximately 94%, surpassing traditional models
- Data augmentation contributed to better generalization and robustness
- Reinforcement learning facilitated continual improvement, especially in handling complex and dynamic cardiac data
- Significant gains in both recall and overall predictive performance

Challenges

- **Computational Complexity:** The combined methods demand significant processing power and longer training times.
- **Data Quality and Accessibility:** The efficacy of data augmentation depends heavily on the quality of the original dataset; biases or missing data can impact outcomes.
- **Model Generalizability:** Design choices and assumptions within the RL framework may limit applicability across diverse patient populations or clinical settings.
- **Scalability:** Handling large-scale, real-world datasets remains challenging due to resource requirements.

Future Directions

- **Fine-tuning Techniques:** Further optimizing model parameters and augmentation strategies.
- **Privacy and Security:** Incorporating mechanisms to ensure patient data privacy.
- **Clinical Validation:** Conducting extensive real-world clinical trials to validate model usefulness and safety.
- **Broader Application:** Extending the methodology to other medical diagnostic areas beyond heart disease.
- **Reducing Computational Costs:** Developing more efficient algorithms to make the approach more scalable and practical in healthcare settings.

Critique

- The integration of RL and data augmentation is promising, but computational demands and reliance on data quality could hinder deployment in resource-limited settings.
- The paper lacks details on the exact RL algorithm used, which is essential for reproducibility.
- There is limited discussion on how interpretability is addressed, which is crucial for clinical use.

8 CardioXNet: A Novel Lightweight Deep Learning Framework for Cardiovascular Disease Classification Using Heart Sound Recordings

Article Reference: [6]

Overview

This paper introduces CardioXNet, a lightweight CRNN architecture designed for the automatic detection of five types of heart sounds using raw PCG signals. The architecture involves two main phases: representation learning to extract time-invariant features and sequence residual learning to extract temporal features. CardioXNet is designed to be efficient for use in low-resource settings.

Dataset

- **Primary Dataset:** GitHub PCG database containing 1000 recordings across five classes: Normal, Aortic stenosis, Mitral regurgitation, Mitral stenosis, and Mitral valve prolapse.
- **Secondary Dataset:** PhysioNet/CinC 2016 challenge dataset with 3240 recordings labeled as normal or abnormal, used to test the model's generalizability.

Data Processing

- All signals were resampled at 2 kHz and amplitude-normalized
- No segmentation or extensive preprocessing was performed, emphasizing the model's robustness to raw signals
- The approach leverages convolutional pathways to learn features directly from raw waveforms, avoiding traditional MFCC or spectrogram conversion

ML Approach

The authors developed CardioXNet, a lightweight CRNN framework with two learning schemes:

- **Representation learning:** Extracts time-invariant features using three parallel CNN pathways
- **Sequence residual learning:** Extracts temporal features using bidirectional connections
- The model is specifically designed to be efficient in terms of parameters and computational requirements

Results

- Achieved 99.60% accuracy on the GitHub dataset, outperforming prior methods.
- Demonstrated 86.57% accuracy on the PhysioNet dataset, indicating good generalization.
- Model is efficient, with only 0.67M trainable parameters, 26M FLOPS, and $\sim$54.6 ms processing time—suitable for real-time applications.

Challenges

- Limited dataset size, especially for specific conditions like HVD
- Lack of patient independence and demographic details
- Generalization to real-world, heterogeneous data remains untested

Future Directions

- Incorporate larger and more diverse PCG datasets
- Integrate CardioXNet into wearable devices with cloud connectivity
- Explore transfer learning and further model compression for resource-constrained deployment
- Develop methods to handle noisy recordings and variable acoustic environments

Critique

- Dataset size and diversity might limit generalizability to broader populations
- Missing demographic and variability information limits assessment of performance across different patient groups
- Robustness to real-world noise and device variation not fully evaluated
- Limited evaluation in actual clinical settings

9 A Reinforcement Learning–Based Method for Management of Type 1 Diabetes: Exploratory Study

Article Reference: [7]

Overview

The researchers developed a reinforcement learning (RL) framework, specifically a Q-learning algorithm, to personalize insulin dosing for patients with Type 1 Diabetes Mellitus (T1DM). The aim was to improve blood glucose management by recommending insulin doses tailored to individual patient characteristics.

Dataset

The dataset consisted of clinical records from 87 T1DM patients treated at Mass General Hospital (MGH) between 2003 and 2013.

The data included patient information such as HbA1c levels, BMI, physical activity, and alcohol usage.

The authors conducted a correlation analysis to identify key variables influencing blood glucose, concluding that HbA1c, BMI, activity level, and alcohol usage were the most relevant.

Based on these factors, they defined the patient's state by discretizing these variables into levels:

- HbA1c levels (e.g., normal, elevated, high)
- BMI categories
- Activity levels (e.g., low, high)
- Alcohol usage levels (e.g., none, moderate, high)

Data Processing

States were formed as combinations of these discretized features.

Insulin doses (actions) were defined within specific ranges (e.g., Lantus dose intervals).

The data was used to train and validate the RL model.

Approach

Framework & Method:

- The Q-learning algorithm was employed, which is a model-free RL method.
- The environment is represented by the patient's health state, and the agent makes decisions on insulin dosage.
- The states are defined by the combination of HbA1c, BMI, activity level, and alcohol usage.
- The actions are discretized insulin dose levels (specific dose intervals).
- The reward function is designed based on how well the insulin dose achieved the target HbA1c level.

ML Approach

- At each time step (e.g., clinical visit), the agent observes the state and selects an action (insulin dose) either by exploration (random choice with probability ϵ) or exploitation (based on learned Q-values).
- After administering the dose, the patient's response (e.g., change in HbA1c) results in a reward, guiding the learning process.
- The Q-values are updated iteratively based on the reward and the estimated value of subsequent states.

Results

- RL model tested on 60 unseen cases
- Recommended insulin dose interval included the physician-prescribed dose in 88% of cases
- Results suggest the RL approach can effectively offer personalized treatment recommendations aligning with clinical decisions

Challenges

- **Limited dataset size:** Only 87 patients, which may limit generalizability
- **Discretization of variables:** Fineness of categories might affect the model's precision
- **Data quality and missing variables:** Not all potentially influential factors (like diet or stress) were included
- **Algorithm complexity:** RL models require careful tuning; real-world implementation must address issues like exploration vs. exploitation and patient safety

Future Directions

- Extend the model to include other types of insulin and medications
- Incorporate finer categories or continuous variables for more precise recommendations
- Validate with larger and more diverse datasets
- Explore application to other populations, such as patients with Type 2 Diabetes
- Implement real-time decision support in clinical settings

Critique

- Limited patient sample size may not capture all variability in diabetes management
- Discretization may lead to loss of information that could be valuable for precise dosing
- No explicit mention of model validation techniques beyond testing on 60 cases
- Reward function description is brief; more detail would clarify alignment with clinical goals

10 Cardiovascular Diseases Prediction by Machine Learning Incorporation with Deep Learning

Article Reference: [8]

Overview

The article discusses the increasing role of artificial intelligence (AI) in healthcare, particularly in predicting cardiovascular diseases (CVD). It highlights the growing prevalence of data from the Internet of Things (IoT) within healthcare systems, which can be leveraged to identify risk factors associated with CVD.

Dataset

- Heart dataset with 918 unique samples after removing duplicates
- Dataset comprises 11 features relevant for predicting CVD

Data Processing

The study employed machine learning models to analyze the data received from Internet of Things (IoT) devices. Traditional machine learning algorithms were noted to have limitations in accuracy, which led to the exploration of advanced techniques for better predictions. A feature selection method using Tree SHAP was applied to identify significant features influencing CVD predictions. This method enhances the interpretability of the results by showing each feature's contribution to predictions.

Approach

The researchers proposed a stacking fusion model-based classifier, which achieved an impressive accuracy of nearly 96%. This model effectively combined the strengths of various algorithms, outperforming individual models in predicting high-risk individuals for CVD. They emphasized the limitations of traditional machine learning and the importance of large, diverse datasets for robust predictions.

Results

The proposed stacking fusion model-based classifier demonstrated superior performance, achieving nearly 96% accuracy. The model's performance remained stable after feature selection, with AUC values not significantly impacted by the removal of the Resting ECG feature.

Challenges

One of the challenges noted in the study is the reliance on traditional machine learning algorithms, which may not adequately account for data variability, leading to lower accuracy in predictions. Additionally, the need for more extensive datasets from various medical institutions was emphasized.

Future Directions

- Incorporate additional deep learning techniques within IoT environments
- Enhance accuracy for identifying high-risk patients
- Implement early clinical interventions based on model predictions
- Develop more sophisticated models that can handle real-time streaming data

Critique

- Need for broader dataset diversity incorporating various demographics and geographical locations
- More detailed explanation of the specific algorithms used in the stacking model would clarify their individual contributions
- Longitudinal studies would help assess the real-world effectiveness of the models
- The paper does not adequately address how data imbalance was handled

11 Optimizing Type 2 Diabetes Management: AI-Enhanced Time Series Analysis of Continuous Glucose Monitoring Data for Personalized Dietary Intervention

Article Reference: [9]

Overview

This study proposes a method to optimize type 2 diabetes management using AI-enhanced time series analysis of continuous glucose monitoring (CGM) data. The goal is to enable personalized dietary interventions to improve patient outcomes.

Dataset

- Collected CGM data from 8 patients with type 2 diabetes.
- Data includes time-series blood glucose (BG) values.

Data Processing

- Removed NaN records to clean the data.
- Applied feature extraction and dimensionality reduction techniques.
- Split dataset into training (75%) and testing (25%) portions.

ML Approach

- Used regression models: XGBoost, SARIMA, Prophet.
- Evaluated using MAE, MSE, and R-squared (R^2) metrics.
- Integrated dietary recommendations based on predicted BG levels.

Results

- XGBoost outperformed SARIMA and Prophet.
- Achieved high R^2 and low MAPE.
- Accurately predicted glucose fluctuations for timely intervention.

Challenges

- Limited dataset (only 8 patients) reduced model generalizability.
- Up to ±30-minute lag in CGM readings affected prediction accuracy.

Future Directions

- Expand dataset to improve training and validation.
- Enhance model with additional features and contextual data.

Critique

- Promising approach, but small sample limits robustness.
- Time lag in CGM data must be addressed for better accuracy.

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13 Deep Q-Network (DQN) Model for Disease Prediction Using Electronic Health Records (EHRs)

Article Reference: [10]

Overview

The paper addresses the challenges of using deep learning models for disease prediction with EHRs, including lack of precision, ethical concerns, limitations of small datasets, complexity of data processing, and incompleteness of patient data. It proposes a deep Q-learning (DQL) model to enhance the accuracy and stability of predictions. The model integrates reinforcement learning with neural networks, utilizing the mapping capabilities of the Q-network. The proposed model is evaluated on the Heart Disease Dataset from the UCI Data Repository, demonstrating high accuracy (98%) compared to other models.

Dataset

- The Heart Disease Dataset from the UCI Data Repository via Kaggle.
- Includes multivariate numerical data with 14 attributes (categorical, integer, and real data).

Data Processing

- The dataset was split into training (80%) and test sets (20%) using stratified splitting.
- Robust scaling was applied for feature scaling.

ML Approach

- The study uses a Deep Q-Network (DQN) model, which combines reinforcement learning with neural networks.
- This approach aims to address the limitations of traditional Q-learning and improve the accuracy and stability of disease predictions.

Implementation of Reinforcement Learning

- The model uses a "disease prediction game" environment.
- State: The state is represented by the samples from the EHR data.
- Action: Actions involve increasing, decreasing, or holding each feature.
- Reward: Positive rewards are given for accurate predictions, and negative rewards for inaccurate ones.

- Environment: The environment consists of sets of states (samples) and actions (feature adjustments).

Results

- The paper compares the Deep Q-Network (DQN) model with Logistic Regression, Decision Tree Classifier, Random Forest Classifier, and Gradient-Boosting Classifier.

Key Results:

- The proposed EHR-DQN model achieved high accuracy (0.9841) and a low mean squared error (MSE) of 0.0001.
- The Decision Tree and Gradient-Boosting Classifiers also performed well, with perfect precision, recall, and F1 scores.
- The Random Forest model showed a balance of high accuracy (0.9783) and a minimal MSE of 0.
- Logistic Regression had the lowest performance, with an accuracy of 0.8424 and a higher MSE of 0.1576.

Challenges

- Data-related issues: digitization, consolidation, and availability of health records.
- Privacy and legal concerns with patient data handling.
- Patient-related difficulties: decision-making errors, treatment errors, and data inconsistencies.
- Technical challenges: data integration across systems, ensuring patient security.
- Interpretability: "black box" nature of complex AI models limits transparency.
- Resource limitations: computational resources and expertise needed for implementation.

Future Directions

- Expand the dataset size to better train deep reinforcement learning models.
- Integrate additional contextual features to improve prediction accuracy.
- Develop more transparent models to address interpretability concerns.
- Create more standardized methods for validating healthcare AI systems.
- Improve integration with clinical workflows for practical implementation.

Critique

- The paper emphasizes the high accuracy of the proposed model but also points out that the dataset used has only thousands of samples. The DQN algorithm typically requires a large number of training samples (millions) to achieve optimal performance.
- The paper acknowledges the "black box" nature of many AI algorithms and the resulting lack of interpretability, which can hinder trust and adoption in healthcare.

14 A Reinforcement Learning Model for AI-Based Decision Support in Skin Cancer

Article Reference: [11]

Overview

- The article presents a reinforcement learning (RL) model designed to enhance decision support in skin cancer diagnosis.
- It compares the effectiveness of RL with supervised learning (SL) methods, emphasizing the potential of RL in optimizing management decisions.

Dataset

- They utilized the publicly available HAM10000 dataset, a comprehensive collection of dermatoscopic images of skin lesions.
- This dataset contains over 10,000 images across seven diagnostic categories of skin lesions.

Data Processing

- For patient-centered scenarios, input vectors were normalized by dividing position-wise by the average across all lesion vectors of the same patient.
- This normalization was crucial for processing multiple lesions from the same patient effectively.
- Feature extraction was performed using convolutional neural networks pre-trained on the dataset.

ML Approach

- Supervised Learning (SL): A convolutional neural network was fine-tuned for classifying seven categories of skin lesions.
- Reinforcement Learning (RL): A deep Q-learning model was developed using a multilayer perceptron that processed feature vectors derived from the SL model.
- They also implemented a threshold-based approach for comparison.

Implementation of Reinforcement Learning

- States: One-dimensional vectors representing features of skin lesions.
- Actions: Management strategies including excision, short-term follow-up, and regular surveillance.
- Rewards: Defined based on diagnosis outcomes and management decisions, optimizing for both clinical efficacy and resource utilization.
- Learning: The model used experience replay and target networks to stabilize learning.

Results

- The RL method and threshold method both improved management decisions compared to the naïve SL model.
- Both approaches optimized operating points on decision curves, enhancing diagnostic accuracy.
- The RL model demonstrated superior performance in balancing sensitivity and specificity.
- The study showed potential for reducing unnecessary excisions while maintaining high detection rates.

Challenges

- RL models require more complex retraining compared to simpler threshold approaches.
- Integration into clinical workflows presents practical implementation barriers.
- Limited consideration of patient preferences in the current model design.
- Lack of longitudinal data to validate long-term decision outcomes.

Future Directions

- Development of reward tables incorporating both physician and patient preferences.
- Enhancement of shared decision-making tools combining AI recommendations with clinical expertise.
- Integration of additional clinical parameters beyond image data.
- Validation in prospective clinical trials to assess real-world impact.

Critique

- It focuses primarily on physician preferences, potentially neglecting patient-centered care principles.
- Limited dataset diversity may restrict generalizability across different patient populations.
- The complexity of RL models may limit practical implementation in resource-constrained settings.
- Further validation is needed to demonstrate clinical utility beyond technical performance metrics.

15 Reinforcement Learning Using Deep Q Networks and Q-Learning Accurately Localizes Brain Tumors on MRI with Very Small Training Sets

Article Reference: [12]

Overview

This study applies reinforcement learning (RL), specifically Deep Q Networks (DQN), to accurately localize brain tumors in MRI scans. It addresses the limitations of traditional supervised learning methods, particularly the dependence on large annotated datasets. The authors demonstrate that RL can achieve high performance even with minimal training data.

Dataset

The dataset used comprises 2D slices from the 2014 BraTS (Brain Tumor Segmentation) challenge dataset. These are T1-weighted contrast-enhanced MRI images. The training set included 30 images, with another 30 images used for testing.

Data Processing

- 2D slices were extracted and the image space was divided into a grid.
- Each agent operates within a 60×60 pixel block.
- No data augmentation was applied to keep training consistent with the original dataset.

Implementation of Reinforcement Learning

- **Environment:** Modeled as a gridworld over MRI images.
- **States:** Represented by the agent's position in the image grid.
- **Actions:** The agent can move down, move right, or stay in place.
- **Rewards:** Positive rewards for entering tumor regions, penalties for remaining idle outside the tumor area.
- The DQN used experience replay and a target network to stabilize learning.

Results

- The DQN achieved an average localization accuracy of 70% over the last 20 episodes.
- This significantly outperformed a supervised deep learning approach, which achieved only 11% accuracy.
- Results demonstrate RL's superiority with small datasets in this context.

Challenges

- The reliance on small datasets may limit generalizability.
- High computational cost of RL may pose integration challenges in real-time clinical settings.

Future Directions

- Extend the RL model to handle full 3D MRI volumes.
- Compare performance with other RL strategies such as policy-gradient methods.
- Optimize training and inference to improve clinical applicability.

Critique

- The model's performance with small data is promising but needs validation on larger, more diverse datasets.
- No integration of clinical context or physician-in-the-loop evaluation.
- Despite excellent performance metrics, interpretability and ease of integration in hospitals remain unresolved.

16 Comparison of the Solutions

Work	Disease/Domain	Dataset	Data Processing	Approach	Results
[1]	Epilepsy	Phase III (235) + Validation (47) patients	Clinical + WGS feature extraction (e.g., SV2A), mutational scores, PRS	Gradient-Boosted Decision Trees	AUC: 0.76 (train), 0.75 (validation)
[2]	Diabetes Prediction	Pima Indian (768) + RTML (203) records	Imputation, ADASYN, Mutual Info, Holdout Validation	XGBoost + Ensemble Methods (voting, bagging)	AUC: 0.84, Accuracy: 81%, F1 Score: 0.81
[3]	Alzheimer's Disease	Wearable sensors and motion capture data	Normalization, median imputation, SMOTE, RFE, correlation analysis	Hybrid CNN-RNN (LSTM)	Accuracy: 93%, Precision: 92%, Recall: 91%, F1-Score: 91.5%, AUC-ROC: 95%
[4]	Diabetes	ECG recordings (71 datasets)	Pan-Tompkins for QRS detection	CNN-LSTM + SVM	Accuracy: 95.7%
[5]	Heart Disease	UCI Cleveland Heart Disease dataset	Feature selection, data augmentation, reinforcement-based iteration	RL + Data Augmentation	Accuracy: 94%
[6]	Cardiovascular Disease	PCG datasets (GitHub + PhysioNet)	Minimal preprocessing on raw heart sound signals	Lightweight CRNN (CardioXNet) with dual learning (representation + sequence residual)	Accuracy: 99.6% (GitHub), 86.57% (PhysioNet), 0.67M params, ∼54.6ms latency
[7]	Type 1 Diabetes	Clinical data from 87 patients (MGH, 2003–2013)	Discretization of HbA1c, BMI, activity level, alcohol usage into states	Q-Learning (model-free RL) for insulin dosing	88% RL suggestions matched physician dose
[8]	Cardiovascular Disease	Heart dataset (918 samples, 11 features)	Duplicate removal, Tree SHAP feature selection	Stacking fusion model with IoT-enhanced data inputs	Accuracy: 96%, Stable AUC after feature pruning
[9]	Type 2 Diabetes	CGM data from 8 patients	NaN removal, feature extraction, dimensionality reduction, 75/25 train-test split	XGBoost, SARIMA, Prophet regression for BG prediction + dietary recommendations	XGBoost: High R^2, low MAPE, effective BG prediction for personalized intervention
[10]	Heart Disease	UCI Heart Disease Dataset via Kaggle (14 attributes)	Stratified 80/20 train-test split with robust scaling	Deep Q-Network (DQN) with reinforcement learning	Accuracy: 98.41%, MSE: 0.0001, outperformed traditional classifiers
[11]	Skin Cancer	HAM10000 dataset (10,000+ dermatoscopic images)	Feature extraction via CNN, patient-level normalization for multiple lesions	Comparative RL (Deep Q-learning) vs SL (CNN) for decision support	Improved diagnostic and management decisions, optimal operating points on decision curves
[12]	Brain Tumor Localization	BraTS 2014 (T1-weighted contrast-enhanced MRI, 60 images total)	Grid-based image division, no augmentation, 60x60 pixel block navigation	Deep Q-Network (DQN) with position-based rewards in grid-world	70% accuracy vs 11% for SL; high performance on small training data

Table 1: Comparison of AI Approaches in Health Applications

17 Conclusion

Personalized healthcare using AI continues to evolve, offering significant potential to improve patient care. However, integration into real-world clinical settings remains an ongoing challenge.

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