Related Works on Personalized Healthcare using Artificial Intelligence

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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).

Processing

Clinical data included demographic and seizure-related information. Whole Genome Sequencing (WGS) data ($\sim$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

The GBDT classifier achieved:

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

Future Directions and 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 $\sim$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.

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

The best results were obtained using the XGBoost classifier with ADASYN:

- 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. Preprocessing steps involved normalization, handling missing data via median imputation, class balancing with SMOTE, and feature selection through Recursive Feature Elimination.

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

The hybrid CNN-RNN model achieved the highest accuracy of 93%, with other metrics like precision, recall, and F1-score also indicating strong performance. Traditional models like Random Forest and SVM performed well but with slightly lower accuracy (88% and 86%, respectively). These results demonstrate the potential of deep learning models in accurately detecting early AD.

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. The dataset consisted of ECG recordings from 20 individuals, each providing 10-minute samples, which were processed to extract HRV data without extensive preprocessing. The study demonstrated that deep learning models could effectively identify diabetes from HRV signals, with future work aimed at expanding datasets, improving model robustness, and exploring anomaly prediction for earlier diagnosis. 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.

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. The combination of CNNs and LSTMs is well-suited for processing time-series data like HRV signals.

Results

The study achieved a maximum classification accuracy of 95.7% using a CNN-LSTM architecture combined with SVM for placement of the final classifier. This result represents the highest accuracy reported so far for non-invasive diabetes detection using HRV signals as input. The detailed results showed that:

- The combination of deep learning feature extraction with SVM classification outperformed using deep learning alone.
- Various architectures tested yielded accuracies ranging from around 68.% (CNN 1 with SVM) to 95.7% (CNN 5-LSTM with SVM).
- The high accuracy indicates that the proposed model effectively captures the complex temporal and spatial features of HRV signals associated with diabetic and normal individuals, confirming the potential of this approach for reliable, non-invasive diabetes detection.

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, 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.

Processing

- **Feature Selection:** Techniques such as feature importance scores and recursive feature elimination are used to identify the most impactful variables for heart disease prediction.
- **Model Training:** The models are trained on augmented data, using reinforcement learning strategies to iteratively improve predictions based on feedback.
- **Evaluation:** The models are 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

- The integrated approach achieved an accuracy rate of approximately 94%, surpassing traditional models.
- Data augmentation contributed to better generalization and robustness of the models.
- Reinforcement learning facilitated continual improvement, especially in handling complex and dynamic cardiac data.
- Visual comparisons indicated 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.

Approach

- The authors developed CardioXNet, a lightweight CRNN framework with two learning schemes: representation learning and sequence residual learning.
- Representation learning extracts time-invariant features using three parallel CNN pathways.
- Sequence residual learning extracts temporal features using bidirectional connections.

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 ∼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.

Critique

- Dataset size and diversity might limit generalizability.
- Missing demographic and variability information.
- Robustness to real-world noise and device variation not fully evaluated.

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.

Details of Implementation:

- 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

The RL model was trained on the data and then tested on 60 unseen cases.

The recommended insulin dose interval from the RL agent included the physician-prescribed dose in 88% of the cases.

This suggests 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 the 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.
- Discretization may lead to loss of information.
- 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

The research utilized a Heart dataset, which was refined to include 918 unique samples after removing duplicates. This 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

Future research should incorporate additional deep learning techniques and algorithms within Internet of Things (IoT) environments. This integration could enhance accuracy and provide valuable insights for hospitals in identifying high-risk patients and implementing early clinical interventions.

Critique

The paper presents a comprehensive approach to predicting cardiovascular diseases using machine learning and deep learning techniques. However, it could benefit from:

- **Broader Dataset Diversity:** Incorporating data from various demographics and geographical locations could enhance the model's generalizability.
- **Detailed Methodology:** A more in-depth explanation of the algorithms used in the stacking model would clarify their individual contributions.
- **Longitudinal Studies:** Including longitudinal studies would help assess the real-world effectiveness of the models.
- **Addressing Data Imbalance:** The paper does not discuss how data imbalance was handled, which is crucial for improving model performance.

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.
- Split dataset into training (75%) and testing (25%).

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.

12 Comparison of the Solutions

13 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.

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

Table 1: Comparison of AI Approaches in Health Applications

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