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| **Author** | **Objective (in short)** | | **Data Sets** | | **ML Models Used** | | **Evaluation Metrics** | | **XAI Models Used** | |
| Francesco Curia | To analyze Dry Eye Disease (DED) in HIV-positive patients using explainable AI and machine learning models to interpret the influence of cytokines. | | Case-control study data involving a population with HIV and a healthy control group | | Clustering algorithms (k-means, agglomerative, spectral, BIRCH), supervised learning methods (logistic regression, decision trees, neural networks). | | Precision, recall, accuracy, homogeneity, Gini Importance (GI), Variable Importance (VI). | | LIME (Local Interpretable Model-agnostic Explanations), Shapley, Individual Conditional Expectation (ICE). | |
| Guleria et. al | To develop an explainable AI (XAI) framework for predicting cardiovascular diseases using various classification techniques. | | Cardiovascular dataset with 303 instances and 14 attributes, involving categorical, integer, and real data types. | | Support Vector Machine (SVM), AdaBoost, K-nearest neighbor (KNN), Bagging, Logistic Regression (LR), Naive Bayes | | Area Under Curve (AUC), Receiver Operating Characteristic (ROC), Sensitivity, Specificity, F1-score | | Shapley Additive Explanation (SHAP), Local Interpretable Model-agnostic Explanation (LIME) | |
| ALLERGY | | 2021 | |  | |  | |  | |
| Kavya, et. al | Develop a computer-aided framework for allergy diagnosis | | Intradermal skin test results of 878 patients from South India | | Decision Tree, Support Vector Machine, Random Forest | | Accuracy, Sensitivity | | Post-hoc explainability approaches | |
| ASTHAMA | | 2023 | |  | |  | |  | |
| Narteni, et. al | To identify the main causes of chronic cough-related quality of life impairment in asthmatic patients using a rule-based classification model | | Cohort of asthmatic patients from NCT04796844 trial | | Logic Learning Machine (LLM) | | Accuracy, F1-score, Positive Predictive Value (PPV), Negative Predictive Value (NPV), True Positive Rate (TPR), True Negative Rate (TNR) | | Rule-based model with if-then rules | |
| LIVER | | 2023 | |  | |  | |  | |
| Agbozo, .et al | To classify liver disease using deep learning and explainable AI (XAI) | | Indian Patient Liver Dataset (IPLD) | | Deep learning models built on Keras-Tensorflow | | Accuracy, Precision, Recall, F-Measure | | SHAP (Shapley Additive Explanations) | |
| MONKEY POX | | | | 2023 | |  | |  | |
| Nayak, .et al | Detection of Monkeypox from skin lesion images using deep learning networks and explainable artificial intelligence | | images of Monkeypox, Chickenpox, Measles, and Healthy skin lesions from Kaggle | | ResNet-18, ResNet-50, ResNet-101, SqueezeNet | | Accuracy, Precision, Recall, F1-Score | | Local Interpretable Model-Agnostic Explanations (LIME) | |
| BREAST CANCER | | | | 2023 | |  | |  | |
| Aravena, .et al | Develop a clinical decision support methodology using ML and XAI for breast cancer prevention | | Public data of Indonesian women with and without breast cancer | | XGBoost, Logistic Regression, Random Forest, SVM | | Accuracy, Precision, Recall | | SHAP (Shapley Additive Explanations) | |
| DIABETES | | 2023 | |  | |  | |  | |
| Ilhan Uysal | Investigate the application of XAI techniques in diabetes prediction | | Diabetes dataset with 768 rows and 9 columns | | KNN, Naive Bayes, SVM, Decision Tree, Random Forest, Logistic Regression | | F1 Score, Accuracy, Balanced Accuracy, Precision, Recall, ROC AUC, Time Taken | | SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations) | |
| PCOS | 2023 | |  | |  | |  | |  | |
| Khanna, et. al | To accurately detect PCOS using AI and propose an automated screening architecture with explainable ML tools. | | Open-source dataset of 541 patients from Kerala, India. | | LR, SVM (linear, polynomial, Gaussian, Sigmoid), DT, RT, XGBoost, AdaBoost, ExtraTrees, DNN, 1-D CNN, and ensemble stacking models. | | Accuracy, Precision, Recall, F1-score, AUC-ROC score, Precision-Recall curve. | | SHAP, LIME, ELI5, Qlattice, Feature importance with Random Forest. | |
| PCOS | 2023 | |  | |  | |  | |  | |
| Moral, et.al | Develop ML methods to predict PCOS using demographic and clinical features | | Kaggle PCOS dataset | | RF, ADB, GB, XGB, CATB, PODBoost | | Accuracy, Error-Rate, ROC-AUC Score, Recall, Precision, F1-Score | | LIME | |
| PCOS | 2023 | |  | |  | |  | |  | |
| Elmannai, et. al | Early detection of PCOS using optimized feature selection and explainable AI | | PCOS dataset from Kaggle (541 instances, 41 attributes) | | Logistic Regression, Random Forest, Decision Tree, Naive Bayes, SVM, KNN, XGBoost, AdaBoost, Stacking ML | | Accuracy, Precision, Recall, F1 Score, AUC | | Local and Global Explainability | |
| TYHROID | | 2023 | |  | |  | |  | |
| Hossain, .et al | Predict hypothyroidism and hyperthyroidism using machine learning algorithms and explainable AI | | UCI Machine Learning Repository (hypothyroid, hyperthyroid, and sick datasets) | | Decision Tree, Random Forest, Gradient Boosting, Naive Bayes, K-Nearest Neighbor, Logistic Regression, Support Vector Machine | | Accuracy, Precision, Recall, F1-Score | | SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations) | |