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Computational Analysis Of Healthcare Inequality Using AI-Based Decision Support Systems

M. Santhosh Kumar[1], Dr. Shweta Saxena[2], Dr. Chetansinh R. Vaghela[3], Pushpalatha P[4], Hadasha Nobel Tune[5], Subramanian Karthick[6], Rakesh Arya[7], Mathan Kumar B[8]

[1] Assistant Professor, Department of Computer Science and Business Systems, K. Ramakrishnan College of Engineering, India. Email: santhoshkumarm.csbs@krce.ac.in
[2] Associate Professor, Amity Business School, Amity University Madhya Pradesh, Gwalior, Madhya Pradesh, India. Email: er.saxenashweta15@gmail.com ORCID: 0000-0002-6386-6253
[3] Associate Professor, Faculty of Science, Gokul Global University, Sidhpur, Gujarat, India. Email: crvaghela.maths.gsc@gokuluniversity.ac.in ORCID: 0000-0001-5692-5190
[4] Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: pushpalathap@maher.ac.in
[5] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: nobel@maher.ac.in
[6] Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra 411037, India. Email: karthick.sb@vit.edu
[7] Assistant Professor, Department of Computer Application, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email: pc.mtech.mca@dbuu.ac.in ORCID: 0000-0003-2436-3060
[8] Assistant Professor, Department of Information Technology, PSNA College of Engineering and Technology, Dindigul, Tamil Nadu 624622, India. Email: mathan81@gmail.com ORCID: 0000-0003-1861-6500

Abstract
Healthcare inequality remains a critical global issue, driven by disparities in access, quality, and outcomes across diverse populations. This research presents a computational framework for analyzing inequality in data-driven systems, implemented through an Artificial Intelligence (AI)-based Decision Support System (DSS). The proposed approach integrates heterogeneous data sources, including electronic health records (EHRs), social determinants of health (SDOH), and Healthcare Inequality Analytics datasets, to integrate demographic, clinical, access, and social determinants data for fairness evaluation and data-driven healthcare decision systems. The methodology combines a machine learning (ML) based Prairie Dog Optimized Kernel-tuned Support Vector Machine (PDO-Kernel SVM) model for predictive analytics to detect disparities and support equitable decision-making. Data preprocessing techniques, such as Synthetic Minority Over-sampling Technique (SMOTE), are used to address imbalance and distribution bias. Feature extraction with the Independent Component Analysis (ICA) algorithm is used for extracting independent informative components from the data. While explainable AI (XAI) ensures transparency and interpretability of model outputs. PDO optimizes model parameters and features to improve performance, while Kernel SVM handles nonlinear classification and regression by mapping data into a higher-dimensional space for better separation. The suggested PDO-Kernel SVM, which is simulated using Python, has shown excellent results in the analysis of healthcare inequality. It has an accuracy of 94.9%, precision of 93.4%, recall of 96.1%, and F1-score of 96.7%. In conclusion, the proposed AI-driven DSS provides a scalable and transparent solution for computational analysis of inequality, enabling data-driven, inclusive healthcare interventions. This research highlights the potential of fairness-aware intelligent systems to mitigate disparities and support equitable healthcare delivery across diverse population groups.

Keywords: Computational Inequality Analysis, Data-Driven Systems, Decision Support Systems (DSS)

1. Introduction

The problem of bias, ethics, and inequity raises significant barriers to the computer analysis of healthcare disparities using predictive analytics in the allocation of healthcare resources via AI-enabled clinical decision making [1]. The development of new instruments is necessary because of an increase in mental disorders, resource scarcity, and problems with diagnosis. It led to the introduction of the AI-based DSS [2]. AI-powered CDSSs help in healthcare decision-making by analytics that enable diagnosis, individual treatment, and efficiency [3]. Despite its long-term effect, bias, and evidence-based usage, AI-based DSS in clinical practice facilitates the decision-making process for medical professionals by analyzing data [4]. There are advantages of Clinical Decision Support (AI-CDS), but also some limitations, including complex data, false alarms, poor specificity, alert fatigue, clinical overload, poor damage assessment, and inability to utilize large amounts of data [5]. The application of artificial intelligence in healthcare poses many challenges, such as privacy threats, lack of transparency, ethical issues, algorithmic bias, regulation, and implementation [6]. The traditional approach to solving problems utilizes human judgment, statistics, and rules-based systems. Yet the traditional approach lacks scalability, is biased, inflexible, and not suited to handling big data in the medical field [7]. However, individuals suffering from diabetes can be assisted using manual tracking, rules-based treatment approaches, and traditional statistics, yet they lack scalability, current data, and personalized care [8].

Research Aim: The objective of this research is to propose PDO-Kernel SVM is used to detect and predict healthcare disparity patterns from integrated heterogeneous healthcare data. Even though XAI ensures model interpretability, bias-aware data pre-processing is utilized to achieve a more balanced data usage.

Research Organization: Background and motivations for this research have been presented in Section 1. In Section 2, some solutions using ML, optimization, health care analytics, and explainable AI approaches have been reviewed. In Section 3, the methodology. Section 4 provides an overview of the experimental design and findings. Section 5 includes a discussion of conclusions and future work.

2. Related Works

In Table 1, some research about AI applications in healthcare is listed, pointing out the aims, methods, findings, and weaknesses of each research, particularly focusing on fields like clinical decision-making, cancer therapy, healthcare management, and ethics.

Table 1: AI-Based Healthcare Studies Performance and Limitation Analysis

Ref	Objective	Method	Result	Limitations
[9]	Reduce cancer disparities using AI, SDOH integration	Natural Language Processing (NLP), Deep Learning (DL)	Improved cancer detection prediction and personalized care	Bias, underrepresentation, ethical, regulatory, and fairness challenges
[10]	Apply Computational Intelligence (CI) techniques to improve female cancer care.	AI, ML, data science, Sustainable Development Goals (SDG)	Diagnosis and treatment aligned with multiple SDGs	Implementation gaps, data bias, and scalability issues
[11]	Evaluate XAI in clinical DSS	Meta-analysis of 62 studies across domains	Improved interpretability but limited clinical validation	Lack of usability, trust, and ethical evaluation gaps.
[12]	Improve clinical diagnosis using AI.	ML, DL, NLP, and medical imaging	Enhanced accuracy, efficiency, and disease detection	Data bias, interpretability, regulation, and quality issues
[13]	Design fair AI clinical decision systems	Qualitative interviews, thematic inductive coding	Identified themes improving equitable AI-CDS design	Small sample, subjective bias, limited generalizability
[14]	Explore AI Internet of Things (IoT) roles in healthcare systems	Analytical review of AI IoT healthcare applications	Improved diagnostics, real-time data, and personalization	Privacy, security, ethical, and equity concerns remain
[15]	Transform healthcare using AI applications	ML, DL, data analysis systems	Improved diagnosis, and healthcare efficiency	Privacy bias, transparency, acceptance, and access disparities
[16]	Develop an AI decision support healthcare administration system	ML, DL, fuzzy NLP evaluated patient dataset	Improved accuracy, efficiency, resource allocation	Improved accuracy, efficiency, resource allocation

The research currently identifies a number of problems with AI-based healthcare applications, including data bias, poor interpretability, poor scalability, privacy concerns, and unfairness. However, PDO-Kernel SVM can resolve these difficulties by feature selection, parameter tweaking, improved fairness, balanced data processing, and increased prediction accuracy.

3. Methodology

The presented method for analysis of healthcare inequalities based on the learning process described in Figure 1 includes five stages, which consist of data collection, preprocessing, extraction of relevant features, and classification by applying an optimization approach. At the first stage, SMOTE is applied to solve problems of class imbalance and equalize values within datasets. After that, ICA is applied for extracting informative features. Finally, the PDO-Kernel SVM model is utilized for classification based on the optimization approach.

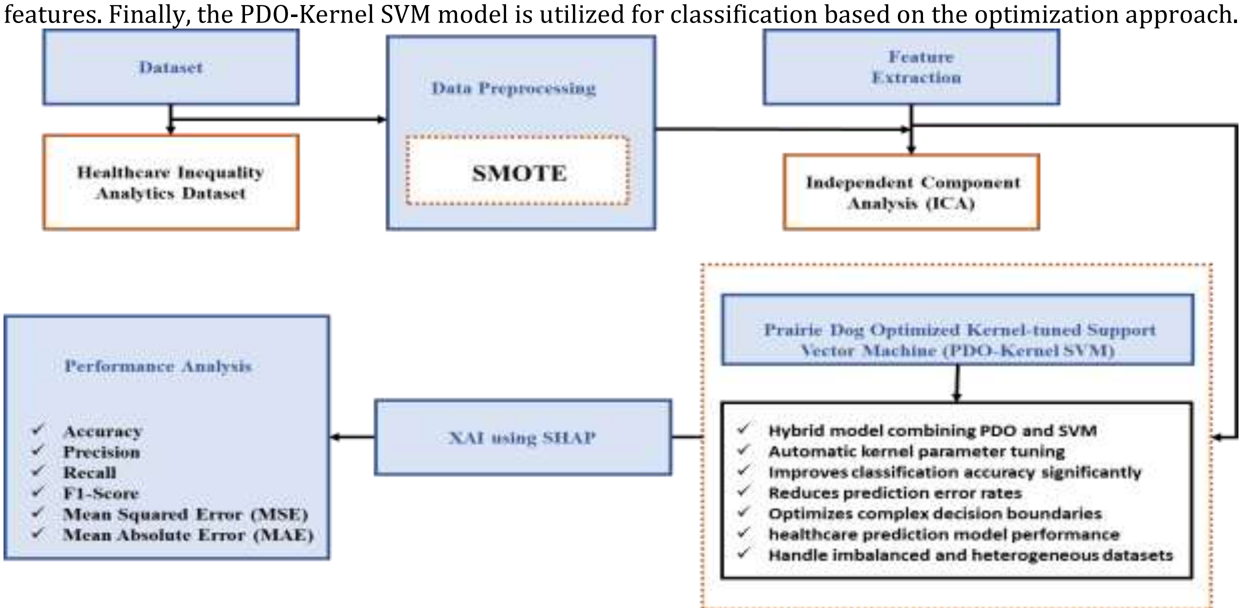
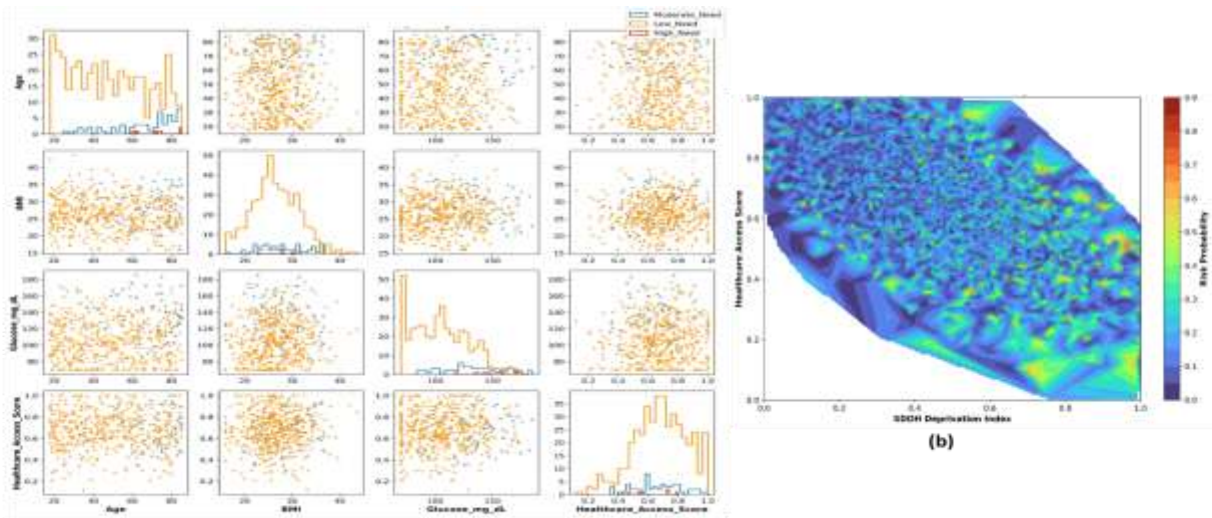


Figure 1: Healthcare Inequality Analysis and Prediction Framework Architecture

3.1 Data collection

The current dataset of Healthcare Inequality Analytics is particularly developed to aid in analyzing disparities using data-enabled DSS. It includes 8,500 records that include demographic, clinical variables, healthcare access metrics, and social determinants of health. The attributes considered are those of demographic characteristics of patients, chronic disease condition, hospitalization, adherence to medications, and social deprivation index. The attributes assist in detecting marginalized groups, assessing equity, and estimating healthcare accessibility. For effective modeling, the dataset is divided into 75% for training and 25% for testing purposes. Kaggle Source: https://www.kaggle.com/datasets/colabsss/healthcare-inequality-analytics-dataset

Data feature exploration analysis: Figure 2 demonstrates the analysis of health disparity using feature distribution and risk visualization techniques. Figure 2 (a) shows multivariate interactions among the variables age, body mass index, glucose, and health care access for various needs groups, emphasizing the class separability. Figure 2 (b) shows a risk probability map based on the contour plot of the SDOH deprivation index and health care access score, pointing out areas with higher risk levels.



(a) (b)

Figure 2: Healthcare Inequality Feature Distribution and Risk Visualization (a) Multivariate Class-Based Analysis (b) Risk Probability Contour Mapping Using SDOH and Access

3.2 Data preprocessing using SMOTE

In the context of healthcare inequity research, SMOTE can be applied to overcome class imbalance by creating artificial examples from underrepresented patient groups. In this way, SMOTE makes the model fairer and improves the capability to identify vulnerable populations. Furthermore, SMOTE helps avoid any model bias against majority classes.

$$o_{ji} = w_j + rand(0,1) \times \left(w_{ji} - w_j\right) \quad (1)$$

In Equation (1), the optimized feature o_{ji} improves representation of healthcare disparities using clinical and socio-economic data. Here, i denotes the feature dimension, and j indicates the solution index. w_j represents current feature importance, while w_{ji} reflects alternative values from neighboring solutions. $rand$ refers to the random factor that ensures exploration, reducing bias.

3.3 Feature extraction using Independent Component Analysis (ICA)

A feature extraction technique is employed to convert high-dimensional health data into independent components, providing a better representation of healthcare disparity patterns. The procedure is grounded in ICA, which refers to a blind source separation approach that enables one to extract underlying independent components from heterogeneous data sets, including EHR, SDOH, and demographic information. As opposed to simple correlations, ICA provides a means of removing redundancies and capturing higher-order statistics, thus contributing to higher-quality features.

$$w = Gt \quad (2)$$

In Equation (2), w represents the output vector or transformed feature set obtained after processing. G denotes the transformation or mixing matrix that defines how input information is linearly combined. t represents the input vector containing original healthcare features or signals.

$$v = Xw = XGt \quad (3)$$

Equation (3) contains, v represents the final transformed output vector in the reduced or extracted feature space. X denotes the observed data matrix containing healthcare-related variables such as EHR, SDOH, and demographic attributes. w represents the weight or feature transformation vector derived from independent components. G is the mixing or transformation matrix.

$$e_v(v) = \Pi_j \, e_{v_j}(v_j) \quad (4)$$

In Equation (4), $e_v(v)$ represents the joint probability density function of the transformed feature vector v. The symbol Π_j denotes the product over all components indexed by j, indicating statistical independence among variables. $e_{v_j}(v_j)$ represents the marginal probability density function of each independent component v_j.

3.4 Prairie Dog Optimized Kernel-tuned Support Vector Machine (PDO-Kernel SVM)

PDO-Kernel SVM is an innovative methodology that aims at improving the efficiency of ML through the integration of PDO to achieve smart parameter selection. The algorithm automatically identifies appropriate kernel SVM functions and parameters, thus making it possible for the model to effectively analyze the presence of a nonlinear relationship in the input data.

Kernel SVM for Nonlinear Classification: The Kernel SVM approach is commonly used for analyzing inequalities in the healthcare system by building nonlinear models of interrelations between socio-demographic variables, clinical characteristics, and healthcare accessibility measures. Current healthcare data often reveal disparities resulting from various intertwined factors that are hard to disentangle through linear approaches. The kernel function, especially the Radial Basis Function (RBF), helps convert the input space into a feature space of a higher dimensionality and, therefore, identify any latent patterns of inequality. Kernel SVM creates the most effective separating hyperplane in the feature space that helps distinguish the target populations, such as vulnerable and served individuals.

$$l(\vec{W}_j, \vec{W}_i) = exp\left(-\gamma \left|\left|\vec{W}_j, \vec{W}_i\right|\right|^2\right) \quad (5)$$

In Equation (5), l represents the RBF kernel function, $l(\vec{W}_j, \vec{W}_i)$ (Kernel Similarity Function) describes the degree of similarity between two feature vectors. i represents a specific data sample, j denotes another data sample or feature set. $\vec{W}_j$, $\vec{W}_i$ (Features Vector) multi-dimensional data points are found in EHR and SDOH databases. $\left(\left|\left|\vec{W}_j, \vec{W}_i\right|\right|^2\right)$ describes the distance between two vectors, the health care disparity model. The kernel parameter, γ, is used to control the influence of distance on similarity. Lower values take into account even distant points. The exponential function, $exp\left(-\gamma \left|\left|\vec{W}_j, \vec{W}_i\right|\right|^2\right)$ transforms distance into similarity in the range of 0 and 1.

PDO for hyperparameter tuning and global optimization: The metaheuristic approach is applied to the investigation of inequality in healthcare by means of optimizing machine learning algorithms when analyzing heterogeneous healthcare data sets. The key PDO concepts are inspired by the prairie dog's social life and feeding style, making it extremely efficient in finding an optimal solution while maintaining a proper exploration-exploitation balance. In this algorithm, each prairie dog represents an individual solution – a set of parameters or features regarding sociodemographic, clinical, and health care factors. Inequality, disparities, and vulnerable populations in healthcare systems are considered the main criteria of solution evaluation.

$$PD_{j+1,i+1} = GBest_{j,i} - fCBest_{j,i} \times \rho - CPD_{j,i} \times Levy(m) \quad (6)$$

Equation (6), $PD_{j+1,i+1}$ represents the potential solution produced following optimization in the subsequent iteration and dimension. i represents the specific parameter, j denotes the current iteration step. $GBest_{j,i}$ shows the finest solution found thus far to direct the quest for ideal solutions. $fCBest_{j,i}$ refers to the optimal result obtained with the objective function during the current iteration. ρ is a control option that establishes the search process's step size. $CPD_{j,i}$ represents the current parameters by indicating the prairie dog's current position. $Levy(m)$ creates stages for global investigation in the search space at random.

$$DS = 1.5 \times q \times \left(1 - \frac{s}{S}\right)^{\left(2\frac{s}{S}\right)} \quad (7)$$

In Equation (7), DS is the intensity of the search procedure, which is determined by the strength of the digging. 1.5 (Scaling Constant) is a constant that multiplies the overall intensity of the search. q is a random value that adds variety to the search procedure. s represents the current iteration number that controls how the optimization process is carried out. S indicates the total number of iterations used to gradually reduce the intensity of the search. $1 - \frac{s}{S}$ guides the algorithm toward exploitation by decreasing over iterations. $2\frac{s}{S}$ dynamically modifies the decay of exploration.

$$PE = 1.5 \times \left(1 - \frac{s}{S}\right)^{\left(2\frac{s}{S}\right)} \quad (8)$$

In Equation (8), PE (Predator Escape/Exploitation Factor) manages the move towards exploitation and further improves the solutions and their convergence in subsequent optimization phases. $1.5 \times \left(1 - \frac{s}{S}\right)^{\left(2\frac{s}{S}\right)}$ expression represents an adaptive control factor in PDO that decreases over iterations.

$$PD_{j+1,i+1} = GBest_{j,i} \times PE \times rand \quad (9)$$

Equation (9), $PD_{j+1,i+1}$ is the position of the prairie dog in the next iteration/dimension as a result of the enhancing procedure. $GBest_{j,i}$ the path to obtaining the ideal parameter values is represented by the optimal solution that has been reached thus far. PE helps to improve solutions and is utilized for exploitation. $rand$ is the random factor, a randomly generated number between 0 and 1. The introduced PDO-Kernel SVM combines the advantages of PDO and Kernel SVM to improve classification effectiveness, as represented in Algorithm 1. Fitness value is computed by means of classification error for each solution. As a result of iterative foraging, burrowing, maintenance, and predator avoidance procedures, the best SVM parameters are found.

Algorithm 1: AI-Based Healthcare Inequality Analysis using PDO-Kernel SVM

Input D → Healthcare dataset (EHR, SDOH, demographic data), MaxIter → Maximum PDO iterations, N → Population size, γ → RBF kernel parameter
Output:O → Optimized healthcare inequality prediction model
Begin

1. Load dataset D
2. Data Preprocessing using SMOTE:
3. Handle missing values and noise, normalize features
4. Balance minority classes using SMOTE
5. Feature Optimization:
6. Initialize feature weights $o_{ji} = w_j + rand(0,1) \times (w_{ji} - w_j)$
7. Feature Extraction using ICA:
8. Compute transformation$w = G^T \;\; v = Xw = XG^T$
9. Select significant components
10. Create training and testing sets from the dataset.
11. Kernel Similarity using RBF-SVM: $K(x_i, x_j) = exp(-\gamma \parallel x_i - x_j \parallel^2)$
12. Initialize PDO population within bounds
13. Evaluate classification accuracy and fairness
14. PDO Optimization:
15. For t = 1 to MaxIter:
    a. Exploration: $PD_{new} = GBest - f \cdot CBest \cdot \rho - CPD \cdot Levy(m)$
    b. Exploitation factor: $PE = 1.5 \times (1 - s/S)^{(2s/S)}$
16. Train the PDO-Kernel SVM model
17. Evaluate performance on test data
18. Output optimized model O

End

3.5 XAI using SHAP

To enhance model transparency and interpretability, SHapley Additive exPlanations (SHAP) is employed to explain the predictions generated by the proposed PDO-Kernel SVM model. SHAP quantifies the contribution of each feature, such as demographic factors, healthcare access, and social determinants, toward the final prediction outcome. This enables the identification of the most influential variables responsible for healthcare disparities and supports fairness-aware decision analysis. By providing both global and local interpretability, SHAP improves the reliability, accountability, and trustworthiness of the AI-based decision support system.

4. Result and Discussion

The proposed method of PDO-Kernel SVM, incorporated within an AI-driven DSS, has been researched and observed to be more accurate, unbiased, and equitable when used to measure health care inequality using different types of data, such as EHRs and SDOHs. The algorithm is coded in Python and executed in a cloud-based simulation environment.

Outcome of SHAP analysis: Understanding the significance of factors in forecasting health care inequity in Figure 3 illustrates how each feature influences the model's result. Predictions heavily rely on variables such as the likelihood of a risk, hospitalization history, and clinical considerations.

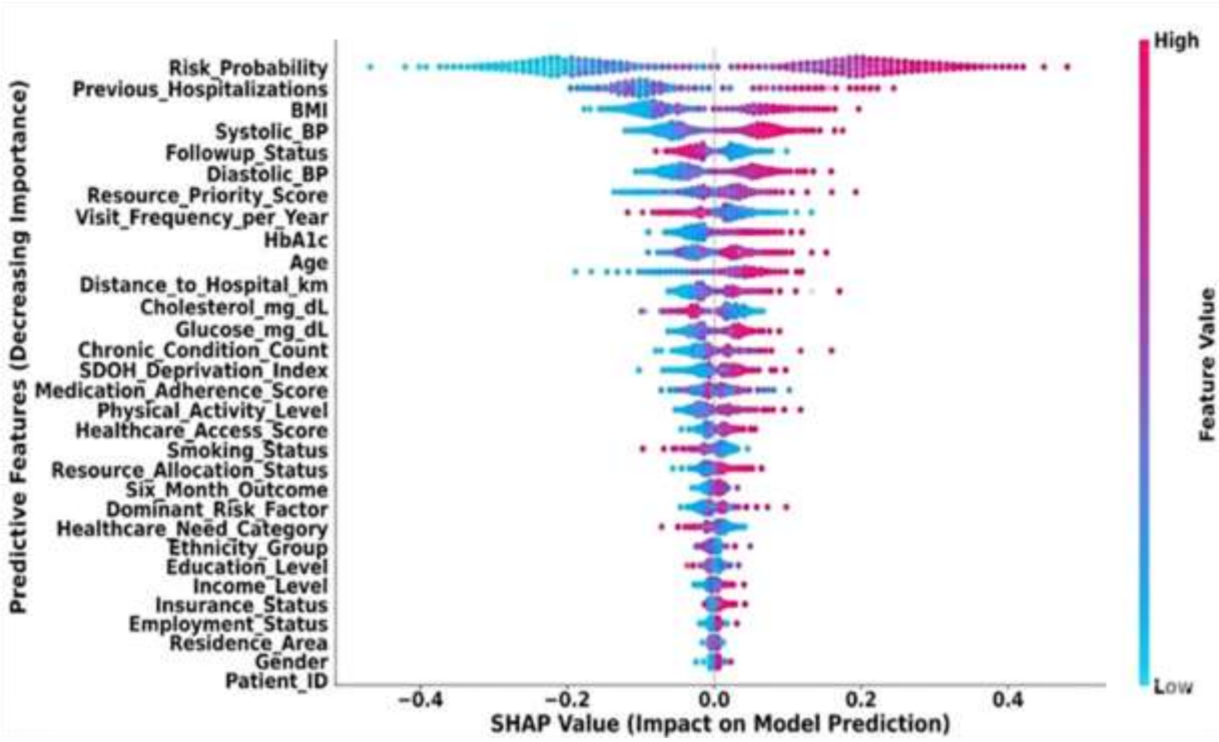


Figure 3: SHAP-Based Feature Importance Analysis for Healthcare Inequality Prediction

Differentiating analysis: Performance metrics are used to assess how well the AI decision-making technology detects and predicts health disparities. They can be used to evaluate categorization errors, accuracy, and disparity identification skills. **Accuracy**: It's an indicator that reflects the general accuracy of the AI-based DSS in detecting patterns of healthcare inequality in population datasets. **Precision:** Represents the accuracy with which the AI-based system detects real healthcare inequality instances from the predicted positive disparity classification. **Recall:** shows the capability of the AI-based system to detect all real healthcare inequality instances in population datasets. **F1-score:** offers a fair assessment of recall and precision to assess how well AI-based systems perform in healthcare detection. **Mean Squared Error (MSE):** The average squared difference between expected and actual healthcare inequality numbers is known as the, which indicates the degree of prediction error. **Mean Absolute Error (MAE):** The average absolute difference between expected and actual healthcare inequality numbers.

Performance evaluation using the Healthcare Inequality Analytics dataset: The proposed PDO-Kernel SVM model and existing models trained on the Healthcare Inequality dataset, comprising demographic, clinical, and social determinants of health features, are utilized to train and evaluate multiple ML models under a unified experimental framework. Specifically, the PDO-Kernel SVM model achieves superior performance compared to (Random Forest (RF), Rule-Based, Regression Analysis, Support Vector Machine (SVM), Logistic Regression, Decision Tree) [16] across all evaluation metrics. It attains the highest accuracy 94.9%, F1-score 96.7%, the lowest MSE of 0.007, and MAE of 0.079, indicating robust predictive capability for healthcare inequality analysis, as shown in Table 2 and Figure 4. Experimental results analysis confirms.

Table 2: Comparative Performance of existing and proposed model in Healthcare Inequality data

Models	Accuracy	Precision	Recall	F1-score	MSE	MAE
Random Forest (RF)	93.6%	92.4%	94.1%	93.2%	0.013	0.089
Traditional Rule-Based	79.8%	77.5%	80.6%	79.0%	0.054	0.186
Regression Analysis	86.9%	84.7%	87.3%	86.0%	0.027	0.124
Support Vector Machine (SVM)	89.4%	87.8%	90.1%	88.9%	0.020	0.103

Logistic Regression	82.7%	80.6%	83.5%	82.0%	0.039	0.149
Decision Tree	84.8%	82.9%	85.4%	84.1%	0.033	0.136
PDO-Kernel SVM [Proposed]	94.9%	93.4%	96.1%	96.7%	0.007	0.079

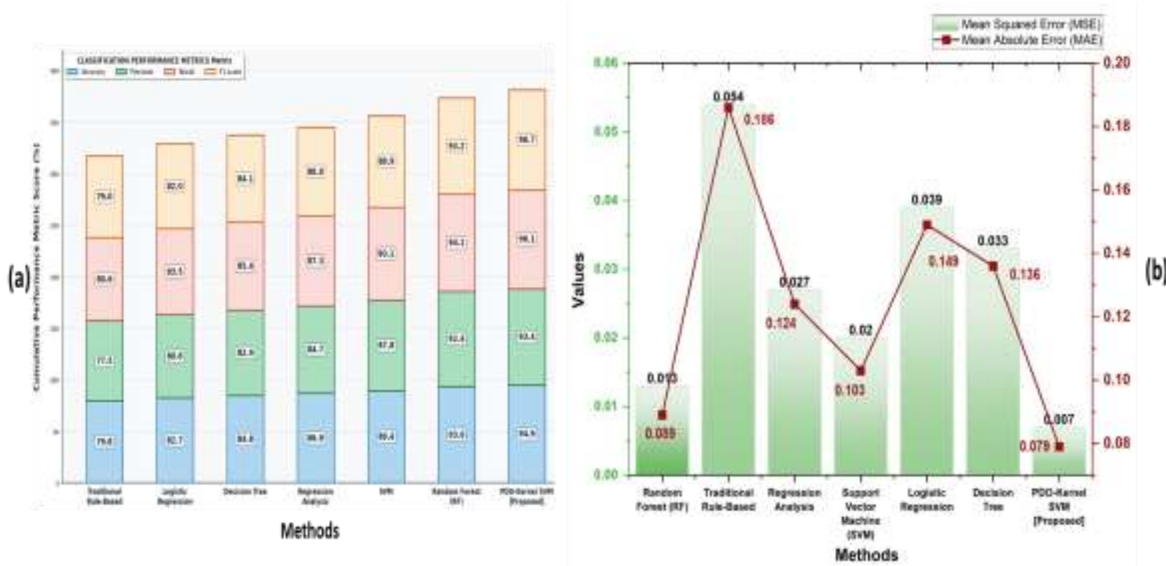


Figure 4: Cumulative Classification Performance and Error Metrics Comparison (a) Cumulative Classification Performance Metrics (b) Error Metrics Comparison Across Classification Methods

However, there are some disadvantages associated with the current methods [16]. These include poor prediction accuracy, challenges in dealing with complex health care data, and high errors. The Traditional Rule-Based and Regression techniques can hardly detect nonlinear relationships among demographic and clinical attributes. The Decision Tree and SVM models might face the problem of overfitting and parameters. To address these limitations, PDO-Kernel SVM model has been developed through combining PDO optimization with Kernel SVM. Therefore, PDO-Kernel SVM can offer more accurate and precise results than the current methods with improved F1-score and reduced MSE and MAE.

5. Conclusion

The proposed PDO-Kernel SVM-based DSS is a very effective and efficient system for the analysis of healthcare disparities using heterogeneous healthcare datasets. Data preprocessing SMOTE and feature exaction enhance data quality and improve the learning capability and performance of ML models. The utilization of the hybrid PDO-Kernel SVM helps in learning the complicated patterns from the healthcare data. Based on the experimental results, it is clear that the proposed DSS is superior to all other baselines and achieves an accuracy rate of 94.9%, a precision rate of 93.4%, a recall rate of 96.1%, an F1-score of 96.7%, an MSE of 0.007, and an MAE of 0.079. However, there are some constraints of the suggested model, such as reliance on high-quality labeled data, susceptibility to noise or incompleteness in the dataset, and somewhat high computational costs. The model could also encounter difficulties when implementing it in real-time due to constrained environments. Possible directions of future research include building lightweight hybrid models, employing federated learning for privacy, and using edge/IoT computing for scalability and efficiency.

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