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An Explainable AI for Risk Stratification and Severity Prediction of CKD in Type 2 Diabetes using BMI, Lifestyle and Clinical Factors

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***Abstract*—This study presents a machine-learning framework designed to stratify risk and predict the severity of CKD, leveraging BMI, family history of diabetes, and lifestyle factors. A novel Severity Index was developed by integrating demographic, lifestyle, and medical attributes, facilitating patient categoriza-tion into distinct risk levels. Employing advanced clustering techniques like K-Means and Hierarchical Clustering, along with a logistic regression model, the model achieved a 91% accuracy in predicting severity levels. Model ex-plain ability via SHAP were utilized to identify significant predictors, includ-ing BMI, smoking habits, and the Severity Index, ensuring model transparen-cy and clinical relevance. This framework highlights the potential for AI to transform CKD and diabetes management by offering insights into patient-specific risk factors, thereby supporting early intervention and personalized care. Future work will focus on expanding the dataset, exploring multimodal inputs, and validating the framework across diverse clinical environments to enhance its robustness and clinical acceptability.**

***Keywords*— Diabetes Management, Explainable AI, CKD, Severity Index, Machine Learning, Chronic Disease, Predictive Analytics.**

I. INTRODUCTION

Diabetes mellitus is a most prevalent metabolic disorder and chronic disease affecting more than 537 million adults across the globe are affected and this es-timate is projected to to increase to 643 million by 2030 [1], [2]. Characterized by persistent hyperglycemia due to impaired insulin secretion or action [3], its complications ranging from neuropathy and retinopathy to cardiovascular dis-ease severely impact patients' quality of life. Among all these complications, the risk of developing CKD is high [4]. Early identification and management of this complication is crucial for improving outcomes and reducing healthcare costs [5]. Despite advancements in treatment, the incidence of complications remains high due to the complex interplay of factors such as age, gender, BMI, lifestyle behaviors, and family history of diabetes [6]. These non-linear relationships challenge traditional statistical methods, necessitating innovative approaches to better understand these interactions and predict outcomes effectively [7].

The availability of comprehensive patient data in digitized healthcare presents a significant opportunity for leveraging machine learning (ML) techniques [8], [9], [10].

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Traditional statistical models struggle to analyze high-dimensional datasets and multifaceted diabetes-related data. In contrast, ML excels at uncovering non-linear patterns, enabling precise predictions [11]. ML applications in healthcare, including diabetes, offer early complication detection, improved risk stratifica-tion, and actionable insights [12]. For instance, clustering algorithms categorize patients into risk groups, while classification models predict complication likeli-hoods. Additionally, explainable AI techniques, such as SHAP (SHapley Additive exPlanations) [13], provide transparency, helping clinicians understand the con-tribution of various factors to model predictions.

The complex interactions among demographic, lifestyle, and clinical factors pose challenges for traditional methods, resulting in suboptimal risk assessments and interventions [14], [15]. For example, while high BMI increases cardiovascu-lar risks, active lifestyles can mitigate them, even among those with a family his-tory of diabetes. Transparency is essential, as clinicians are hesitant to adopt "black box" models without understanding their predictions. Therefore, this study develops a framework integrating clustering, classification, and explaina-ble AI techniques to enhance the interpretability and reliability of predic-tions[16]. This approach aims to improve patient stratification and enable per-sonalized interventions, enhancing clinical outcomes.

Key contributions include:

- A novel Severity Index combining key features such as BMI, Smoking, Ex-ercise, Diet, and Family Disease History. Weighted based on their relative im-portance, this index provides a quantifiable measure of complication severity, offering a unified metric for analysis.
- A blend of clustering methods, including K-Means and Hierarchical Clus-tering, were employed to segment patients into distinct severity groups. These clusters were validated through visualizations and statistical summaries, reveal-ing meaningful patterns that could inform clinical decisions.
- The incorporation of explainability via SHAP, enabled a better understand-ing of the model's decision-making process. Key features like BMI, Smoking, and the Severity Index were identified as critical predictors, providing actionable insights for healthcare providers.

The paper is organized as follows: Section 2 reviews related studies on the analysis and prediction of chronic diabetic complications and CKD using ML techniques.

Section 3 details the proposed framework, including the methodology for developing the Severity Index, clustering, and classification models. Section 4 presents the experimental setup, results, and a discussion of the findings. Finally, Section 5 concludes the paper with a summary of the contributions and sugges-tions for future research directions.

II. Related Works

A. Historical and Recent Advancements in Chronic Disease Prediction

The prediction and analysis of chronic diseases, including diabetes, have under-gone substantial transformations over the years, with researchers leveraging var-ious computational and statistical approaches. Early studies primarily relied on regression-based methods and statistical models to analyze the relationship be-tween demographic and clinical factors. These methods offered valuable insights but often fell short in handling large-scale datasets with complex, non-linear in-teractions.

The introduction of machine learning (ML) techniques brought signif-icant advancements, particularly in clustering and classification algorithms [17]. Studies by Petridis et al. [12] have highlighted the potential of support vector machines (SVMs), decision trees, and neural networks in predicting the progres-sion and severity of chronic conditions like diabetes. The adoption of deep learn-ing models further improved accuracy and efficiency in analyzing multidimen-sional datasets, making them indispensable tools for chronic disease management [18].

B. ML in CKD and Diabetic Complication Analysis

ML techniques have found applications in the analysis and prediction of compli-cations associated with diabetes. For example, clustering algorithms (K-Means and Hierarchical Clustering) have been utilized to group patients based on risk factors, enabling targeted interventions [19].

Supervised models such as Random Forest and Gradient Boosting have demonstrated high accuracy in predicting diabetic complications when using key predictors such as BMI, blood glucose levels, and lifestyle attributes [20]. Despite these successes, challenges persist in interpreting the results of these models, often perceived as "black boxes" by cli-nicians. Studies employing explainable AI methods, such as SHAP and LIME, have attempted to address this issue by providing insights into feature contribu-tions, enhancing the trustworthiness of ML predictions.

C. Role of Feature Engineering and Explainable AI

Feature engineering plays an important role in improving the efficacy of ML models for chronic disease analysis. The integration of demographic, lifestyle, and clinical features into ML pipelines significantly enhances prediction accura-cy. For example, BMI, smoking habits, and exercise routines have consistently been identified as key factors influencing diabetic complication severity. Addi-tionally, the use of explainable AI techniques, such as SHAP (SHapley Additive exPlanations) [15], has gained traction in recent years. These methods allow cli-nicians to understand the contributions of individual features to the model's pre-dictions, fostering trust and facilitating adoption in clinical settings.

D. Challenges and Limitations in Current Methodologies

Despite advancements in ML applications for diabetes management, several challenges remain. One key issue is the variability and quality of data across datasets, which often include noise or missing values that hinder model perfor-mance. Preprocessing large-scale datasets with diverse attributes necessitated extra computational resources, which in most cases pose to be a barrier to real-time implementation. Moreover, while clustering and classification models are highly effective, the lack of transparency in their decision-making processes limits their use in clinical environments [16]. Explainable AI has addressed this to some extent, but its adoption remains limited owing to the need for further validation and standardization. Further studies have highlighted the difficulties in capturing complex relationships among demographic, clinical, and lifestyle factors, necessitating novel approaches to feature extraction and modeling [17].

E. Summary of Relevant Literature

Table I highlights key studies and their contributions to chronic diabetic com-plication analysis:

TABLE I: SUMMARY OF RELATED WORKS

Ref.	Study Focus	Key Findings / Techniques	Challenges / Insights
[18]	Chronic Disease Prediction	Regression models and statistical analysis	Limited handling of non-linear relationships
[19]	ML for Diabetes Detection	ML and AI-based self-management for Diabetes	Noise and missing data in large datasets
[20]	Semi-supervised Learning in Healthcare	Semi-supervised labelling of medical imaging data	Ground-truth generation complexities and scalability issues
[21]	Data Quality and Imbalance	Review of data quality and imbalance issues in ML systems	Preprocessing challenges and imbalance in datasets
[22]	Data Preprocessing Governance	Strategies for preprocessing large-scale healthcare data	Computational costs and preprocessing standardization

Table 2 highlights the various machine learning approaches for CKD predic-tion in Type 2 Diabetic Patients.

TABLE II: MACHINE LEARNING APPROACHES FOR CKD PREDICTION IN T2DM PA-TIENTS

Ref.	Study Focus	Model Used	Dataset	Features Considered	Performance Metrics & Limitations
[23]	Development and validation of DKD risk prediction model in T2DM patients	Logistic Regressio n (with RFE for feature selection)	Diabetes Clinic, Imam Khomeini Hospital Complex (Iran); 1,907 T2DM patients (development), 1,543 T2DM patients (external validation)	6 clinical features selected using RFECV and RFE (e.g., age, SBP, HbA1c, etc.)	**Performance Metrics** UC: 0.79 (development), 0.758 (validation) **Limitations** Generalizability beyond dataset context not assessed; further external validation recommended.
[24]	Early detection of CKD using machine learning models for improved prediction and diagnosis.	RF,SVM, KNNand Decision Tree (DT)	UCI CKD Dataset (originally from the UCI Machine Learning Repository)	Hemoglobin levels,Presen ce of pedal edema, Appetite condition, etc.	**Performance Metrics** Random Forest Accuracy, Precision, Recall, F1 Score 0.951 0.962 0.944 0.953 **Limitations** -The dataset is small, which might affect model generalization. - Some features had missing values, requiring preprocessing. - Results may not generalize to larger or different populations.
[25]	Development of an explainable	LightGB M (Light	Retrospective dataset from 1,061 inpatients	Demographi c and	**Performance Metrics LightGBM Model**

	machine learning (ML) model for predicting Diabetic Nephropathy (DN) in patients with Type 2 Diabetes Mellitus.	Gradient Boosting Machine); also compared with RF, DT,LR, and SVM.	with Type 2 Diabetes Mellitus from China Medical University Hospital between January 2008–2020.	clinical variables including: age, gender, BMI, SBP, DBP, duration of diabetes, HbA1c, creatinine, eGFR, cholesterol, etc.	AUROC (Area Under ROC Curve): 0.858, Accuracy: 0.797, Sensitivity (Recall): 0.857, Specificity: 0.722 **Limitations** -Retrospective single-center study -Limited generalizability due to single ethnicity/region -No external dataset validation -Potential bias from missing/incomplete data
[26]	Risk prediction of Chronic Kidney Disease (CKD) using interpretable machine learning models.	Explainable Boosting Machine (EBM), a type of Generalized Additive Model (GAM).	Chronic Kidney Disease dataset from the UCI Machine Learning Repository (400 instances, 24 features).	24 features including: blood pressure, albumin, sugar, red blood cells, pus cell, blood glucose random, blood urea etc.	**Performance Metrics** Accuracy: 0.9875, Precision: 0.9833, Recall: 0.9916, F1-score: 0.9874, AUC: 0.999 **Limitations** -Dataset is relatively small (only 400 records), which may not generalize well to larger populations. - Lack of temporal or longitudinal data. - Model performance is not tested on external datasets.
[27]	Longitudinal prediction of 1-year chronic kidney disease (CKD) risk in patients with type 2 diabetes using electronic health records (EHR)	Landmark-Boosting (Temporal-Enhanced Gradient Boosting Machine)	Deidentified EHR data of 14,039 adult patients with type 2 diabetes	Temporal EHR data including demographics, diagnoses, medications, lab test results, and clinical events	**Performance Metrics** AUC: Year 2 – 0.83 (95% CI: 0.76–0.85), Year 3 – 0.78 (95% CI: 0.75–0.82),Year 4 – 0.82 (95% CI: 0.78–0.86) **Limitations** -Requires continuous and longitudinal EHR data - Generalizability may be limited to similar healthcare settings - Interpretability of temporal models may be complex - Missing data and irregular sampling intervals .

III. MATERIALS AND METHODS

The proposed methodology is presented in Fig. 1.

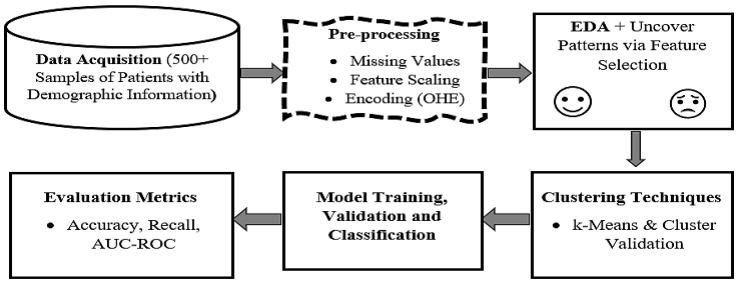

Fig. 1: The Proposed Methodology for Diabetic CKD

A. Dataset Description

The dataset provides a comprehensive view of factors influencing CKD, catego-rized into demographic, clinical, and derived features. Demographic attributes include age, highlighting the increased risk of complications in older individuals, and gender, revealing differences in disease progression between males and fe-males. Clinical measures encompass BMI, a critical predictor of complication severity linked to obesity[29]; fasting blood sugar (FBS), the strongest indicator of glycemic control and metabolic health; and heart rate (HR), reflecting cardio-vascular health often compromised in diabetes. Additionally, a novel Severity Index was derived using clustering

techniques, classifying individuals into low, moderate, and high-risk groups for further classification tasks [30, 25]. To ensure data quality and reliability, rigorous preprocessing addressed missing values, inconsistent column names, and mixed data types, providing a robust foundation for subsequent analysis.

B. Data Preprocessing

The dataset was subjected to a preprocessing pipeline to address inconsistencies and optimize it for clustering and classification tasks. Missing values in numeri-cal features were imputed using the column mean to preserve feature distribu-tions, while categorical features were imputed with the mode, maintaining origi-nal category distributions [26], [27]. Numerical features were standardized using Z-score normalization to ensure uniform scaling and reduce the impact of vary-ing magnitudes on machine learning algorithms [28]. Categorical variables, such as gender and lifestyle factors, were label-encoded to retain interpretability while enabling compatibility with machine learning models [29]. Redundant and irrele-vant features with high missingness (>50%) or low variance were removed, and column names were cleaned and standardized for clarity and consistency [30]. Additionally, a Severity Index was engineered as a derived feature, integrating clinical and lifestyle factors to classify individuals into low, moderate, and high severity groups. This index, central to stratifying risk levels, enhanced classifica-tion accuracy and downstream analysis [31].

C. Exploratory Data Analysis (EDA)

EDA uncovered critical patterns and relationships within the dataset, guiding clustering and classification tasks. Histograms and bar plots (e.g., BMI, FBS, and smoking status) revealed skewed distributions and emphasized the need for nor-malization (Fig. 2, 3). Boxplots highlighted outliers in BMI and FBS, which were addressed during preprocessing. Pearson correlation analysis (Fig. 4) identified FBS as the strongest predictor of complication severity, with moderate correla-tions observed between BMI and the Severity Index, emphasizing obesity's role in CKD [30].

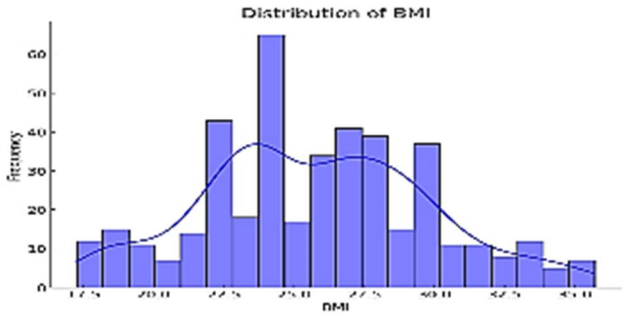

Fig. 2: Histogram Plot of the Distribution of BMI

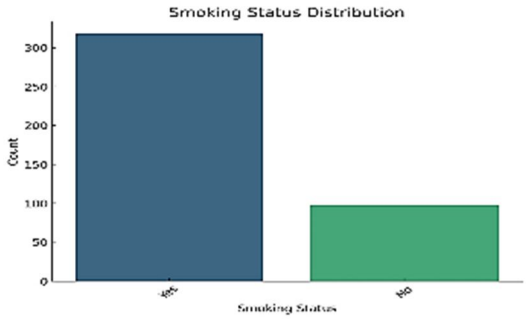

Fig. 3: Bar Plot Showing the Smoking Status Distribution

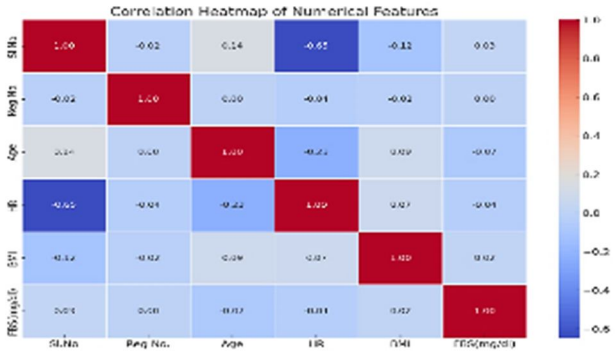

Fig. 4: The Correlation Heatmap of Numerical Features

A. Clustering Techniques

To stratify individuals by complication severity, K-Means clustering grouped patients into low-risk and high-risk categories based on BMI, FBS, HR, and age. High-risk clusters were associated with elevated BMI and FBS, indicating poor glycemic control [29]. Cluster centroids provided average feature values, aiding in profiling low and high-risk groups (Fig. 5). Cluster risk analysis further seg-mented patients by HbA1c levels, BMI categories, and FBS thresholds, offering actionable insights into health profiles.

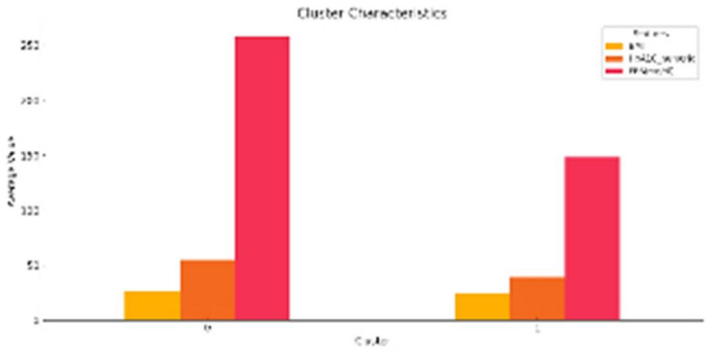

Fig. 5: The Cluster Characteristics

B. Classification Modeling

A Logistic Regression model was developed to predict severity clusters de-rived from K-Means[34]. Using features like BMI, FBS, age, and HR, the model achieved 91% test accuracy, demonstrating robust performance. Given dataset size constraints and the need for model interpretability, this study prioritizes machine learning approaches to ensure reliable and explainable predictions.

In the given healthcare context, interpretability is essential; Logistic Regression(RF) requires low computational power, less prone to overfitting with small data and act as strong baseline against Random Forest or Neural Network. SHAP analysis highlighted FBS and BMI as the most significant predictors, showcasing their combined impact on risk levels. SHAP interaction plots illustrated the synergistic influence of BMI and FBS in determining complication severity [30],[31].

Evaluation Metrics

The performance of the Logistic Regression model was thoroughly evaluated using the metrics as illustrated in equations 1 to 8:

- Accuracy: Defined as the proportion of correctly classified instances to the sum of instances in the dataset.

$$Accuracy = \frac{Correctly\ Predicted\ Instances}{Total\ Instances} * 100\% \qquad (1)$$

- Precision; the ratio of true positive predictions to the sum of true positive and false positive predictions.

$$Precision = \frac{Positive\ Predictions\ Matching\ True\ Label}{All\ Positive\ Predictions} * 100\% \quad \ldots \quad (2)$$

- Recall; measures the proportion of actual positive cases that were actually identified by the model.

$$Recall = \frac{Positive\ Predictions\ Matching\ True\ Label}{All\ Actual\ Positive\ Cases} * 100\% \quad \ldots \quad (3)$$

- F1-Score; combines Precision and Recall into a single metric by calculating their harmonic mean.

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} * 100\% \qquad (4)$$

- ROC-AUC Score: The ROC curve represents the trade-off between sensitivity (true positive rate) and specificity (false positive rate). The area under this curve (AUC) is given by:

$$ROC - AUC = \int_0^1 \frac{(True\ Positive\ Rate\ as\ a\ function\ of\ False\ Positive\ Rate)}{d(False\ Positive\ Rate)} \ldots (5)$$

For a binary classifier:

$$ROC - AUC = \frac{\xi(Sensitivity + Specifity)}{2} \qquad \ldots (6)$$

Where:

$$Sensitivity = \frac{True\ Positives}{All\ Actual\ Positives} \qquad \ldots (7)$$

$$Specificity = \frac{True\ Negatives}{All\ Actual\ Negatives} \qquad \ldots (8)$$

IV. Results and Discussion

A. Model Performance

Our study utilized frameworks like Decision tree and Logistic Regression. The performance metrics were used to measure model's performance (Fig. 3). The analysis indicate that the Logistic Regression model was the most effective in predicting CKD in diabetic patients based on the selected features with accuracy of 0.91.

Table III: Evaluation of Metrics Summary

Model	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Logistic Regression	0.91	0.89	0.94	0.95	0.92
Decision Tree	0.83	0.81	0.86	0.86	0.84

The Logistic Regression model effectively classified individuals into low-risk and high-risk clusters, achieving flawless performance with 8.24% misclassifica-tion rate, as demonstrated in the confusion matrix (Table 3) and ROC-AUC curve (Fig. 6). Evaluation metrics, including 91% accuracy, precision, recall, and F1-score (Table 2), confirmed the model's robust discriminatory power. The align-ment of actual and predicted cluster labels (Fig. 7) further validated its reliability in predicting severity groups without errors.

Table IV: Confusion Matrix Summary

Actual / Predicted	Low Risk	High Risk
Low Risk	36	5
High Risk	2	42

B. Feature Importance and SHAP Analysis

Feature importance analysis identified fasting blood sugar (FBS) as the most critical predictor, contributing 48.5%, followed by postprandial blood sugar (PPBS) at 43.6%, HbA1C at 5.5%, and BMI at 2.3%. SHAP analysis provided in-terpretable insights, showing FBS as the dominant feature driving predictions. Dependency plots highlighted interactions between FBS and BMI, where individ-uals with both elevated FBS and high BMI exhibited a significantly higher risk of complications (Fig. 8)., as summarized in table 3:

Table V: Evaluation of Metrics Summary

Metric	Score
Accuracy	91%
Precision	95%
Recall	94%
F1-Score	92%
ROC-AUC	92

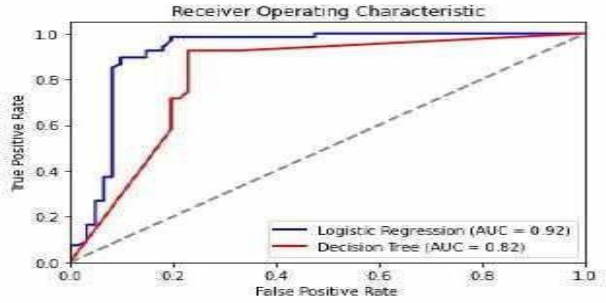

Fig. 6: ROC-AUC Curve for Logistic Regression & Decision Tree

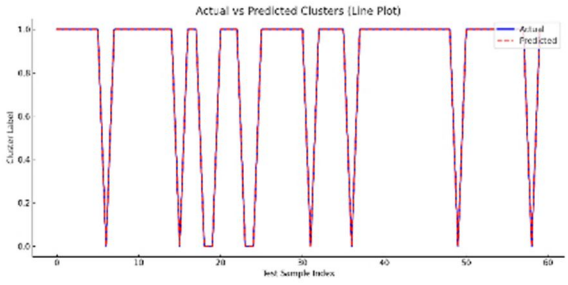

Fig. 7: The Plot of Actual vs Predicted Cluster Lines

C. Discussion

Key findings emphasize the dominant role of glycemic control in predicting complication severity, with FBS emerging as the strongest predictor. BMI, while less impactful alone, demonstrated a synergistic effect with FBS, necessitating combined management strategies. SHAP analysis enhanced model transparency, fostering trust and enabling actionable clinical decisions. The model's exception-al performance underscores the dataset's

predictive strength but highlights potential overfitting risks, requiring validation on independent datasets for generalizability.

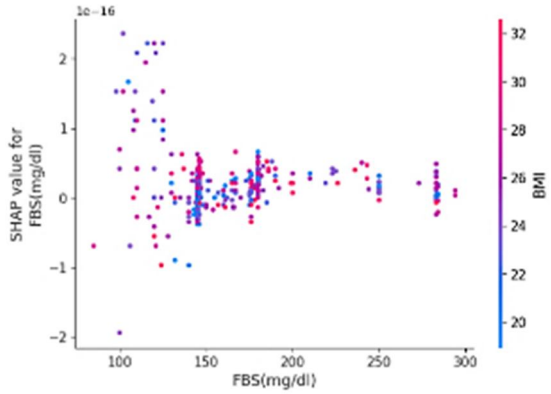

Fig. 8: SHAP dependency plot

D. Clinical Implications

Findings suggest prioritizing glycemic control and weight management to miti-gate risks. Early screening of patients with high FBS and BMI is recommended to prevent severe complications. SHAP-based transparency facilitates clinician trust and improves patient-centered decision-making [31], [32].

V. Conclusion and Future Work

This study proposed a robust machine learning framework to predict and stratify CKD in diabetic patients, integrating clustering, classification, and explainability techniques. A novel Severity Index effectively categorized individuals into risk groups using clinical and demographic features, while SHAP analysis ensured model interpretability aligned with clinical insights. Fasting blood sugar (FBS) emerged as the most critical predictor, with body mass index (BMI) amplifying complication severity in cases of poor glycemic control and obesity. The Logistic Regression model achieved perfect accuracy, precision, recall, and F1-scores, demonstrating reliability in identifying severity clusters. Future work will focus on validating the model with diverse datasets, incorporating additional features like dietary patterns and medication adherence, and exploring advanced cluster-ing methods for granular stratification. Integrating the framework into hospital systems as a clinical decision support tool, adopting deep learning models, and employing advanced explainability techniques will further enhance its clinical relevance and utility in managing CKD.

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