Enhancing Diabetes Diagnosis and Complications Prediction with Automated Machine Learning in a Clinical Decision Support System

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***Abstract*— Diabetes mellitus (DM) is a metabolic disorder marked by elevated blood sugar levels, posing serious health risks if unmanaged. Advancements in artificial intelligence (AI) have revolutionized healthcare, particularly in clinical decision support systems (CDSS). This study utilized AutoGluon, an automated machine learning technique, to develop a CDSS aimed at improving DM diagnosis and predicting complications such as Coronary Heart Disease and Neuropathy. The system, implemented at Taipei Medical University Hospital, features a user-friendly Graphical User Interface (GUI). Machine learning models were trained on a dataset combining Iraqi and Chinese populations, incorporating 13 critical features, including HbA1c, age, urea, and triglyceride. Five classification models—AutoGluon, Random Forest, LightGBM, CatBoost, and XGBoost—were evaluated using metrics such as AUROC, accuracy, F1-score, recall, and precision. AutoGluon outperformed other models, achieving F1-scores of 0.9648, 0.8642, and 0.8619; recall values of 0.9552, 0.7609, and 0.8547; precision scores of 0.9745, 0.9844, and 0.7692; accuracy rates of 0.9604, 0.9609, and 0.9110; and AUROC values of 0.9853, 0.9814, and 0.9838 across the outputs. SHAP analysis identified HbA1c as the most significant predictor, confirming its critical role in DM diagnosis and complication prediction. These findings support AutoGluon as the optimal CDSS model, offering improved accuracy and utility in clinical practice.**

***Keywords*— Diabetes Mellitus, Clinical Decision Support System, Automated Machine Learning, AutoGluon.**

I. INTRODUCTION

Diabetes mellitus, commonly known as diabetes, is a chronic condition characterized by elevated blood sugar levels [1]. This occurs when the body either fails to produce sufficient insulin, cannot produce insulin at all, or is unable to use the insulin it produces effectively.

When diabetes progresses unfavorably, whether due to negligence or simply as part of its natural course, various complications tend to unfold [2]. Complications of diabetes can be classified into “acute” and “chronic”. Acute complications of diabetes, such as hyperglycemia, hypoglycemia, and ketoacidosis, are direct outcomes of the disruption of the body’s metabolism. Chronic diabetes complications result from elevated blood glucose levels, which deal accumulated damage over long periods of time. This, in turn, leads to microvascular and macrovascular complications, foot ailments, and other diseases including nephropathy, retinopathy, and neuropathy. Given the above, it is readily apparent that diabetes mellitus is not a disorder to be treated lightly. Since there is currently no known cure for diabetes, it is best to take preventive measures to detect and prevent the onset of the disease, eliminating even the slightest chance of its progression.

The global prevalence of diabetes among individuals aged 20–79 in 2021 was estimated at 10.5% (536.6 million people), and this is projected to rise to 12.2% (783.2 million) by 2045 [3]. According to the latest Diabetes Atlas of Taiwan, the prevalence rate has reached a new high of 10.6%, surpassing neighboring countries such as Japan, South Korea, and Hong Kong. The total number of patients is expected to exceed 3 million, with the disease becoming more common among younger populations. The prevalence among the labor force under 40 has increased from 0.77% to 0.98%. Experts warn that diabetes is being diagnosed earlier, and its complications are appearing sooner, which could significantly impact Taiwan’s workforce. The healthcare burden related to diabetes has been rising year by year, posing a substantial challenge to Taiwan's competitiveness.

Artificial intelligence (AI) is increasingly used in diabetes management, improving patient care and medical workflows. For instance, AI models can predict diabetes risk [4], allowing early intervention to delay or prevent disease progression. AI is also applied to blood sugar prediction [5], using deep learning to forecast next-day levels based on diet, exercise, and sleep patterns, helping patients maintain stable glucose levels through lifestyle and medication adjustments.

In recent years, some approaches for diabetes and its complications prediction have been proposed and documented. The first article [6] contributes to developing ML models specifically tailored to predict the risk of transitioning from prediabetes to type 2 diabetes. It analyzed data from 13,943 individuals with prediabetes and integrated various predictors, such as age, body mass index (BMI), blood glucose, and HbA1c, to create a simplified prediction model suitable for clinical practice. The model achieved an AUROC of 0.753, demonstrating good predictive performance and highlighting its potential for early identification and intervention in clinical settings. The second article [7] employed the XGBoost algorithm to construct predictive models for different diabetes complications, including nephropathy, retinopathy, cardiovascular disease, and others. The study utilized big data from electronic medical records to make stratified predictions in the short term (within 2 years) and medium-term (3 to 5 years). The predictive accuracy and AUROC values for all complications exceeded 0.80, with nephropathy achieving an AUC of 0.97, demonstrating the powerful capabilities of XGBoost in analyzing complex, multidimensional data.

In this paper, we present an automated learning approach using AutoGluon [8] to train models efficiently and accurately. We propose an AI-based Clinical Decision Support System (CDSS) with a user-friendly graphical user interface (GUI) designed to assist doctors in classifying diabetes conditions and predicting diabetic complications, thereby reducing the likelihood of misdiagnosis. The main contributions of this paper include:

- Utilizing AutoGluon to train a multi-output classification model. The model produces three outputs: CLASS (multiclass: Diabetes, Pre-diabetes, and Non-diabetes), Coronary Heart Disease (CHD) (binary: Yes or No), and Neuropathy (NEUR) (binary: Yes or No). Coronary Heart Disease and Neuropathy were chosen as outputs because they are common complications associated with diabetes and have a high prevalence in Taiwan [9].
- Conducting a comparative analysis of AutoGluon against other popular machine learning models [10] to identify the best-performing model for integration into the GUI.
- Designing a user-friendly GUI to enhance accessibility and usability.

II. DATA AND METHODOLOGY

The proposed methodology consists of four stages. The first stage focuses on exploratory data analysis (EDA) to understand and summarize the dataset. In the second stage, data preprocessing is performed, where raw data is cleaned and transformed into a format suitable for analysis. The third stage involves experimentation to identify the best-performing model. Finally, in the fourth stage, the selected model is integrated into a graphical user interface (GUI). Fig. 1 illustrates the block diagram summarizing the entire process.

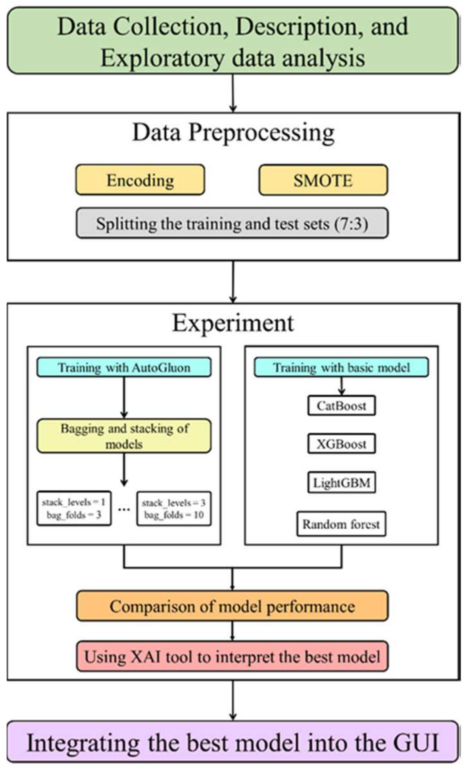


Figure 1. Block diagram for the proposed methodology.

A. *Data Collection, , Description, and Exploratory data analysis*

The data were collected from societies in Iraq and China, specifically from the Specialized Center for Endocrinology and Diabetes at Al-Kindy Teaching Hospital [11], as well as Shanghai East Hospital and Shanghai Fourth People’s Hospital [12]. In this research, we combined these data and ensured that no identifiable private information was included. The combined dataset consists of 13 features, comprising 281 observations after duplicate entries were removed and missing values were addressed using mean imputation, as shown in TABLE I. HbA1c is measured as a percentage (%), while age is measured in years. Gender and alcohol-drinker are categorical variables. Cr is measured in µmol/L, and BMI is measured in kg/m². All other features, except age, gender, alcohol-drinker, Cr, BMI, and HbA1c, are measured in mmol/L. The dataset is imbalanced: out of the 281 labels, 125 are diabetic, 103 are non-diabetic, and 53 are pre-diabetic. Coronary heart disease is observed in 32 diabetic cases, and neuropathy occurs in 31 diabetic cases.

TABLE I. THE FEATURES IN THE DATASET AND THEIR DESCRIPTION

Feature	Description	Statistics	
		Mean ± Std	***Variance***
Age	Measured in years	51.10 ± 13.80	190.00
Urea	Urea measured in mmol/L	5.20 ± 2.18	4.75
Cr	Creatinine ratio in µmol/L	64.00 ± 28.40	805.00
HbA1c	Glycated Hemoglobin (%)	6.80 ± 2.68	7.19
Chol	Cholesterol in mmol/L	4.37 ± 0.90	0.81
TG	Triglyceride in mmol/L	1.75 ± 1.02	1.04
HDL	High density lipoprotein (mmol/L)	1.18 ± 0.42	0.18
LDL	Low density lipoprotein (mmol/L)	2.80 ± 0.95	0.91
VLDL	Very low density lipoprotein (mmol/L)	1.00 ± 0.92	0.84
BMI	Body mass index (weight in kg/height in m^2)	23.30 ± 2.81	7.89
Smoking	Smoking History (pack year)	2.00 ± 9.06	82.00

B. *Data Preprocessing*

The preprocessing of the dataset involved several steps. First, the target variable, consisting of three classes — "Non-Diabetes", "Pre-Diabetes", and "Diabetes" — was encoded into numerical labels 0, 1, and 2, respectively. Coronary heart disease was encoded as 0 for "No" and 1 for "Yes," and neuropathy was encoded similarly. Next, all numerical features were standardized to ensure they were on the same scale. Additionally, the categorical feature "Gender" was encoded, with females labeled as 0 and males as 1, while "Alcohol-drinker" was encoded as 0 for "No" and 1 for "Yes".

When splitting the dataset into training and testing sets (7:3 ratio), we used a stratified sampling method based on multiple fields to ensure that the proportions of these fields remain consistent across both datasets. Specifically, we first divided the data based on the "diabetes classification" (CLASS). Then, we combined the fields that required stratification (e.g., the presence of complications) into a new "stratification key" (e.g., 1-0-1). Using this stratification key, we applied SMOTE (Synthetic Minority Oversampling Technique) [13] to generate additional samples and selected the required number of samples from the augmented data. This approach helps to prevent imbalances in data distribution, ensuring that the model is trained on a more representative dataset. In simpler terms, it ensures that the training and testing datasets maintain consistent proportions, improving the model's accuracy and robustness.

C. *Experiment*

In our study, we utilized AutoGluon, an AutoML framework created by Amazon Web Services, to train our model. AutoGluon simplifies the workflow of model selection, training, and deployment, making the machine learning process more efficient and accessible. Its primary goal is to make advanced machine learning techniques accessible to a broad range of developers without requiring deep expertise in underlying technical details. Key features of AutoGluon include:

- Automated Feature Handling: Simplifies data preparation by automating feature generation, selection, and transformation, enhancing model performance.
- Model Integration with Stacking and Bagging: Combines multiple models effectively using stacking (meta-models for optimal prediction integration) and bagging (aggregating predictions from diverse data subsets), improving accuracy, robustness, and generalization.
- Optimized Efficiency: Designed to work within limited computational resources, it efficiently produces high-quality models, adapting to predefined time and resource constraints while maintaining performance.

By leveraging both stacking and bagging for robust ensemble learning, it enhances predictive performance while maintaining computational efficiency. Additionally, we trained four individual machine learning models outside of AutoGluon. For the multi-output classification task, we selected CatBoost, XGBoost, LightGBM, and Random Forest as the individual models. A comparison of model performance will be discussed in the next section.

D. *Integration Best Model to GUI*

The GUI was developed using the Python open-source package PyQt5. Fig. 2 and Fig. 3 illustrate the functionality of the GUI. Figure 2 displays the input section, where the doctor inputs the relevant feature values and presses the "Evaluate" button to obtain the results. Fig. 3 shows the output in two windows: one visualizes the input data and displays the diabetes classification result along with its probability, while the other provides information about complications. If complications are detected, they are highlighted in the red area. Additionally, the doctor can save the patient's data for further training to enhance the model's performance.

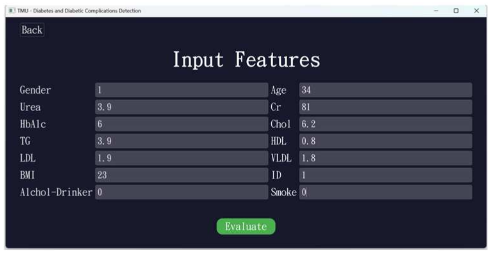


Figure 2. GUI designed for AI-Based CDSS. Input page.

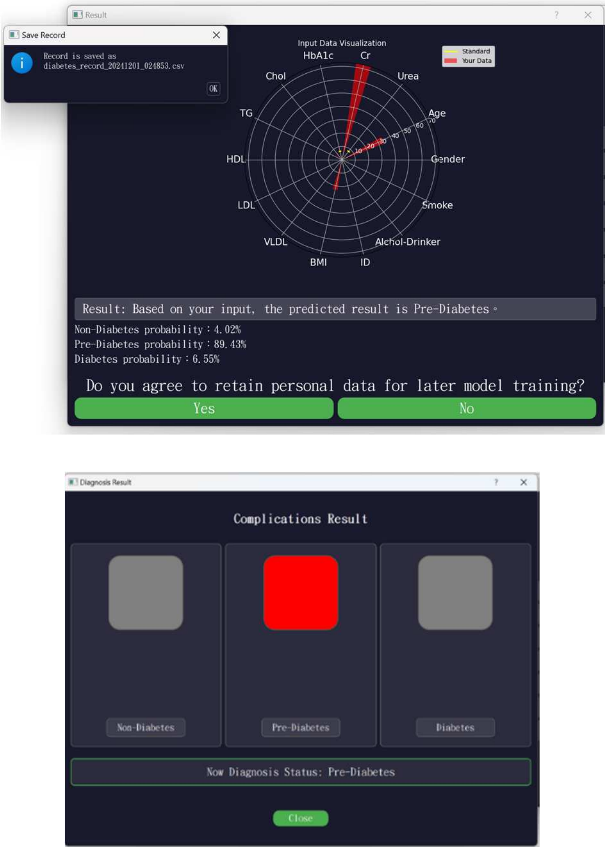


Figure 3. GUI designed for AI-Based CDSS. Execution Result page and Save Data Function.

III. RESULT AND DISCUSSION

TABLE II, TABLE III, and TABLE IV present the comparative performance of nine different parameter combinations of the AutoGluon model across five key metrics: F1-score, Recall, Precision, Accuracy, and Area Under the Receiver Operating Characteristic Curve (AUROC). Notably, the AutoGluon model demonstrates superior performance across all outputs (CLASS, CHD, and NEUR) at a stack level of 3 and a bag fold of 3, achieving the highest F1-scores (0.9648, 0.8642, and 0.8619), Recall (0.9552, 0.7609, and 0.8547), Precision (0.9745, 0.9844, and 0.7692), Accuracy (0.9604, 0.9609, and 0.9110), and AUROC (0.9853, 0.9814, and 0.9838). While the accuracy metric is slightly lower compared to the model configuration with a stack level of 1 and a bag fold of 3, this parameter combination showcases exceptional performance, particularly in NEUR prediction. Overall, all twelve different parameter combinations of the AutoGluon model demonstrate consistently high scores across the five evaluation metrics. This highlights the robust performance of the AutoGluon model and confirms its reliability in automating the prediction tasks for CLASS, CHD, and NEUR. The consistently strong results across various metrics indicate that AutoGluon is highly effective in these complex classification scenarios, providing confidence in its use for automating such assessments.

TABLE II. CLASS PERFORMANCE OF THE PREDICTION MODELS GENERATED BY AUTOGLUON WITH TWELVE PARAMETER COMBINATIONS

Stack-level	Bag-fold	Accuracy	F1-score	Precision	Recall	AUROC
1	3	0.9604	0.9648	0.9745	0.9552	0.9803
1	4	0.9322	0.9425	0.9531	0.9322	0.9512
1	5	0.9557	0.9528	0.9611	0.9447	0.9722
1	10	0.9557	0.9534	0.9622	0.9447	0.9710
2	3	0.9604	0.9648	0.9745	0.9552	0.9823
2	4	0.9322	0.9425	0.9531	0.9322	0.9536
2	5	0.9568	0.9549	0.9622	0.9477	0.9699
2	10	0.9557	0.9534	0.9622	0.9447	0.9730
3	3	**0.9604**	**0.9648**	**0.9745**	**0.9552**	**0.9853**
3	4	0.9348	0.9425	0.9531	0.9322	0.9548
3	5	0.9422	0.9528	0.9611	0.9447	0.9620
3	10	0.9557	0.9534	0.9622	0.9447	0.9712

TABLE III. CORONARY HEART DISEASE PERFORMANCE OF THE PREDICTION MODELS GENERATED BY AUTOGLUON WITH TWELVE PARAMETER COMBINATIONS

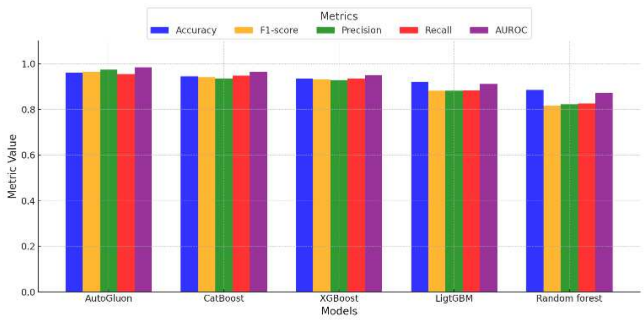
Stack-level	Bag-fold	Accuracy	F1-score	Precision	Recall	AUROC
1	3	0.9430	0.7895	0.9801	0.6521	0.9668
1	4	0.9288	0.7222	0.9801	0.5652	0.9790
1	5	0.9217	0.6857	0.9801	0.5217	0.9722
1	10	0.9323	0.7532	0.9355	0.6304	0.9782
2	3	0.9110	0.6268	0.9802	0.4565	0.9552
2	4	0.8968	0.5797	0.8696	0.4348	0.9711
2	5	0.8968	0.6329	0.7576	0.5435	0.9152
2	10	0.9075	0.6286	0.9167	0.4783	0.9627
3	3	**0.9609**	**0.8642**	**0.9844**	**0.7609**	**0.9814**
3	4	0.8968	0.5915	0.8400	0.4565	0.7546
3	5	0.9395	0.8000	0.8718	0.7391	0.9736
3	10	0.9253	0.7470	0.8378	0.6739	0.9005

TABLE IV. NEUROPATHY PERFORMANCE OF THE PREDICTION MODELS GENERATED BY AUTOGLUON WITH TWELVE PARAMETER COMBINATIONS

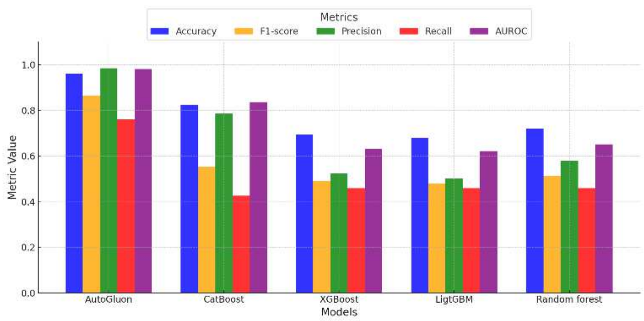
Stack-level	Bag-fold	Accuracy	F1-score	Precision	Recall	AUROC
1	3	**0.9271**	0.8036	0.7627	0.8491	0.9801
1	4	0.8968	0.7521	0.6875	0.8302	0.9242
1	5	0.8292	0.4419	0.5756	0.3585	0.9097
1	10	0.8861	0.6800	0.7234	0.6415	0.9243
2	3	0.8861	0.6734	0.7333	0.6226	0.9435
2	4	0.8790	0.6667	0.6939	0.6415	0.9211

Stack-level	Bag-fold	Accuracy	F1-score	Precision	Recall	AUROC
2	5	0.9075	0.7451	0.7755	0.7170	0.9520
2	10	0.8932	0.7170	0.7170	0.7170	0.9336
3	3	0.9110	**0.8619**	**0.7692**	**0.8547**	**0.9838**
3	4	0.9074	0.7451	0.7755	0.7170	0.9469
3	5	0.8683	0.6021	0.7000	0.5283	0.9522
3	10	0.8968	0.7129	0.7500	0.6792	0.9265

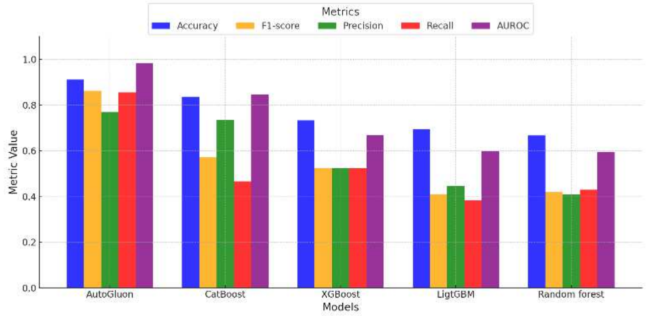
Fig. 4 presents a comparative analysis of five key metrics across different machine learning models for the three outputs. In the CLASS chart (Fig. 4 (a)), AutoGluon demonstrates the highest performance across all metrics, underscoring its superiority in handling general classification tasks. While other models perform reasonably well, their performance varies across metrics. For CHD (Fig. 4 (b)), the metrics reveal a sharper distinction between the models. AutoGluon excels, particularly in Precision and AUROC, highlighting its strong ability to minimize false positives and deliver robust classification for this specific condition. Models like CatBoost and Random Forest show competitive performance but do not match AutoGluon's overall effectiveness. In the NEUR chart (Fig. 4 (c)), AutoGluon maintains its lead, particularly in AUROC and Recall—critical metrics for identifying true positives. However, there is a noticeable performance gap among the other models. Random Forest and LightGBM, in particular, show lower scores in Precision and F1-score, indicating challenges in effectively handling this condition. Overall, AutoGluon consistently demonstrates superior performance, outperforming all other models across the three outputs.



(a) CLASS Metrics Comparison



(b) Coronary heart disease Metrics Comparison

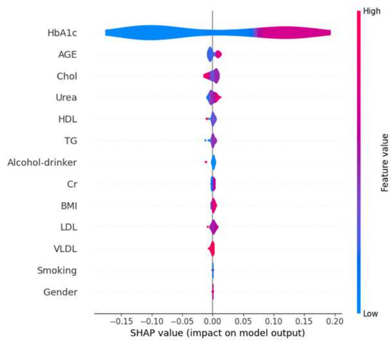


(c) Neuropathy Metrics Comparison

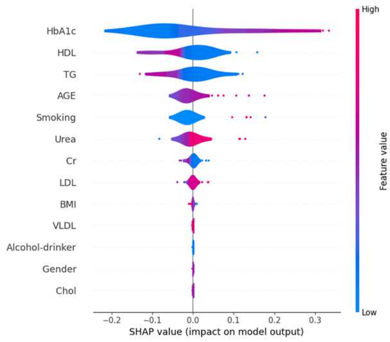
Figure 4. Output Performance of AutoGluon and baseline models.

Despite the high performance of the AutoGluon model, its lack of interpretability remains a challenge. Often called "black boxes," such models make predictions based on complex data relationships that are difficult for humans to understand. This opacity can limit trust and acceptance, particularly in healthcare, where understanding the reasoning behind predictions is critical. Shapley Additive Explanations (SHAP) [14], based on cooperative game theory, addresses this issue by fairly attributing the contribution of each feature to the model's predictions. Using SHAP, we can interpret how features influence diabetes predictions, making the decision-making process transparent and aligning with healthcare professionals' need to validate predictions against their expertise.

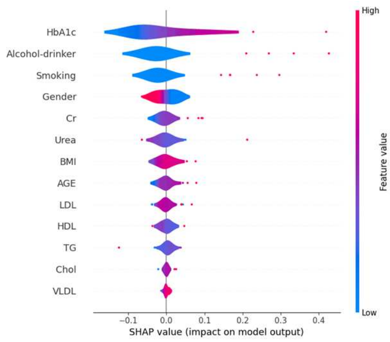
SHAP analysis showed that, for diabetes prediction, HbA1c is the most influential feature. Higher HbA1c leads to a greater likelihood of having diabetes [15], while other factors such as age, cholesterol, urea, VLDL, smoking, and alcohol consumption have minimal overall impact. As for complications, HbA1c exhibits the same pattern as in the previous classification [16]. Regarding other features, there appears to be a difference in their relative importance. In the case of CHD classification, larger HDL values correspond to a lower risk [17], whereas TGL [18] and Age follow the opposite trend. For neuropathy, alcohol consumption [19] and smoking levels strongly affect the likelihood of developing the condition—higher alcohol intake and greater smoking exposure increase the risk.



(a) CLASS



(b) Coronary heart disease



(c) Neuropathy

Figure 5. SHAP summary plot.

In conclusion, the SHAP summary plots underscore the significance and relationships of the features used in training the AutoGluon models. These findings align with existing research on the associations between the features and diabetes and its complications, reinforcing the robustness of the model predictions.

IV. CONCLUSION

In our research, AutoGluon proved to be the most suitable machine learning model for our CDSS with a GUI. By leveraging SHAP values to explain the model's decision-making process, we ensure that the system is not only accurate but also interpretable and trustworthy—key factors for gaining clinician confidence and facilitating its adoption. Moving forward, we aim to enhance the robustness of our model by incorporating additional clinical data through Institutional Review Board approval, enabling better training and external validation. Implementing a CDSS in real-world clinical settings is not without its challenges. One major hurdle is the training required for healthcare providers, who must adapt to new workflows and decision-making processes introduced by the system. Tailored training programs and intuitive user interfaces are essential to reduce the learning curve and support effective adoption. Another critical challenge lies in the integration of CDSS with existing EHR systems. Achieving seamless interoperability requires standardized data formats, robust IT infrastructure, and compliance with data privacy regulations such as GDPR and HIPAA. Addressing these issues calls for close collaboration among healthcare institutions, EHR vendors, and regulatory bodies to create scalable and secure solutions. Despite these challenges, our findings highlight the immense potential of combining automated machine learning models with interpretable tools like SHAP values. This approach offers a promising pathway to building a robust, trustworthy, and efficient CDSS. With strategic planning, ongoing refinements, and continued collaboration with clinical stakeholders, we are confident that this system can significantly enhance clinical workflows, support data-driven decision-making, and ultimately improve patient outcomes.

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