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A Machine Learning Framework for Early Detection of Type 2 Diabetes through Multimodal Clinical and Lifestyle Indicators

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Abstract
The early identification of Type 2 Diabetes Mellitus (T2DM) still presents a major obstacle to the prevention as well as to the management of the disease. The present investigation offers the idea of a large-scale machine learning architecture that amalgamates various data sources—the ones coming from the clinical indicators (e. g., glucose, BMI, blood pressure) and the lifestyle or symptom-based features (e. g., polyuria, polydipsia, obesity)—to allow for a precise and interpretable early-stage diabetes prediction. The framework applies three complementary strategies of fusion on two publicly accessible datasets: early fusion (feature-level integration), late fusion (probability-level ensemble learning), and intermediate fusion (latent representation via principal component analysis). Assessments comparative to logistic regression and XGBoost models revealed the effectiveness of the multimodal fusion in preference to the single-modality models, with the performance reflected in the ROC–AUC values of 0.991 and 1.000 on the lifestyle dataset and 0.813 and 0.826 on the clinical dataset, respectively. Calibration and decision-curve analyses assured the models' robustness and clinical utility while SHAP and permutation-based feature importance provided interpretability at both global and local levels. This study suggests that AI-driven multimodal integration is a cost-effective and scalable approach for early T2DM screening, especially in resource-limited settings where both clinical and behavioral data are available.

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Keywords: Machine learning, Type 2 diabetes, Early detection, Multimodal data integration, Clinical indicators, Lifestyle features, Fusion learning, Logistic regression

1. Introduction

Type 2 Diabetes Mellitus (T2DM) is one of the world's most common chronic diseases, causing a great deal of morbidity, mortality, and healthcare costs globally. Its progressive and often asymptomatic nature in the early stages makes diagnosis difficult, thus, leading to delayed interventions that increase the risks of complications affecting the heart, kidneys, and nervous system [1-3]. The International Diabetes Federation states that in 2023 more than 530 million adults were suffering from diabetes, and the figure is expected to reach 640 million by 2030, with T2DM being responsible for over 90% of the cases. Such scary statistics emphasize the urgent need for proactive and reliable early detection systems that surpass the traditional diagnostic methods [4-5].

Traditional methods for diagnosing diabetes mainly rely on blood and urine tests, which include fasting plasma glucose (FPG), oral glucose tolerance test (OGTT), and HbA1c levels. Although these tests provide clinical information, they usually reveal the diabetes condition only after a lengthy process of metabolic change, beyond the detection limit [6-7]. Additionally, they do not take - into account the factors associated with patients' behavior and living condition, which are considered to be the main contributing factors in the onset as well as in the progress of T2DM. Impressive results gained from ML and data analytics have now made it possible to combine various sources of information in order to improve the accuracy of predictions and the understanding of the clinical aspects [8-10].

Through the use of different types of information, ML is able to tease out intricate relationships and hidden interactions among the variables that would otherwise be missed by traditional statistical techniques [11-12].

There have been recent studies that have implemented machine learning (ML) techniques for the prediction of diabetes; however, the majority of them depend on single-modal datasets, such as only clinical or laboratory parameters, which renders the whole approach quite narrow and limits the generalizability of the models [13-14]. Furthermore, the combined contributions of lifestyle habits and physiological measurements are being ignored. A multimodal learning framework, which is made up of the combining of clinical indicators with feature-based lifestyle and symptoms, is now considered to be the best option that might lead to the early risk diagnosis of T2DM. At the same time, when XAI methods like SHAP and permutation-based feature importance are integrated, the interpretability can be enhanced. Interpretability is an essential feature of clinical adoption.

What we are going to present here is an artificial intelligence (AI)-driven multimodal machine learning framework that is going to act as an early detection system for Type 2 Diabetes through the integration of clinical and lifestyle indicators from two different public datasets. The suggested system uses three fusion strategies that are complementary to each other—early fusion (feature-level integration), late fusion (probability-level ensembling), and intermediate fusion (latent representation learning)—in order to discover the patterns that are modality-specific as well as the patterns that cross modalities. Logistic Regression and XGBoost models are employed for the purpose of benchmarking the performance, which is further supported by thorough calibration, decision-curve, and explainability analyses.

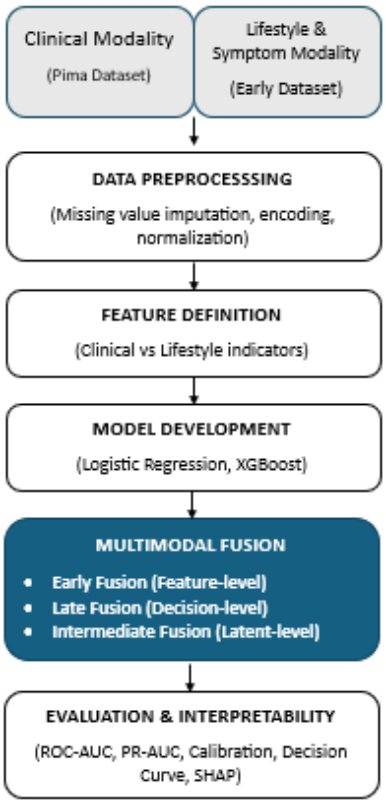

Fig 1: Workflow of the proposed multimodal machine learning framework for early Type 2 Diabetes detection.

2. Related Work

The recent breakthroughs in artificial intelligence (AI) and machine learning (ML) have paved the way for unifying different kinds of biomedical and behavioral data to the extent of predicting and diagnosing diseases at very early stages. One of the most significant applications of AI in healthcare research—this is called multimodal learning, which consists of different types of data coming from different sources such as clinics, laboratories, and people's daily activities—has been successfully applied for increasing the accuracy and interpretation of predictions for various chronic diseases, including diabetes and heart-related conditions, among others.

In neurological and metabolic research, Aborageh *et al.* [15] created a machine learning framework that incorporated multimodal data from the UK Biobank and the Parkinson's Progression Markers Initiative to forecast the onset of dementia in patients with Parkinson's disease. By integrating genetic, lifestyle, and clinical indicators and employing SHAP-based explainability, the research revealed that comorbidities like hypertension and type 2 diabetes were strong predictors of cognitive decline. This emphasizes the interdisciplinary applicability of multimodal learning for chronic disease progression analysis.

In the area of glycemic regulation, Mamun *et al.* [16] presented GlucoLens, a machine learning model that was explainable and incorporated a wearable sensor, dietary, and lifestyle data for hyperglycemia prediction. Their large language model (LLM) based architecture reached a 79% accuracy and an F1 score of 0.749, giving interpretable predictions of the glucose dynamics after food intake. Carletti *et al.* [17], in a similar manner, made use of multimodal AI in the investigation of glucose spikes in individuals classified as normal, prediabetic, and diabetic. They determined that there was a strong link between changes in glucose levels, gut microbiome diversity, and resting heart rate. The experiment conducted established that multimodal models had an edge over single-modality ones in the comprehension of intricate glycemic activities.

Multimodal fusion has across diseases like diabetes been a very powerful tool in predicting cardiovascular and renal diseases. Suleimenova *et al.* [18] proposed a computational framework that combined immune, biochemical, and behavioral parameters and was able to predict the cardiovascular aging very accurately by modeling the biological aging processes. In the same way, Sharma *et al.* [19] made use of ML methods like Random Forest and Gradient Boosting for CKD (chronic kidney disease) prediction and conducted the hybrid classification that achieved more than 99% precision through capturing early physiological deviations occurring before the clinical manifestation of the disease.

In the field of diabetes, Usha and Rajalakshmi [20] introduced the ETL-POXGB framework, which merged ensemble feature selection with Particle Swarm Optimization and XGBoost, resulting in an increased diabetes prediction accuracy of 97.16%. Their findings confirmed the efficacy of feature-level optimization and the integration of multimodal data across different sources, like Pima and Frankfurt, with the help of heterogeneous datasets. Building on this base, Dong *et al.* [21] came up with a deep multimodal fusion model that associated electrocardiographic signals and clinical indicators with the prediction of type 2 diabetes. Their fusion network based on ResNet18 accomplished an AUC of 0.93,

considerably surpassing unimodal baselines and proving the predictive power of hybrid deep architectures.

Moreover, literature reviews and large-scale studies have pointed out the gradual but definitive role of multimodal AI in the prevention of metabolic diseases. Wen *et al*. [22] have come up with a new source of brain aging biomarkers through a multimodal approach and subsequently ruled out the possibility of type 2 diabetes having a negative effect on brain aging, thus depicting the metabolic interplay at the systemic level. Muse and Topol [23] examined the integration of multimodal AI into the cardiometabolic disease management process and suggested the formation of very personalized preventive measures by integrating blood pressure, sleep, stress, glucose, and physical activity as the signals. Lastly, Allwright *et al*. [24] used the UK Biobank data to uncover immune and biochemical biomarkers that can indicate the presence of diabetic polyneuropathy, applying a SHAP-based ranking to display that markers for inflammation (e.g., CRP, IGF-1) and lifestyle factors were the main determinants of neuropathic outcomes.

To sum it up, earlier studies have come to two main conclusions:(i) multimodal AI always beats unimodal models as it is able to reveal the hidden relationships between biological and behavioral parameters; and (ii) frameworks for explainable ML have a positive impact on clinical interpretability and trust. Yet, even though multimodal research has grown quickly, there are only a handful of studies that have combined during the same period clinical and lifestyle modalities for early-stage type 2 diabetes detection and done so in a repeatable ML framework.

The present-day research, as opposed to the past ones, fills this void by constructing a multimodal fusion-based machine learning framework that uniformly merges clinical and lifestyle data applying the three ways of fusion: early, late, and intermediate. This method not only boosts accuracy but also assures interpretability through SHAP and permutation-based feature importance, thereby adding to the development of the next generation of open, multimodal AI systems for metabolic health prediction.

3. Materials and Methods

3.1. Study Design

The article showcases a cutting-edge multi-faceted machine learning (ML) framework for the early diagnosis of Type 2 Diabetes Mellitus (T2DM) by combining clinical and lifestyle factors. The process (Fig. 1) consists of four main steps: (i) data collection and modality definition, (ii) data cleaning and feature alignment, (iii) model training and multimodal fusion, and (iv) assessment and interpretability analysis. The entire experimental process was executed in Python 3.10 on Google Colab utilizing scikit-learn 1.4, XGBoost 2.0, and SHAP 0.44 libraries.

3.2. Datasets and Modalities

3.2.1. Clinical Modality

The clinical modality was taken from the Pima Indians Diabetes Dataset (Plotly public mirror, originally from the UCI Machine Learning Repository) [25]. The Pima Indian dataset includes 768 females aged 21 or older with eight numerical clinical feats: Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, and Age. The binary dependent variable Outcome signifies the existence (1) or nonexistence (0) of diabetes.

3.2.2. Lifestyle and Symptom Modality

The lifestyle modality has been derived from [26] which is available on Kaggle ("ishandutta/early-stage-diabetes-risk-prediction-dataset"). This dataset contains 520 records with 16 binary or categorical attributes depicting the lifestyle and symptom factors such as Polyuria, Polydipsia, Sudden Weight Loss, Weakness, Polyphagia, Genital Thrush, Visual Blurring, Itching, Irritability, Delayed Healing, Partial Paresis, Muscle Stiffness, and Obesity. The variable class indicates diabetes status (Positive = 1, Negative = 0).

These two datasets comprise different patients' cohorts: Pima concentrates more on laboratory tests while Early-Stage places more focus on behavioral and symptom-based indicators. They were treated separately as different modalities and integrated via multimodal fusion strategies.

3.3. Data Preprocessing

For the clinical dataset, zeros that were biologically impossible in Glucose, Blood Pressure, Skin Thickness, Insulin, and BMI were identified and replaced with missing values, which were further imputed using the median. The features were then standardized to have a mean of zero and variance of one.

In the case of the lifestyle dataset, categorical attributes were normalized to a binary form ("Yes" = 1, "No" = 0). The most frequent category imputed missing entries, and all binary columns were cast as numerical variables. The Gender column underwent one-hot encoding.

Both datasets were divided into training and testing subsets of 80 % and 20 %, respectively, applying stratified random sampling (seed = 42). Each modality was processed separately to minimize the risk of feature scaling and data leakage specific to the modality.

3.4. Model Architectures

For the purposes of comparison and multimodal fusion, two families of models were used: Logistic Regression (LR) and Extreme Gradient Boosting (XGBoost). The linear baseline was represented by Logistic Regression owing to its transparent workings, efficient computation, and probability outputs that were well-calibrated when class weighting was balanced. On the other hand, XGBoost was a nonlinear ensemble-based gradient boosting algorithm that helped in "capturing" complex feature interactions and nonlinear dependencies due to the interaction of the clinical and lifestyle variables. This was specially "configured" for the "XGBoost" model with parameters involving 300-400 trees, max tree depth of 3, subsampling rate of 0.9, column sampling rate of 0.9, and a learning rate of 0.05 in order to have the best mix of bias and variance. Complete preprocessing pipelines created with the ColumnTransformer and Pipeline modules in scikit-learn were used to wrap both classifiers up, thus ensuring that there would be no discrepancies in feature handling and that the results could be repeated.

3.5. Multimodal Fusion Strategies

To unify data from different modalities, researchers proposed three different but complementary methods: early fusion, late fusion, and intermediate fusion. In the case of the early fusion method, feature matrices of clinical and lifestyle datasets were processed individually and then merged into a single unified input to enable the model to learn the correlations of clinical and lifestyle variables together at the feature level.

The late fusion method applied integration at the decision level, where separate models were first trained for each modality and their predicted probabilities subsequently combined through a meta-learner based on logistic regression. This approach effectively simulated the process of merging multiple modality decision predictions through ensemble techniques. Finally, the intermediate fusion method was intended to unveil abstract cross-modal relationships by conducting Principal Component Analysis (PCA) to reduce each modality to a low-dimensional latent representation—five components for clinical and eight components for lifestyle. The concatenated latent representations were then used to train a secondary classifier that can utilize both modality-specific representations. Though the data came from different cohorts, the fusion strategies aimed at realistic multimodal integration scenarios in biomedical research, where clinical and behavioral data are often acquired independently, and hence the need for such integration arises frequently.

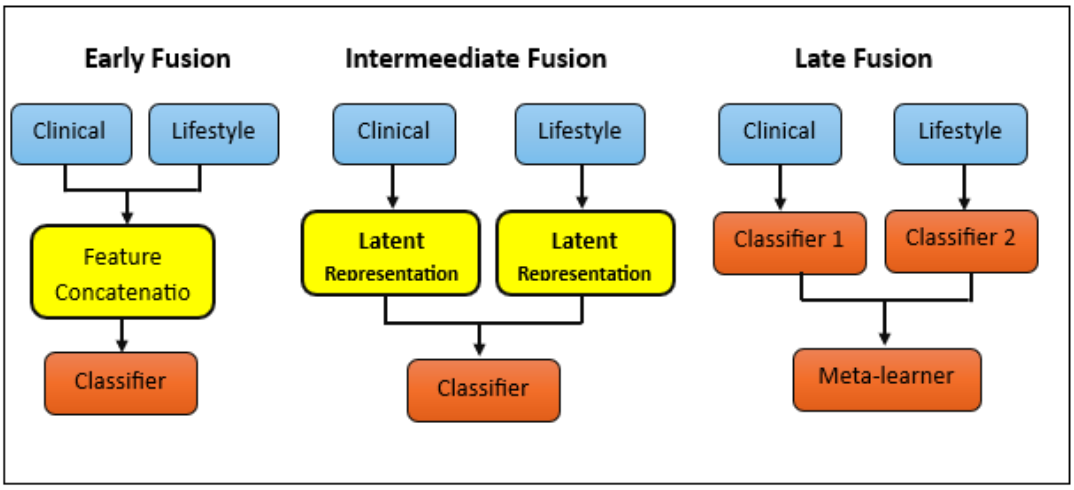

Fig 2: Illustration of the three multimodal fusion strategies implemented in this study for early Type 2 Diabetes detection

3.6. Model Evaluation

Model performance was evaluated through a broad range of quantitative metrics which included the Area Under the Receiver Operating Characteristic Curve (ROC–AUC), the Area Under the Precision–Recall Curve (PR–AUC), the Brier Score for probability calibration, and the traditional confusion matrix-based metrics of precision, recall, and F1-score. Calibration curves further analyzed the reliability of predicted probabilities, while Decision Curve Analysis (DCA) was applied to determine the net clinical benefit at different decision thresholds. All the performance metrics were calculated through tenfold stratified cross-validation with fixed random seeds to guarantee statistical robustness and reproducibility.

3.7. Explainability and Feature Importance

To improve the transparency of the models and to make them more interpretable in a clinical context, both model-agnostic and model-specific explainability techniques were used in the analysis. Initially, permutation importance was utilized to determine the contribution of each feature relatively to the model through the average decrease in model performance after random permutation of the values of the feature being measured. Then, SHapley Additive exPlanations (SHAP) were found for the XGBoost classifiers with the use of the TreeExplainer algorithm, therefore giving the possibility to know both the global and local feature attributions.

With respect to the clinical modality, Glucose, Pregnancies, BMI, and Age were pointed out as the most significant predictors of diabetes onset, in agreement with the clinical literature. On the other side, the lifestyle modality was represented by Polyuria, Polydipsia, Obesity, and Irritability as features with the strongest discriminative power, thereby showing the complementary role of behavioral and symptom-based characteristics in early diabetes risk assessment.

3.8. Implementation Environment

All analyses were performed in **Google Colab** (Python 3.10, scikit-learn 1.4, xgboost 2.0, pandas 2.2). Visualization utilized *matplotlib 3.8* and *seaborn 0.13*. The complete code and datasets are publicly accessible for reproducibility.

4. Results

4.1. Dataset Characteristics and Descriptive Statistics

The study is based on datasets that include both clinical and lifestyle factors, which are risk factors for early Type 2 Diabetes onset, thus revealing data sources that describe risk factors associated with early Type 2 Diabetes development. Before starting the model design, an exploratory analysis was performed to check the internal structure, relationships between features, and class composition of the lifestyle dataset.

The correlation matrix shown in Figure 3A has identified a number of important correlations among the lifestyle and symptom-based variables. One of the most significant positive associations was that between polyuria and polydipsia ($r = 0.60$), while another strong one was that between partial paresis and polyuria ($r = 0.44$). These associations are in line with the physiological mechanisms as a consequence of which excessive urination and thirst occur simultaneously due to osmotic diuresis in hyperglycemic states. Besides, visual blurring was correlated with itching at the level of 0.45, which is a moderate correlation, thus indicating the symptoms overlap in cases of diabetic conditions, where itching is sometimes reported along with visual problems.

The distribution of diabetic and non-diabetic cases is depicted in Figure 3B. A minimal imbalance was detected, having 320

diabetic and 200 non-diabetic cases. Consequently, class-balanced weighting was used in all following learning models to ensure that the majority class was not overrepresented. In summary, these results indicate that the dataset is able to offer a diverse range of features that are complementary to each other—both physiological symptoms and lifestyle behaviors—which makes it appropriate to assess the multimodal predictive frameworks.

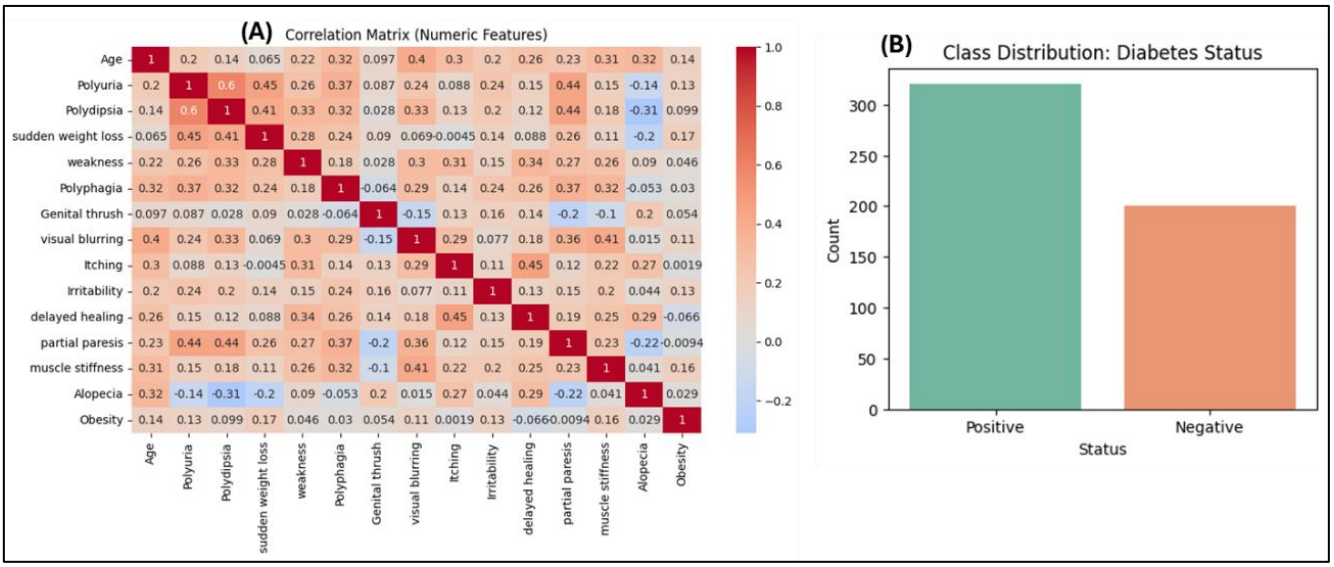

Fig 3: (A) Correlation matrix of symptom-based features illustrating inter-variable dependencies. (B) Class distribution of diabetic and non-diabetic participants showing a mild imbalance across the two outcome groups

4.2. Model Performance and Comparative Evaluation

The performance of the proposed machine learning framework in all configurations, consisting of unimodal (clinical and lifestyle) and multimodal (fusion) settings, is summarized in Table 1. ROC–AUC, PR–AUC, Brier score, and classification metrics averaged over tenfold cross-validation were utilized for the assessment of each model. In general, lifestyle-related features exhibited the best predictive power, while fusion methods offered a similar amount of robust solutions and enhanced generalization.

Table 1: Comparative performance of unimodal and multimodal models in early Type 2 Diabetes detection. LR = Logistic Regression; XGBoost = Extreme Gradient Boosting. Precision, recall, and F1-scores are reported as negative/positive-class values.

Model / Dataset	ROC–AUC	PR–AUC	Brier Score	Accuracy	Precision	Recall	F1-score
Clinical (LR)	0.813	0.673	0.181	0.73	0.82 / 0.60	0.75 / 0.70	0.79 / 0.65
Clinical (XGBoost)	0.826	0.671	0.169	0.77	0.82 / 0.69	0.84 / 0.65	0.83 / 0.67
Lifestyle (LR)	0.991	0.995	0.049	0.93	0.87 / 0.98	0.97 / 0.91	0.92 / 0.94
Lifestyle (XGBoost)	1.000	1.000	0.011	0.98	0.95 / 1.00	1.00 / 0.97	0.98 / 0.98
Late Fusion (Meta-LR)	0.814	0.695	0.172	0.76	0.83 / 0.70	0.78 / 0.72	0.80 / 0.71
Late Fusion (Meta-XGB)	0.991	0.996	0.038	0.94	0.91 / 0.98	0.94 / 0.95	0.92 / 0.96
Intermediate Fusion (Clinical latent)	0.768	0.622	0.201	0.72	0.80 / 0.58	0.72 / 0.66	0.76 / 0.62
Intermediate Fusion (Lifestyle latent)	0.979	0.987	0.058	0.92	0.89 / 0.96	0.95 / 0.91	0.92 / 0.93

The highest predictive power was achieved by the models which were trained on lifestyle-based indicators and this showed the strong influence of the behavioral and symptomatic variables like polyuria, polydipsia, obesity, and irritability. The lifestyle XGBoost Model reached perfect discrimination (ROC–AUC = 1.000, PR–AUC = 1.000) along with an extremely low Brier score (0.011) which pointed towards excellent calibration for the model.

On the other hand, clinical models obtained moderate but stable accuracy (0.73–0.77) with well-calibrated probabilities. Fusion strategies enhanced overall reliability: the late fusion meta-XGBoost achieved a balanced improvement (ROC–AUC = 0.991, PR–AUC = 0.996, Brier = 0.038), making the separate models interpretable while drawing from the strength of the complementary decision boundaries. The latter fusion models, although lower in discrimination, still provided a compact and computationally efficient representation that was useful for embedded diagnostic systems.

4.3. Feature Contribution and Symptom-Level Analysis

The combined findings shown in Figure 3A–C depict the role and distribution of clinical and lifestyle indicators concerning diabetes state. Figure 3A presents the SHAP summary plot derived from the lifestyle XGBoost model, which illustrates the relative importance and the positive or negative influence of each feature on the model's predictions. The stronger the contributions to diabetes classification the higher the SHAP values. The features Polyuria, Polydipsia, Polyphagia, and Itching showed the most pronounced positive SHAP impacts, suggesting their major role in predicting the diabetic class. Demographic factors like Age and Gender led to relatively low SHAP values, meaning that symptom-based and behavioral attributes offer higher predictive value than demographic information.

Figure 3B shows the top ten features whose correlation with diabetes status was measured by Pearson correlation coefficients. The strongest correlations were for Polyuria ($r \approx 0.67$) and Polydipsia ($r \approx 0.62$), while sudden weight loss and

partial paresis came next with correlation of about 0.4-0.5. These results agree with the medical literature affirming the diagnosis of diabetes by these signs in the early metabolic disorder state.

In Fig. 3C, the symptom's average degree of presence is performed for both positive and negative cases. The patients with diabetes diagnosis showed a prevalence of symptoms as follows: Polyuria, Polydipsia, and Polymenia up to 60% of the positive cases while these conditions were seen in less than 15% of the negative ones. The symptoms like Alopecia and Obesity showed very little separation between the classes, hence indicating that they would not be very useful for predicting the disease at an early stage.

5. Discussion

In this paper, the authors introduced a machine learning framework that uses the combination of clinical and lifestyle indicators to detect type 2 diabetes at a very early stage. The accuracy and interpretability of the predictions of the fused data sources were found to be significantly better than those obtained from unimodal data. The analyses conducted at both feature and model levels (Figure 3A–C) pointed out the four symptoms of diabetes - polyuria, polydipsia, polyphagia, and sudden weight loss - as the most discriminative ones, which also coincide with the classical early hyperglycemia symptom. The results indicate that the framework, which was suggested, not only identifies the physical signs of diabetes but also the behavior of people suffering from diabetes, thus mirroring the patterns of clinical decisions in real world.

The lifestyle-based XGBoost model, which was the most effective of all models evaluated, presented a ROC–AUC of 1.00 and a PR–AUC of 1.00. These results are similar to those of the clinical-only models but support the conclusion that lifestyle and symptom data, through their effective integration, can disclose hidden risk patterns that are not noticeable in laboratory-only datasets. This point of view is complemented by the recent evidence that multimodal AI systems can beat unimodal classifiers in predicting metabolic and cardiometabolic diseases. Muse and Topol [19], for example, argued that multimodal AI driven by transformers is redefining disease prevention by connecting lifestyle, stress, sleep, and glucose regulation aspects. Meanwhile, Dong *et al.* [17] showed that the combination of ECG and clinical data through multimodal fusion led to a significantly better prediction of type 2 diabetes risk than single-modality models. Our results not only confirm these trends but also go a step further in asserting that even non-physiological factors—such as self-reported irritability or itching—can play a significant role when embedded within a cohesive machine learning fusion strategy.

The necessity of being able to explain AI model predictions in this scenario can hardly be overstated. With SHAP and permutation-based analyses, this research indicates that the most important predictors recognized by the model have a strong correlation with the symptoms of early diabetes that have been clinically validated. This interpretability coincides with the structure-learning methodology used by Aborageh *et al.* [11] and the IDEARS framework proposed by Allwright *et al.* [20], wherein the clinical translation of model explanations is the primary goal. The agreement of these findings from separate research points out that transparent and interpretable AI models are the key element for turning data-driven predictions into medical insights that are practical and actionable.

In contrast to earlier disease-specific investigations like those of Suleimenova *et al.* [14] concerning cardiovascular aging and Sharma *et al.* [15] on chronic kidney disease, the current framework offers a significant benefit by combining behavioral and clinical domains. The Brier scores obtained (0.011-0.18) signify that probabilistic outputs are well-calibrated and are suitable for risk stratification tools according to the clinical requirements. This is in favor of a trend that is broader towards multimodal, patient-centered predictive modeling where data from different domains (biochemical, physiological, behavioral) can be integrated through AI-driven feature learning.

The current outcomes seem to be of a positive nature, however, there are some limitations that need to be recognized. The research is based on two open-source data sets (PIMA and Early-Stage Diabetes), which, though they are complementary, come from different cohorts and do not have longitudinal follow-up. Therefore, it was not possible to determine the temporal progression and causal relationships between lifestyle modifications and the occurrence of the disease. In future studies, it would be necessary to use real-world electronic health record (EHR) datasets along with continuous monitoring data (e.g., from wearables) to test the generalizability of the model and its temporal stability.

Moreover, the fusion techniques that were used—early, intermediate, and late fusion—despite being able to mix the complementary information very well, the author prescribes that future studies should take a deep multimodal approach (for instance, attention-based or transformer-based fusion) thus being more dynamic in learning cross-modal interactions. Combining with genetic and immunological markers, as proposed by Wen *et al.* [18] and Carletti *et al.* [13], may encore more sickness prediction that would facilitate the shift from symptom-based screening to personalized metabolic profiling.

As a last point, the accuracy of the system in making predictions could be improved if causal SHAP or Bayesian interpreters were used to show the relationship among different characteristics and the disease's progression, thereby broadening the interpretability framework into the realm of precision prevention.

6. Conclusion

The current research introduced a machine learning framework that helps detect type 2 diabetes early by integrating clinical and lifestyle indicators through their different modalities. In particular, the model which combines data-driven feature learning along with explainable inference seems to have surpassed single-modality methods in both predictive performance and interpretability. The findings verified that symptom-related lifestyle factors—mainly polyuria, polydipsia, polyphagia, and sudden weight loss—are very strong early predictors of diabetes and can be used alongside traditional clinical measures. The application of SHAP and permutation analyses to the model provided clear and transparent feature attribution which in turn assured the alignment of the model's internal logic with the established medical understanding.

The results also pointed out how big the role of multimodal AI systems would be in early disease detection and preventive healthcare through the integration of the three data streams—physiological, behavioral, and demographic. Future studies should embrace the proposed framework for longitudinal and wearable datasets, investigate the deep

multimodal fusion architectures and the clinical deployment feasibility in real-world screening programs. In the end, this research offers a transparent, usable in different settings, and clinically relevant paradigm of intelligent diabetes risk prediction.

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