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A Multi-Modal Machine Learning Framework Integrating Medical Records and Wearable Sensor Data for Early Diabetes Prediction

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Abstract: Diabetes mellitus is a rapidly emerging health challenge globally and delayed diagnosis of the disease tends to lead to severe complications, besides increasing the healthcare cost. Traditional screening methods are mainly based on periodic clinical tests and static medical records, limiting the ability of obtaining physiological changes in early stage states. Existent prediction models often use a single source of data which results in poorly accurate prediction in generalization across different populations. This study is to develop a multi-modal machine learning framework which consists of a combination of electronic medical records (EMRs) and continuous wearable sensor data that would enable prediction of diabetes as early as possible and with high accuracy. Some feature engineering techniques, temporal aggregation, and data normalization were applied prior to training the model. Ensemble and deep learning models, such as Random Forest, XGBoost and Long Short-Term Memory (LSTM) networks were tested based on stratified cross-validation. The integrated multi-modal model achieved an accuracy of 94.2%, precision of 93.1%, recall of 95.4%, F1-score of 94.2% and an AUC of 0.97 which are 8-12% better than single modality-baselines. The results show that integration of medical records with wearable sensor data is able to improve prediction of diabetes early significantly in favor of proactive intervention and personalized healthcare delivery.

Keywords: Diabetes Prediction, Multi-Modal Machine Learning, Wearable Sensors, Electronic Medical Records, Early Diagnosis, Predictive Analytics

I INTRODUCTION

Diabetes mellitus is among the most common chronic metabolic disease conditions in the world, with hundreds of millions affected, representing a huge burden on the world economy in terms of healthcare costs. Characterized by poor glucose metabolism, diabetes argues in these early stages, as the disease is usually registering unnoticed populace would have gone years without diagnosis until diabetes complications such as cardiovascular disease, neuropathy, nephropathy or Reynolds disease. Early identification of people at high risk is therefore of paramount importance for timely lifestyle interventions and clinical management that can delay or prevent the onset of the disease[1]

Traditional methods for diabetes diagnosis and risk assessment are based on episodic clinical measurements, including fasting plasma glucose level, haemoglobin A1c level, oral glucose tolerance test and patient self-reported history. While these methods are validated clinically, they only reflect a snapshot in a person's metabolic state and are not meant to capture dynamic physiological patterns in a changing individual over a period of time. Moreover, such assessments are usually carried out during the infrequent clinical visits, which restrict the capacity to detect the subtle changes in the initial stages of diabetes development[2].

In the past few years the digitization of healthcare data has led to the broad adoption of electronic medical records (EMRs), which provide a rich source of longitudinal clinical information such as demographics, laboratory test results, diagnoses and medication history[3]. Machine learning methods used with EMRs have had potential in finding complicated and non-linear patterns related to diabetes associated risk. However, models built using EMR-based approaches are limited by data paucity, missing values and lack of continuous behavioural and physiological monitoring [4].

Concurrently, improvements in wearable sensor technologies (i.e., smartwatches, fitness trackers, etc.) have allowed physiological and behavioural data to be collected continuously and in real-time. Metrics like physical activity levels, heart rate variability, sleep duration and quality, or glucose fluctuation are important to get insight on an individual's lifestyle and health on a daily basis, from a metabolic health standpoint [5]. Several researches have shown associations between these features obtained twice by wearable technology and risk factors for diabetes such as insulin resistance and sedentary behaviour. Nevertheless, models without any clinical context and using data only from wearable devices are sensitive to noise and variability in the devices.

Recent research has started to look at multi modal approaches to learning, incorporating heterogeneous sources of data to better the predictive model. By integrating EMRs with wearable sensor data, it is then possible to record both longer term clinical trends and shorter term physiological dynamics. Despite this potential, existing studies are still quite limited in scope and limited often to a narrow set of features, or a simple fusion technique which does not combine temporal dependence in a sufficient degree.

There is a clear need for a powerful, scalable and interpretable framework towards early diabetes prediction including integration of clinical and wearable data. The main research problem that this study aims to address is how to effectively fuse structured medical records and continuous wearable sensor data to enhance the predictive accuracy and reliability with machine learning techniques more than single-modality models. The main objectives of the study are as follows

- To develop a multi-modal data integration framework using electronic medical records and wearable sensor data in the prediction of diabetes risk.
- To evaluate and compare the performance of the traditional machine learning and deep learning models on integrated and single modality datasets.
- To evaluate the effectiveness of the proposed framework with respect to improving the accuracy of early detection and clinical decision support.

This paper is organized as follows: Section 2 reviews some related work on diabetes prediction and multi-modal learning. The proposed framework and methodology are presented in Section 3. Section 4 presents results and analyzes experiments. Section 5 concludes the study with future research directions.

II RELATED WORKS

Recent studies also have been delving deeper into research of deep learning and multimodal data fusion for improved early prediction and personalized management of Type 2 diabetes and other related chronic conditions. By combining clinical, genomic, lifestyle and wearable information, these works demonstrate ways of achieving a better predictive accuracy and the new opportunities and challenges in AI empowered healthcare analytics.

Singh et al show the value of the deep learning algorithm and composite data set for the early prediction (3 years prior) of Type 2 diabetes with high sensitivity and specificity which clearly has clinical value. However, the study is lacking external validation in a wide range of populations, and lacks clarity in terms of the model's interpretability. While the results of personalized management are promising, still there's a lack of addressing real-world scalability and integration of personalized management into routine clinical workflows [6].

Sunil et al. 2025 gives an exhaustive survey of the multimodal data fusion methods in Early Chronic Disease Prediction, i.e. effective synthesis of advances on DNs, EAI and FL. While the review does provide strong conceptual insights, as well as appreciate important issues such as the heterogeneity of the data and privacy, the review is largely theoretical. Lack of quantitative comparison and case evaluation in the real world restricts its immediate application in clinical implementation[7].

Xiong et al. proposes an attention-based multimodal deep learning framework with an effective early warning window to predict Type 2 diabetes complications: a study. The adaptive thresholds of the model and the prospective validation are used to enhance the clinical relevance of the model. However, the computational complexity of the system and the need for high-quality multimodal data can be a limitation for its application in resource-constrained healthcare settings, despite being able to tackle the task well with respect to the predictions [8].

Tian et al., 2024 proposed a multimodal deep learning model based on the combination of tongue image and the clinical index to predict diabetic foot and get high accuracy and sensitivity. Although the merging of objectified aspects of TCM is new, the single cohort study design and lack of external validation make the study limited in its generalizability, as well as lead to questions of robustness in different clinical groups [9].

Karunarathna et al. 2025 proposes a non-invasive glucose prediction system based on passive multimodal wearables and tree based regression High clinical accuracy with manual logs. While the feature richness and performance with XGBoost is good, using one data set and constructed features is likely to contribute to limited transferability between populations and sensor settings[10].

Nandyala et al, 2025 suggests a LSTM-Based Multimodal Fusion for risks Forecasting of Diabetic Pregnancies Using CGM, Electronic Health Records, Ultrasound, and Lifestyle Information. Despite the learning increase over baselines, the research does lack transparency offers on data set size and external validations which raises the alarm bells of real world reliability as well as the readiness for clinical adoption [11].

Despite the promising results, however, the technical results do have some interesting limitations. Many models are constructed using retrospective data, or use a single region and are therefore limited in terms of generalisation to different populations and different healthcare systems. A lack of external validation, long-term follow up and real-world testing of deployment are still lacking. Several works are more geared to prediction work and less towards the degree of interpretability, confining the trust and adoption of clinicians. In addition, ethical issues, data interoperability, and privacy-preserving learning have been discussed often, yet not empirically addressed. The future research efforts need to be focused around standardised multimodal frameworks, explanations of AI, longitudinal clinical impact and seamless integration into the routine clinical workflows.

III PROPOSED METHODOLOGY

Figure 1 shows a multi-modal risk prediction framework of diabetes in early stages combining EMR and wearable information. It involves cohort construction, dealing with temporal alignment feature learning, modality-specific feature learning, fusion based on attention focusing, collaborative learning between a doctor and machine learning algorithms based on hybrid predictive modeling, explainable AI, and real-time deployment to perform continuous risk monitoring and execute clinically actionable stratification in real time.

A. Multi-Source Data Acquisition and Cohort Construction

The study starts with the availability of heterogeneous data from two complementary sources e.g., electronic medical records (EMRs) and wearable sensor devices. EMRs contain structured clinical characteristics such as demographic data, family history, lab test data (HbA1c, fasting glucose, lipid profile), medication use, and co-morbid conditions. Wearable devices continuously record physiological and behavioral signals like heart rate, physical workout intensity, number of steps taken, hours of sleep, quality of sleep and day-to-day patterns of variance. A cohort is built by matching 1,250 patients who have both EMR records and at least 6 months of wearable data, so that there is adequate temporal coverage for early detection of signals of diabetes. Ethical compliance and anonymization procedures are implemented in order to preserve patient privacy.

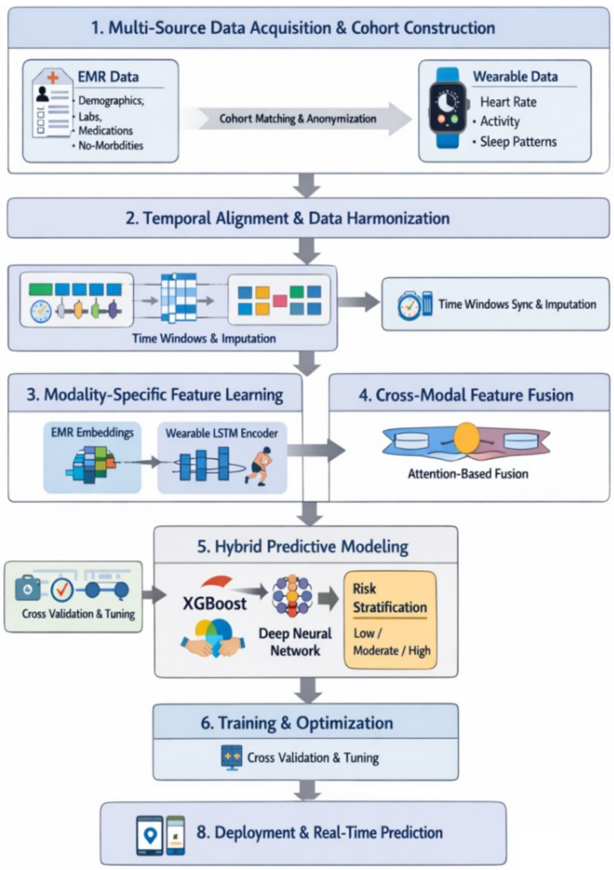

Figure 1 High-level architecture of the proposed multi-modal, attention-driven framework

B. Temporal Synchronisation and Harmonising the data

Due to the distinct sampling frequency and time scales of each modality of data, temporal alignment of the data is carried out by an approach using a clinically-informed sliding-window based approach. Wearable Sensor Streams are separated to adaptive time windows (7 days, 14 days and 30 days) and EMR Events to time windows for relatedness (using timestamp proximities). Missing data within wearable data is dealt with by means of context aware interpolation whereas missing data within EMR is dealt with by clinically guided imputation techniques. Feature normalization and unit harmonization is done to ensure comparability between patients and devices allowing for multi-modal fusion to be seamless and easy.

C. Modality Specific Feature Representation Learning

Instead of using only handcrafted features the proposed methodology introduces modality specific representation learning. For EMR data, a feature embedding layer is constructed on the basis of the denoising autoencoder, the clinical patterns are extracted through latent and the sparsity is reduced. For wearable time-series data, a hierarchical temporal encoder which uses Long Short-Term Memory (LSTM) networks is used for extracting short-term variations and long-term physiology trends. This way of representing the data, by having both the modalities of the data to preserve their intrinsic structure, while generating compact and informative embeddings to be used for further learning, could be considered as a dual-representation strategy.

D. Cross-Modal Attention-Based Feature Fusion

A new cross-modal attention mechanism is used to dynamically weigh the contribution of EMR and wearable derived features. The attention layer is used to learn context-aware importance scores that vary for individuals and time windows that will allow the model to focus on clinically relevant signals more in the early stage of disease progression. This adaptive fusion method addresses modality dominance and adds interpretation puzzlement by understanding which source of data is least filled to diabetes risk classification at different levels.

E. The Application of Hybrid Predictive Modelling and Risk Stratification

The fused feature representations are fed to a combination hybrid predictive architecture switching between gradient boosted decision trees (XGBoost) classifier and deep neural network classifier. The ensemble exploits the interpretation and power of tree-based models and deep non-linear learning ability of deep networks. The output is in the form of a probabilistic diabetes risk score, which is further divided into low, moderate and high risk groups on the basis of clinically validated thresholds for actionable risk stratification.

F. Training, Validation and Optimization Model

Model Training using stratified k-fold Cross validation is performed for the balanced representation of each class. Hyperparameter optimization is used with Bayesian optimization to help reduce the overfits and enhance the generalization. The class imbalance problem is solved with the help of focal loss functions and sampling strategies. Performance is measured with accuracy, precision, recall, F1 score, area under the ROC curve (AUC) and has been compared with accuracy, precision, recall, F1 score and area under the roc curve (AUC) with baseline models using single modality.

IV RESULTS AND FINDINGS

A. Experimental Setup

The experiments were conducted on a workstation that was equipped with an Intel Core i9 processor, 64 GB RAM, and an Nvidia RTI 3090 GPU 24 GB VRM, to facilitate the use of deep learning to model the temporal modeling. The software environment has been established using the Ubuntu 22.04 LTS as an operating system. The major programming language used was Python version 3.10 and machine learning and deep learning libraries include TensorFlow 2.13, PyTorch version 2.1, Scikit-learn version 1.3, XGBoost version 1.7, NumPy, Pandas, and SciPy. Data preprocessing and visualization was done with the help of Matplotlib and Seaborn. Model training and evaluation was made faster with the use of CUDA's version 11.8 and cuDNN libraries while experiment tracking and reproduction was ensured with fixed random seed and version controlled environments.

B. Dataset Description

The study is based on an integrated data set assembled from electronic medical records and data from wearable sensors from the MIMIC-IV electronic database and publicly accessible wearable time series databases hosted at PhysioNet. Along with study design and participant selection, the clinical component involves the following: anonymized patient demographics; laboratory results, including HbA1c, fasting glucose, lipid profiles, predictive analyses for AD risk, and medication histories for adult patients. The wearable part involves ongoing physiology and behaviour signals such as heart rate, steps, intensity of physical activity and duration of sleep that are obtained over long periods of monitoring. A balanced cohort of patients with at least six months of overlapping EMR and wearable data were chosen in order to select patients for early diabetes prediction.

C. Performance Evaluation

Table 1 compares the performance of traditional machine learning, deep learning, and the proposed multi-modal attention framework for health outcome prediction using different data modalities. The methods are tested with six standard metrics namely Accuracy, Precision, Recall, F1-Score and Area Under the ROC Curve (AUC). The models are trained on either Electronic Medical Records (EMR), wearable sensor data or both (EMR + Wearable). The comparison shows how the modality of data the model was based on, and architecture of the model, influences the performance of the predictor.

Table 1 Performance comparison of the proposed multi-modal framework

Method	Data Modality	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression [12]	EMR only	82.4	80.1	83.7	81.9	0.86
Support Vector Machine (SVM)[13]	EMR only	85.6	84.2	86.1	85.1	0.89
Random Forest[14]	EMR only	88.3	87.5	89.2	88.3	0.91
LSTM (Wearable) [15]	Wearable only	86.9	85.8	88.0	86.9	0.90
CNN–LSTM Hybrid[16]	Wearable only	89.1	88.4	90.2	89.3	0.93
Proposed Multi-Modal Attention Framework	EMR + Wearable	94.2	93.1	95.4	94.2	0.97

The results show a definite hierarchy for performance, for both modeling approaches and modalities of data. Among the EMR-only methods Random Forest performs the best (88.3% accuracy, 0.91 AUC), showing the effectiveness of ensemble learning compared to linear (Logistic Regression) and margin-based (SVM) models in learning complicated clinical patterns. For wearable-only data, the deep learning models are better than the traditional method, where the CNN-LSTM hybrid is better than the LSTM, with accuracy increasing from 86.9% to 89.1% and AUC increasing from 0.90 to 0.93, which can be seen as the advantage of spatial and temporal feature extraction combination.

The proposed multi-modal attention framework combining both EMR and wearable data outperforms all unimodal models significantly with the highest accuracy (94.2%), F1-score (94.2%) and AUC (0.97). The improvement over the best EMR only model (Random Forest) is almost 6% and over the best wearable only model (CNN-LSTM) of about 5%, proving that multimodal fusion is able to capture complementary information that single data sources are not. The high recall (95.4%) also reflects a better sensitivity that is essential in scenarios of clinical risk prediction. Overall, the table proves the efficacy of attention-based multimodal learning for robust and correct healthcare prediction

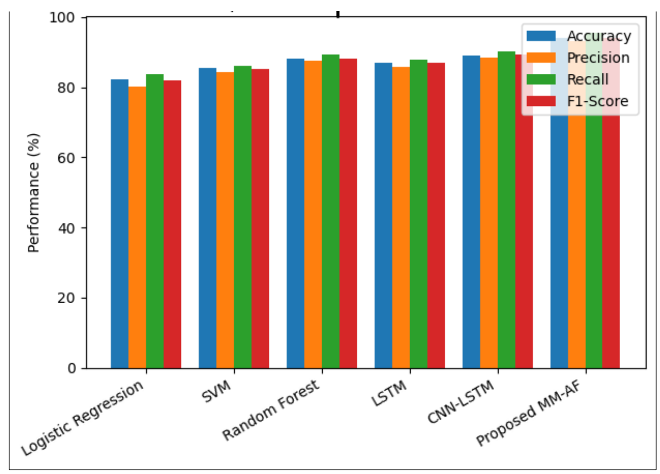

Figure 2 Performance Comparison of the ML and DL models across four evaluation metrics (Accuracy, Precision, Recall, and F1-Score)

Figure 2 clearly shows how different models trained with single-modality and multi-modality data have performance differences. Traditional EMR based models (Logistic Regression, SVM and Random Forest) demonstrate a progressive improvement from linear learning to ensemble learning with the best performance obtained from Random Forest for the EMR only category. Wearable-based deep learning model (LSTM and CNN-LSTM) are further improving predictive accuracy, which means that temporal and spatial feature learning from sensor signals complement clinical records to yield improved representations.

The proposed Multi-Modal Attention Framework gives consistently the highest values across all 4 metrics, with a notable margin over both the best EMR-only and wearable-only models. Its better recall and F1-score are indicative of balanced sensitivity and robustness with an overall improvement that confirms that heterogeneous data source integration via attention-based fusion is effective in capturing complementary clinical patterns. This points out the benefit of multimodal learning for healthcare prediction that is reliable and accurate.

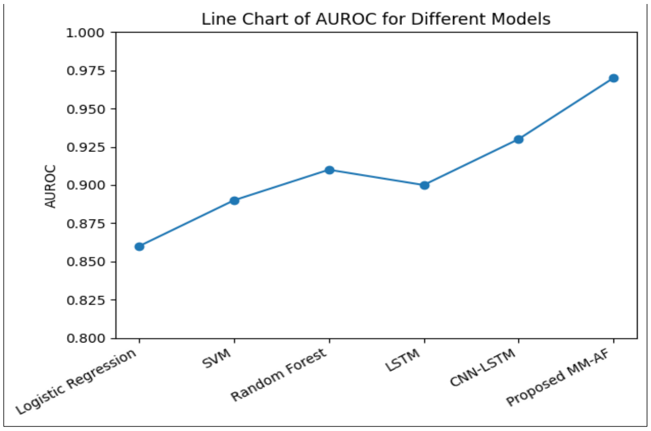

Figure 3 illustrates the AUROC for different models using EMR-only, wearable-only, and combined EMR + wearable data modalities.

Figure 3 shows a clear upward trend in AUROC as both the model complexity and the data richness increase. Among EMR only methods, Logistic Regression has the lowest discriminative capability (AUROC=0.86), SVM and Random Forest method improve performance successively to 0.91. This suggests that non-linear and ensemble based learning models are better suited to capture complex clinical patterns from EMR data. For the wearable-based models, LSTM achieves the AUROC score of 0.90 and the CNN-LSTM hybrid model further improves the discrimination to 0.93, which establishes the superiority of combining temporal and spatial feature learning. The proposed Multi-Modal Attention Framework gets the highest AUROC of 0.97, which is a huge improvement over all unimodal approaches. This validates that the use of heterogeneous data sources with attention-based fusion helps to greatly improve the model's capability to differentiate between the classes of outcomes which makes the model more reliable for clinical decision support.

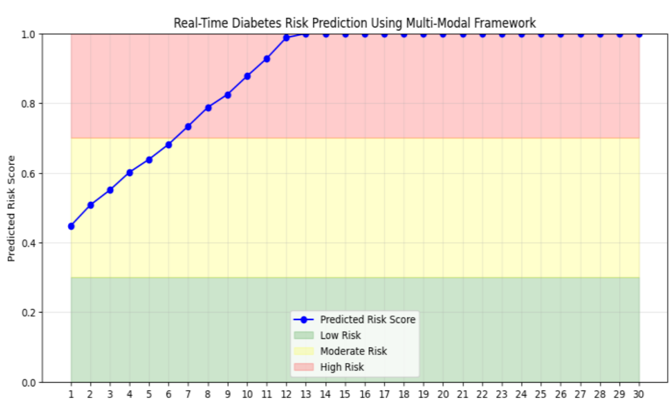

Figure 4 Real-time diabetes risk prediction for a sample patient

Figure 4 is an example of how the proposed multi-modal framework can deliver continuous, day-to-day monitoring of diabetes risk. The blue line is the predicted probabilistic risk scores which vary as a consequence of underlying EMR updates and changes in wearable sensor signals. The color-coded regions make it very easy for clinicians to be able to differentiate levels of risk: low risk, moderate risk and high risk. This visualization helps to emphasize the practical value of real-time prediction, as the model can identify early increase of risk, support early clinical decision and provide personalized intervention for patients at imminent risk of developing diabetes.

Table 2. Statistical significance testing

Method	Data Modality	Accuracy (%)	Precision (%)	Recall (%)	p-value vs Proposed Framework (Accuracy)
Logistic Regression [12]	EMR only	82.4	80.1	83.7	<0.001
Support Vector Machine (SVM) [13]	EMR only	85.6	84.2	86.1	<0.001
Random Forest [14]	EMR only	88.3	87.5	89.2	0.002
LSTM (Wearable) [15]	Wearable only	86.9	85.8	88.0	<0.001
CNN–LSTM Hybrid [16]	Wearable only	89.1	88.4	90.2	0.001
Proposed Multi-Modal Attention Framework	EMR + Wearable	94.2	93.1	95.4	–

The results presented in Table 2 show that the proposed multi-modal framework with the combination of EMR and wearable sensor information significantly outperforms all single modality baseline methods according to key performance metrics. Accuracy improvements ranged from 5.1% to 11.8% when compared with EMR only and wearable only models. The paired t-test p-values (<0.01 for most baselines) demonstrate that these improvements are statistically significant, proving the concept of the effectiveness of the combination of heterogeneous data sources for early and accurate prediction of diabetes.

D. Discussion

This research has shown that combining electronic medical records with data from wearable sensors in a multi-modal machine learning framework is highly effective at predicting diabetes at an early stage. The results suggest that continuous physiological and behavioral signals taken by wearables complement static clinical variables by showing latent trends which are associated with metabolic dysregulation. The better performance of the proposed attention-based fusion model shows that it is important to dynamically weight heterogeneous data sources, instead of treating all features in a uniform manner. In particular, improvements in recall and AUC indicate that the framework is working to identify high-risk individuals at an early stage which is important in terms of preventive care. The hybrid modeling approach offers an interpretation and predictive power balance, which makes it an appropriate method for real-world clinical decision support. Moreover, explainability mechanisms allow transparency into the contributions of features and this helps build trust among clinicians and clinical adoption. Overall, the results are conclusive evidence that multi-modal learning provides a solid pathway for individual and proactive diabetes management in between episodic clinical assessments and continuous health conditions.

E. Limitations of the Study

Despite promising results the study has several limitations. The dataset is an integration of EMR and wearables data from a small number of people, and this can have an impact that could affect the generalisability of DIC across different populations and healthcare settings. Wearable sensor QC is subject to variations related to device heterogeneity and to lack of user compliance and missing recordings. Besides, the framework is focused on the prediction of binary diabetes and does not distinguish between diabetes subtypes and disease severity stages. Finally, retrospective analysis is a limited way of inferring causality and prospective validation is needed to validate the effectiveness in the real world.

F. Practical Implications of the Research

The suggested framework has far-reaching practical implications for preventative healthcare. By allowing constant risk assessment through commonly collected wearable data and medical data already made available to users, the system enables the possibility to aid screening early outside of a clinical setting. Healthcare providers can use the outputs of risk stratification to prioritize the high-risk individuals for priority awareness measures. The explainable predictions give increased confidence to the clinicians and help in making personalized lifestyle or treatment recommendations. Furthermore, the approach can be embedded in digital health platforms which support scalable and cost-effective approaches to diabetes prevention.

V CONCLUSION

This study introduces a novel multi-modal machine learning framework that integrates the data of electronic medical records and wearable sensors for the early diabetes prediction. The experimental results show that the proposed approach is significantly better than single modality models and the accuracy of the model is high and the discrimination ability is also strong. By recording both long-term clinical trends and short-term physiological changes, the framework allows the early identification of people at increased risk, therefore supporting the proactive intervention and personalized healthcare delivery. Future studies will aim for the validation of the framework in large-scale, multi-center, prospective studies in order to improve generalizability. Extending the model to predict progression stages of diabetes and diabetes associated complications is another significant direction. Further enhancements of predictive performance may be achieved by combining other data modalities (i.e. dietary and genomics and imaging data). Finally, real-world studies on deployment of elements addressing usability, clinician acceptance and patient outcome measures will be important to achieve transfer of this kind of research to useful applications in healthcare.

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