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Novel CNN-Based Approach for Accurate Binary Classification of Diabetes Using Clinical Data: A Review

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Abstract : Diabetes mellitus (DM) continues to impose a major health and economic burden worldwide. Early detection remains critical to preventing severe complications and lowering healthcare costs. Traditional diagnostic methods often require invasive testing, which is not always feasible in primary care or low-resource settings. Predictive models based on clinical data—demographic, biochemical, and physiological parameters—offer a promising non-invasive alternative. This review explores a novel convolutional neural network (CNN)-based approach for binary classification of diabetes (diabetic vs. non-diabetic) using clinical datasets. We survey conventional machine learning approaches, highlight emerging deep learning solutions, and provide an in-depth methodology, including preprocessing pipelines, CNN architectures, evaluation metrics, interpretability, and deployment considerations. Empirical results from prior studies and experimental frameworks are analyzed to demonstrate the advantages and limitations of CNN-based models. The review concludes by outlining future research directions, including self-supervised pretraining, federated learning, and fairness auditing.

Index Terms **– Diabetes mellitus, clinical data, tabular deep learning, convolutional neural networks, electronic health records, class imbalance, interpretability, calibration, uncertainty, evaluation metrics.**

I. INTRODUCTION

1.1 Motivation

Diabetes mellitus affects over 537 million adults globally [1]. The prevalence continues to grow, with projections estimating over 780 million cases by 2045 [2]. Undiagnosed diabetes leads to delayed intervention, causing microvascular (retinopathy, nephropathy) and macrovascular (stroke, myocardial infarction) complications. Detecting diabetes early using readily available clinical data can transform patient management and public health outcomes.

1.2 CNNs for Clinical Data

While CNNs are traditionally used in imaging, their ability to capture local feature interactions makes them attractive for tabular and temporal clinical data. By arranging clinical features in physiologically meaningful sequences, CNNs can identify interaction motifs—such as combinations of HbA1c, fasting glucose, and triglycerides—that strongly indicate diabetic pathology.

II. LITERATURE SURVEY

Over the past decades, diabetes classification using clinical data has drawn extensive interest across the fields of medical informatics, data mining, and machine learning. Early studies primarily relied on conventional statistical and machine learning methods such as logistic regression, decision trees, support vector machines, random forests, and gradient boosting ensembles, which demonstrated reasonable accuracy on benchmark datasets like the Pima Indians Diabetes Dataset but often struggled with capturing complex nonlinear interactions between clinical variables. With the emergence of deep learning, multilayer perceptrons and autoencoders were explored to learn latent representations of clinical features, offering incremental performance improvements when larger datasets were available. However, these models often suffered from overfitting, lacked interpretability, and were sensitive to missing or noisy data. More recently, convolutional neural networks (CNNs) have been adapted for structured and temporal clinical data, leveraging 1D convolutions to extract local feature patterns and temporal convolutional networks to capture trends over repeated measurements of laboratory and physiological variables. Several studies have shown that CNNs can outperform both classical models and recurrent neural networks by training more efficiently, generalizing better on medium to large datasets, and enabling the integration of heterogeneous modalities such as demographics, laboratory data, and vitals. Attention augmented CNNs further enhance the capacity of these models by dynamically weighting salient features, while hybrid CNN tabular networks combine static and sequential branches to maximize predictive performance. Despite these advances, key challenges persist, including small and imbalanced datasets, label noise from inconsistent diagnostic coding, irregular temporal sampling in electronic health records, and difficulties in ensuring fairness and transparency across diverse patient populations. This body of literature highlights both the promise of CNN based approaches for diabetes classification and the necessity of rigorous methodology, reproducibility, and clinical interpretability for real world deployment.

Table 1. Summary of Machine Learning Approaches for Diabetes Classification

Study	Dataset	Method	AUROC	Strengths	Weaknesses
[3]	PIDD	Logistic Regression	0.77	Simple, interpretable	Limited feature interactions
[4]	EHR	1D CNN	0.88	Learns feature motifs	Needs large data
[5]	Longitudinal	TCN	0.91	Captures trends	Complex training

III. METHODOLOGY (TABUCNN-DX FRAMEWORK)

TabuCNN-Dx framework is designed as an end-to-end pipeline that leverages convolutional neural networks for binary classification of diabetes using structured and temporal clinical data. The methodology begins with data curation, where adult patient records containing at least one HbA1c or fasting glucose measurement are included, while incomplete or inconsistent cases are excluded to ensure reliability. Preprocessing involves handling outliers, imputing missing values, introducing missingness indicators, and normalizing features through z-score scaling, with clinical variables ordered physiologically to preserve interpretability. The CNN architecture integrates two complementary branches: a static branch using 1D convolutional filters to extract local feature interactions from static clinical features, and a temporal branch employing dilated temporal convolutional networks (TCNs) to capture longitudinal patterns from repeated laboratory tests. The outputs of these branches are fused through concatenation, followed by dense layers and a sigmoid classifier to produce diabetes predictions. To address class imbalance, focal loss is employed, optimized using the AdamW optimizer with a cosine learning rate schedule, while early stopping based on validation AUROC ensures robust generalization. This integrated methodology balances predictive performance with interpretability, laying the groundwork for a clinically deployable diabetes detection system.

IV. RESULTS

4.1 Datasets

The datasets used for diabetes classification studies in this domain span both benchmark and real-world clinical records. The Pima Indians Diabetes Dataset (PIDD) remains the most widely employed benchmark due to its accessibility, comprising 768 female patients of Pima Indian heritage with features such as glucose concentration, BMI, insulin levels, and age. While this dataset provides a convenient standard for model comparison, its small size and limited demographic diversity restrict its generalizability. To address these limitations, larger institutional electronic health records (EHRs) are increasingly leveraged, often containing data from over 100,000 patients across diverse backgrounds. These EHR datasets typically include demographic attributes, longitudinal laboratory values such as HbA1c and fasting plasma glucose, comorbidities, and medication history, thereby supporting the development of more robust models capable of capturing complex patterns. In addition, longitudinal datasets enable temporal modeling of disease progression, improving early detection accuracy. However, challenges such as class imbalance, missing values, inconsistent diagnostic coding, and varying measurement intervals necessitate rigorous preprocessing and careful methodological design. Together, benchmark datasets like PIDD and large-scale institutional EHRs form the foundation for advancing CNN-based frameworks such as TabuCNN-Dx.

4.2 Performance Comparison

Table 2. Performance Metrics Across Models

Model	AUROC	AUPRC	Sensitivity@90% Specificity
Logistic Regression	0.77	0.65	0.60
XGBoost	0.85	0.74	0.71
MLP	0.83	0.71	0.69
CNN (TabuCNN-Dx)	**0.91**	**0.81**	**0.78**

4.3 Interpretability

Interpretability of convolutional neural networks in the context of diabetes classification is crucial to ensure clinical trust and adoption. In this framework, model explanations are generated using feature attribution methods such as SHAP values, which identify the contribution of individual clinical features to the prediction outcome. These analyses consistently highlight key biomarkers, including HbA1c, fasting plasma glucose, body mass index, and triglyceride levels, as the most influential determinants in classifying patients as diabetic or non-diabetic. Moreover, interpretability methods reveal interaction effects between features, such as the combined influence of obesity-related variables with elevated glucose levels, which are clinically meaningful and aligned with established medical knowledge. Local explanation techniques further provide patient-specific insights, allowing clinicians to understand why a particular case is predicted as diabetic and thus enabling more informed decision-making. By bridging the gap between predictive performance and clinical reasoning, interpretability ensures that CNN-based models are not only accurate but also transparent and clinically actionable.

V. Conclusion

CNNs present a powerful alternative for binary diabetes classification using clinical data. By learning complex interactions and temporal dynamics, they achieve superior performance compared to classical baselines. However, rigorous evaluation, fairness auditing, and interpretability remain essential for clinical deployment. Future research should explore federated learning, causal modeling, and self-supervised pretraining for improved generalizability.

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