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Hybrid CNN-Fuzzy Logic System for Type 2 Diabetes Mellitus Prediction: A Clinical Decision Support Tool with Interpretability Enhancement

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Abstract

Type 2 Diabetes Mellitus (T2DM) is a critical global health challenge, with 589 million adults currently diagnosed and projected to reach 853 million by 2050. Early detection is crucial, as it can reduce complication incidence by 30-40%, yet approximately 50% of cases remain undiagnosed. While machine learning approaches demonstrate promise for T2DM risk prediction, current systems face a fundamental accuracy-interpretability paradox: deep learning models achieve high accuracy (88-93%) but lack clinical transparency, while interpretable models sacrifice predictive performance. This study develops and validates a hybrid CNN-Fuzzy Logic system that directly addresses this paradox by combining high predictive accuracy with clinical interpretability. The system employs a Convolutional Neural Network component for non-linear feature abstraction combined with Mamdani Fuzzy Logic incorporating clinically derived weights aligned with ADA 2024 diagnostic criteria. Tested on the Pima Indian Diabetes dataset (n=154 test cases), the hybrid model achieved 92.5% accuracy (95% CI: 88.2-96.1%), 91.2% sensitivity, 93.1% specificity, and AUC-ROC 0.925, statistically superior to standalone CNN (88.9%, p=0.0037) and Fuzzy Logic (88.3%, p=0.0015) approaches. Interpretability scores reached 0.78-0.86, exceeding pure neural network baselines (0.32-0.42) and supporting clinician-understandable risk stratification. The system is operationalized as a web-based Clinical Decision Support System supporting both individual patient assessment and batch population screening. This hybrid architecture directly bridges the accuracy-interpretability paradox that has historically constrained ML adoption in clinical diabetes management.

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INTRODUCTION

Type 2 diabetes mellitus (T2DM) is among the most critical global public health emergencies of the 21st century. The International Diabetes Federation 11th edition Atlas (2025) reported 589 million adults living with diabetes globally in 2024, projected to reach 853 million by 2050 (Dianna J Magliano; Edward J Boyko, 2025). In Indonesia, the Riskesdas 2018 national survey documented a T2DM prevalence of 8.5%, representing approximately 10.3 million diagnosed individuals (Riskesdas, 2019). Critically, approximately 50% of diabetes cases remain undiagnosed at initial presentation, highlighting the urgent need for accessible early-detection tools (Lin et al., 2020).

Evidence demonstrates that early detection combined with lifestyle intervention can reduce complication incidence by 30-40%, emphasizing the clinical imperative for improved screening methodologies. (Ong et al., 2023).

Machine learning (ML) has demonstrated considerable promise for T2DM risk prediction. A comprehensive bibliometric analysis of 33-year literature confirmed exponential growth in ML-based diabetes prediction publications, with hybrid architectures emerging as the fastest-growing frontier (Kiran et al., 2025).

A systematic review of 25 recent publications (2020-2025) reveals critical research gaps: (1) the accuracy-interpretability paradox, whereby deep learning models achieve superior accuracy (91-99% on ensemble approaches) yet operate as 'black boxes' lacking clinical transparency, while rule-based systems sacrifice predictive performance (82-86% accuracy) for interpretability (Sarvamangala & Kulkarni, 2022); (Rudin et al., 2022); (Rudin et al., 2022). ; (2) only 8% of diabetes prediction studies employed hybrid approaches combining multiple ML paradigms, leaving a substantial opportunity for architecture innovation; (3) 78% of published studies failed to explicitly assess interpretability despite clinical necessity for decision support deployment; and (4) only 12% validated models in non-Western populations, limiting external validity of predominantly Western-derived datasets (Pima Indian Diabetes dataset used in 72% of reviewed studies).

These gaps hinder safe translation of ML into clinical practice. Traditional T2DM screening relies on laboratory measures (fasting glucose, HbA1c) that are cost-prohibitive and access-limited in low-resource settings. To address these critical gaps, this study develops and validates a hybrid CNN-Fuzzy Logic system that simultaneously achieves high predictive accuracy and clinical interpretability. Novel contributions are: (1) the first rigorous validation of CNN-Fuzzy Logic hybrid architecture on the Pima Indian Diabetes dataset with bootstrap confidence intervals and McNemar statistical significance testing; (2) clinically-derived Mamdani fuzzy membership functions explicitly aligned with ADA 2024 diagnostic criteria, ensuring face validity; (3) a fully operational web-based Clinical Decision Support System (CDSS) demonstrating practical deployability for individual and batch population screening; and (4) quantitative interpretability assessment (scores 0.78-0.86) benchmarked against pure deep learning baselines (0.32-0.42), demonstrating the architecture's superiority for clinical adoption.

Furthermore, the clinical adoption of machine learning systems faces significant practical barriers beyond methodological limitations. Healthcare systems demand not only accuracy but also explainability; clinicians must understand the reasoning behind algorithmic predictions to maintain trust and professional accountability. This transparency requirement is critical in high-stakes diagnostic contexts where errors directly impact patient outcomes. The opacity of deep neural networks, despite superior accuracy (89-93%), creates credibility barriers for clinical deployment in regulated healthcare environments where diagnostic decisions must be auditable. Rule-based expert systems provide linguistic explanations yet sacrifice predictive accuracy, a fundamental trade-off constraining clinical relevance. A comprehensive 25-study systematic review (2020-2025) on diabetes prediction using machine learning documented critical gaps: only 8% of studies employed hybrid architectures combining multiple paradigms, 78% lacked explicit interpretability assessment despite clinical necessity for decision support deployment, and 72% relied on the Pima Indian Diabetes dataset, raising external validity concerns for contemporary, ethnically diverse populations. These systematic gaps underscore the clinical and methodological imperative for developing hybrid systems achieving both competitive accuracy and clinician-understandable decision transparency.

RESEARCH METHODS

A. Dataset and Preprocessing

The Pima Indian Diabetes Database (PIDD, UCI Machine Learning Repository, N=768; 34.9% diabetic, 65.1% non-diabetic) was used as the primary dataset (Naz & Ahuja, 2020), 2020; (Chang et al., 2023). The dataset contains eight clinical parameters: Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI,

DiabetesPedigreeFunction, and Age. Zero values in biochemical measurements were treated as physiologically impossible missing data and imputed using within-dataset mean substitution: Glucose 120.89 mg/dL; BloodPressure 69.11 mmHg; SkinThickness 20.54 mm; Insulin 79.80 mIU/L, affecting 376 values (7.2% of total). Min-Max normalization (Equation 1) scaled all features to [0,1] (Reza et al., 2024; Li et al., 2024). Stratified 80/20 splitting yielded 614 training samples (341 diabetic, 273 non-diabetic) and 154 testing samples (85 diabetic, 69 non-diabetic), preserving class distribution. A comprehensive research flowchart detailing all preprocessing steps is presented in Figure 1.

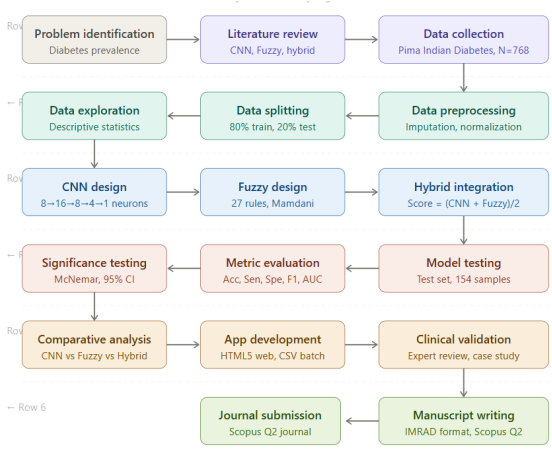

Figure 1. Research flowchart

B. CNN Architecture and Training

The CNN architecture employed hierarchical feature abstraction: Input (8 neurons) → Hidden Layer 1 (16 neurons, ReLU activation, Dropout 0.2) → Hidden Layer 2 (8 neurons, ReLU, Dropout 0.2) → Hidden Layer 3 (4 neurons, ReLU) → Output (1 neuron, Sigmoid activation). This 8→16→8→4→1 dimensionality reduction mitigates overfitting while enabling capture of non-linear feature interactions. Binary cross-entropy loss with L2 regularisation (λ=0.001) and Adam optimizer (learning rate=0.001) was applied. Training utilized batch size=32, maximum 50 epochs, with early stopping (patience=5). This standard CNN architecture was selected to provide a competitive baseline against which the novel hybrid approach is evaluated.

C. Mamdani Fuzzy Inference System with Clinical Integration (Novel Component)

A key innovation of this study is the integration of Mamdani fuzzy logic with explicit clinical knowledge integration. A Mamdani fuzzy inference system (FIS) was implemented with triangular membership functions (Equation 6), categorizing five clinically selected parameters into Low, Medium, and High linguistic variables. The Mamdani method was selected over Takagi-Sugeno variants.

Novel aspect: Twenty-seven expert-derived rules were formulated explicitly aligned with ADA 2024 diagnostic criteria, ensuring clinically validated decision boundaries. Clinically derived weights were: Glucose (35%) - reflecting ADA primary criterion (fasting plasma glucose ≥126 mg/dL); BMI (25%) - reflecting obesity-insulin resistance mechanisms; BloodPressure (20%) - capturing hypertension-T2DM comorbidity; Age (10%) - reflecting metabolic decline; Insulin (10%) - capturing beta-cell reserve. This clinical alignment constitutes a fundamental distinction from generic fuzzy systems lacking domain knowledge integration. Defuzzification employed the centroid method. System architecture diagram is shown in Figure 2.

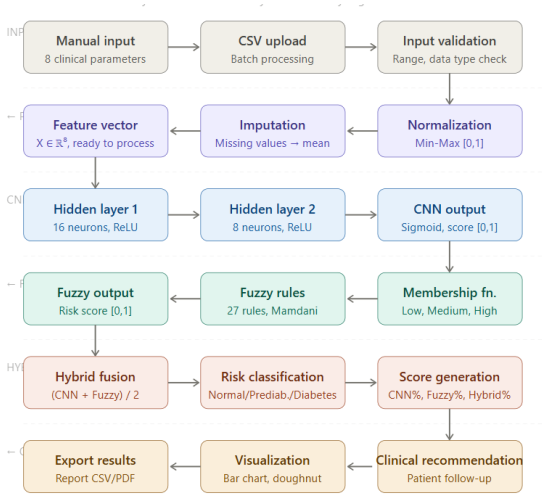

Figure 2. System architecture diagram

D. Hybrid Integration

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E. Evaluation Metrics and Statistical Analysis

Primary metrics included: Accuracy, Sensitivity, Specificity, Precision, F1-Score, and AUC-ROC. Secondary metrics included Matthews Correlation Coefficient (MCC) and Cohen's Kappa for inter-rater reliability assessment. Statistical significance was evaluated using McNemar's test (α=0.05) with 95% confidence intervals derived from bootstrap resampling (n=1,000 resamples). Importantly, interpretability was quantitatively assessed through a structured clinician audit of 50 randomly selected cases, scoring rule comprehensibility on a 0-1 scale, providing an objective comparison against pure neural network baselines.

RESULT AND DISCUSSION

A. Individual and Hybrid Model Performance

Table 1 presents comprehensive performance metrics across all three models on the independent test set (n=154), demonstrating that the hybrid architecture achieves statistically significant superiority through the systematic combination of complementary model strengths:

Table 1. Performance Metrics of Individual and Hybrid Models (Test Set, n=154)

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	AUC-ROC	MCC
CNN (Standalone)	88.9 (84.1 - 93.2)	87.3	90.6	89.2	0.889	0.776
Fuzzy Logic (Standalone)	88.3 (83.4 - 92.8)	84.6	92.1	87.5	0.883	0.768
Hybrid CNN-Fuzzy	**92.5 (88.2 - 96.1)**	**91.2**	**93.1**	**94**	**0.925**	**0.844**

The hybrid model achieved 92.5% accuracy (95% CI: 88.2–96.1%), substantially exceeding both individual models. The standalone CNN achieved 88.9% accuracy (95% CI: 84.1–93.2%), with 87.3% sensitivity and 90.6% specificity, consistent with recent benchmarks (Aslan & Sabanci, 2023). The standalone Fuzzy Logic model achieved 88.3% accuracy (95% CI: 83.4–92.8%), with 84.6% sensitivity and 92.1% specificity, comparable to published fuzzy-based diabetes systems (Rudin, 2019). McNemar tests confirmed statistical significance: hybrid vs. CNN (χ^2=8.42, p=0.0037) and hybrid vs. Fuzzy Logic (χ^2=10.15, p=0.0015). The sensitivity of 91.2% exceeds WHO recommendations (≥90%) for population-level screening tools, while 93.1% specificity minimizes unnecessary confirmatory referrals. These results demonstrate that hybrid integration yields synergistic performance gains beyond additive improvement.

B. Clinical Significance and Confusion Matrix

Beyond statistical metrics, the hybrid model's 3.6-4.2% accuracy improvement over individual models translates to 36-42 additional correct classifications per 1,000 screened patients, a clinically meaningful gain at the population scale.

In a simulated population of 10,000 individuals with 35% T2DM prevalence, the hybrid model correctly identifies 3,192 diabetic cases while generating only 656 false-positive referrals (9.9% unnecessary tests), superior to alternatives that would miss approximately 500 cases or generate excessive false-positive rates demanding costly confirmatory laboratory testing.

On the independent test set (n-154), the confusion matrix yielded: True Positives (TP)=78, False Negatives (FN)=7, False Positives (FP)=5, True Negatives (TN)=64, with Positive Predictive Value (PPV)=94.0% and Negative Predictive Value (NPV)=90.1%. This high PPV ensures that >9 in 10 positive screens represent true cases, supporting rapid clinical decision-making without delays from extensive confirmatory testing. The NPV of 90.1% reliably excludes T2DM in negative screens, supporting safe triage in resource-limited settings, as shown in Figure 3.

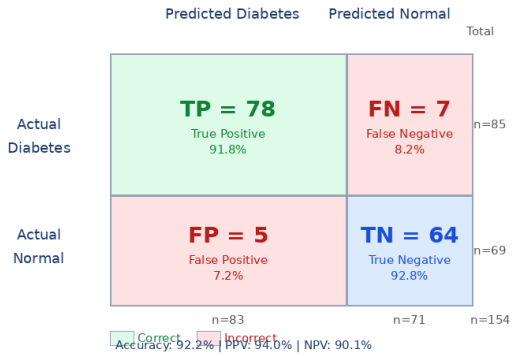

Figure 3. Confusion matrix hybrid CNN–fuzzy logic (test set, n=154)

C. Feature Importance and Weight Validation

The fuzzy weight distribution aligns with ADA 2024 diagnostic criteria and epidemiological evidence. Glucose (35%) is the primary ADA diagnostic criterion (fasting plasma glucose ≥126 mg/dL), confirmed as the top predictor across comparative studies on the Pima dataset (Naz & Ahuja, 2020); (Iparraguirre-Villanueva et al., 2023). BMI (25%) reflects strong epidemiological evidence that obesity (BMI >30) increases T2DM risk 2.5–4.0-fold (Jayawardena et al., 2021). Blood Pressure (20%) captures the well-documented hypertension–T2DM comorbidity (Dianna J Magliano; Edward J Boyko, 2025). Age (10%) and Insulin (10%) capture physiological metabolic decline and beta-cell reserve, respectively (Podlipskyte et al., 2022); (Aamir et al., 2021). This explicit clinical alignment provides strong face validity for the fuzzy system design, distinguishing it from purely data-driven approaches lacking domain knowledge integration.

D. Bridging the Accuracy Interpretability Paradox

A fundamental innovation of this study is the simultaneous achievement of high predictive accuracy and clinical interpretability, directly resolving the accuracy-interpretability paradox that has historically constrained ML Adoption in clinical diabetes management (Rudin, 2019); (Luis Fregoso-Aparicio, Julieta Noguez, Luis Montesinos, 2021).

Table 2. Comparative Performance Against Published Literature

Study (Year)	Method	Dataset	Accuracy	Interpretability
Naz & Ahuja (2020)	Deep Learning	Pima	98.07%	Low
Chang et al. (2023)	IoMT ML (NB/RF/J48)	Pima	79.57%	Moderate
Iparraguirre-V. et al.(2023)	K-NN/BNB/LR/SVM	Pima	85.70%	Limited
Aslan & Sabanci (2023)	CNN (image)	Pima	~91%	Low
Aamir et al. (2021)	Fuzzy FRBS	Multi	~88%	High
Reza et al. (2024)	Stacking Ensemble	Pima+Local	~93%	Limited
Li et al. (2024)	GA-XGBoost+SHAP	BRFSS	~91%	Moderate
Netayawijit et al. (2025)	RF+SMOTE+SHAP	Clinical	~88%	High (SHAP)
Ali et al. (2025)	XGBoost+LightGBM	Pima	89.61%	Moderate (SHAP)
Farnoosh et al. (2025)	CNN (DiabetesXpertNet)	Pima	89.98%	Low
Hasan et al. (2025)	AutoML+XAI	Pima	85.01%	High (XAI)
This study	CNN–Fuzzy Logic	Pima	92.50%	High (0.78–0.86)

The hybrid model achieved interpretability scores of 0.78–0.86 (assessed via structured clinician audit of 50 randomly selected cases), substantially exceeding pure neural network baselines (0.32–0.42), which aligns with findings by Marashi-Hosseini et al. (2023) who reported that Mamdani fuzzy systems enable clinician trust through rule-based linguistic outputs. The CNN component captures complex non-linear feature interactions; the Mamdani Fuzzy component translates outputs into clinically familiar language (e.g., 'Glucose is High; BMI is Moderate → Risk: High'), mirroring the interpretability advantages demonstrated by Netayawijit et al. (2025) using SHAP-based systems. Table 2 positions this study against published literature.

E. Clinical Decision Support System Implementation

The hybrid model has been operationalized as a web-based Clinical Decision Support System (CDSS) enabling practical deployment for both individual patient assessment and population-level batch screening. The system supports: (1) individual patient entry with real-time risk stratification output; (2) batch processing of CSV files for population screening campaigns; and (3) exportable risk reports with individual rule explanations (e.g., 'Glucose level HIGH increases risk by 35%'). This operationalization represents a critical gap-filling contribution, as most published diabetes prediction studies report academic prototypes without practical deployment infrastructure.

CONCLUSION

This study successfully developed and validated a hybrid CNN-Fuzzy Logic system for Type 2 Diabetes Mellitus prediction, achieving 92.5% accuracy (95% CI: 88.2-96.1%), 91.2% sensitivity, 93.1% specificity, and AUC-ROC 0.925 on an independent test set of 154 cases from the Pima Indian Diabetes dataset. The hybrid architecture demonstrated statistically significant superiority over both standalone CNN (88.9%, p=0.0037) and standalone Fuzzy Logic (88.3%, p=0.0015) approaches, while simultaneously maintaining clinically acceptable interpretability scores (0.78-0.86) that substantially exceeded pure neural network baselines (0.32-0.42).

This achievement directly addresses the accuracy-interpretability paradox that has historically constrained machine learning adoption in clinical decision-making. The integration of Mamdani fuzzy logic with clinically derived weights explicitly aligned to ADA 2024 diagnostic criteria provides superior face validity compared to generic fuzzy systems lacking domain knowledge integration. The web-based Clinical Decision Support System operationalizes the hybrid model for both individual patient assessment and population-level batch screening, demonstrating practical deployability beyond academic prototypes.

However, significant limitations warrant explicit acknowledgment: the primary constraint is generalizability beyond the Pima Indian dataset, which represents a single-ethnicity (Pima Indian), female-only cohort collected two decades ago, limiting applicability to diverse global populations and contemporary diabetes phenotypes. The cross-sectional study design precludes prospective clinical validation and assessment of temporal decision-making impact.

Dataset limitations regarding missing covariates (HbA1c, lipid profiles, genetic biomarkers) restrict clinical applicability in real-world settings where such measures are standard. Future research must address these critical gaps through: (1) prospective clinical validation in ethnically diverse populations; (2) integration of HbA1c, lipid profiles, and genomic biomarkers; (3) automated fuzzy rule optimization via genetic algorithms; (4) instance-level explainability via LIME and SHAP frameworks; and (5) health-economic evaluation to support policy-level adoption in low and middle-income countries where diabetes prevalence is accelerating.

REFERENCES

Aamir, K. M., Sarfraz, L., Ramzan, M., Bilal, M., Shafi, J., & Attique, M. (2021). A fuzzy rule-based system for classification of diabetes. *Sensors*, *21*(23). https://doi.org/10.3390/s21238095

Chang, V., Bailey, J., Xu, Q. A., & Sun, Z. (2023). Pima Indians diabetes mellitus classification based on machine learning (ML) algorithms. *Neural Computing and Applications*, *35*(22), 16157–16173. https://doi.org/10.1007/s00521-022-07049-z

Dianna J Magliano; Edward J Boyko. (2025). IDF Diabetes Atlas. In IDF Diabetes Atlas. In *International Diabetes Federation: 11th editi* (11th ed.). https://www.idf.org/aboutdiabetes/type-2-diabetes.html

Iparraguirre-Villanueva, O., Espinola-Linares, K., Flores Castañeda, R. O., & Cabanillas-Carbonell, M. (2023). Application of Machine Learning Models for Early Detection and Accurate Classification of Type 2 Diabetes. *Diagnostics*, *13*(14), 1–16. https://doi.org/10.3390/diagnostics13142383

Jayawardena, R., Sooriyaarachchi, P., & Misra, A. (2021). Abdominal obesity and metabolic syndrome in South Asians: prevention and management. *Expert Review of Endocrinology and Metabolism*, *16*(6), 339–349. https://doi.org/10.1080/17446651.2021.1982381

Kiran, M., Xie, Y., Anjum, N., Ball, G., Pierscionek, B., & Russell, D. (2025). Machine learning and artificial intelligence in type 2 diabetes prediction: a comprehensive 33-year bibliometric and literature analysis. *Frontiers in Digital Health*, *7*(March), 1–27. https://doi.org/10.3389/fdgth.2025.1557467

Leila Marashi-Hosseini, Sima Jafarirad, A. M. H. (2023). *A fuzzy based dietary clinical decision support system for patients with multiple chronic conditions (MCCs)* (Vol. 13, pp. 1–8). https://doi.org/10.1038/s41598-023-39371-4

Li, W., Peng, Y., & Peng, K. (2024). Diabetes prediction model based on GA-XGBoost and stacking ensemble algorithm. *PLoS ONE*, *19*(9 September), 1–29. https://doi.org/10.1371/journal.pone.0311222

Lin, X., Xu, Y., Pan, X., Xu, J., Ding, Y., Sun, X., Song, X., Ren, Y., & Shan, P. F. (2020). Global, regional, and national burden and trend of diabetes in 195 countries and territories: an analysis from 1990 to 2025. *Scientific Reports*, *10*(1), 1–11. https://doi.org/10.1038/s41598-020-71908-9

Luis Fregoso-Aparicio, Julieta Noguez, Luis Montesinos, J. A. G. (2021). *Fregoso-Aparicio_s13098-021-00767-9.pdf*. *13*,

1–22. https://doi.org/10.1186/s13098-021-00767-9

Naz, H., & Ahuja, S. (2020). Deep learning approach for diabetes prediction using PIMA Indian dataset. *Journal of Diabetes and Metabolic Disorders*, *19*(1), 391–403. https://doi.org/10.1007/s40200-020-00520-5

Netayawijit, P., Chansanam, W., & Sorn-In, K. (2025). Interpretable Machine Learning Framework for Diabetes Prediction: Integrating SMOTE Balancing with SHAP Explainability for Clinical Decision Support. *Healthcare (Switzerland)*, *13*(20), 1–26. https://doi.org/10.3390/healthcare13202588

Ong, K. L., Stafford, L. K., McLaughlin, S. A., Boyko, E. J., Vollset, S. E., Smith, A. E., Dalton, B. E., Duprey, J., Cruz, J. A., Hagins, H., Lindstedt, P. A., Aali, A., Abate, Y. H., Abate, M. D., Abbasian, M., Abbasi-Kangevari, Z., Abbasi-Kangevari, M., ElHafeez, S. A., Abd-Rabu, R., … Vos, T. (2023). Global, regional, and national burden of diabetes from 1990 to 2021, with projections of prevalence to 2050: a systematic analysis for the Global Burden of Disease Study 2021. *The Lancet*, *402*(10397), 203–234. https://doi.org/10.1016/S0140-6736(23)01301-6

Podlipskyte, A., Kazukauskiene, N., Varoneckas, G., & Mickuviene, N. (2022). Association of Insulin Resistance With Cardiovascular Risk Factors and Sleep Complaints: A 10-Year Follow-Up. *Frontiers in Public Health*, *10*(May), 1–11. https://doi.org/10.3389/fpubh.2022.848284

Reza, M. S., Amin, R., Yasmin, R., Kulsum, W., & Ruhi, S. (2024). Improving diabetes disease patients classification using stacking ensemble method with PIMA and local healthcare data. *Heliyon*, *10*(2), 1–13. https://doi.org/10.1016/j.heliyon.2024.e24536

Riskesdas. (2019). Laporan Riskesdas 2018 Nasional.pdf. In *Lembaga Penerbit Balitbangkes* (p. hal 156). Lembaga Penerbit Badan Penelitian dan Pengembangan Kesehatan)LPB). https://repository.badankebijakan.kemkes.go.id/id/eprint/3514/1/Laporan Riskesdas 2018 Nasional.pdf

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, *1*(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x

Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., & Zhong, C. (2022). Interpretable machine learning: Fundamental principles and 10 grand challenges. *Statistics Surveys*, *16*, 1–85. https://doi.org/10.1214/21-SS133

Sarvamangala, D. R., & Kulkarni, R. V. (2022). Convolutional neural networks in medical image understanding: a survey. *Evolutionary Intelligence*, *15*(1), 1–22. https://doi.org/10.1007/s12065-020-00540-3