JCBD
JOURNAL OF COMPUTERS AND DIGITAL BUSINESS
Volume 4, Number 3, September 2025, pp. 115-121
Homepage: https://jurnal.delitekno.co.id/index.php/jcbd

# The Hybrid Deep Learning ANN-CNN Model for Enhancing Diabetes Prediction

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https://doi.org/10.56427/jcbd.v4i3.766

**ARTICLE INFO**

**Article History**
Received: April 27, 2025
Revised: August 20, 2025
Accepted: September 25, 2025

***Keywords***
*Diabetes Prediction,*
*Deep Learning,*
*ANN–CNN Hybrid Model,*
*Clinical Decision Support,*
*Medical Data Analysis*

**ABSTRACT**

Diabetes mellitus is a global chronic metabolic disease that poses a serious threat to human health. Accurate and early prediction of diabetes is essential for effective medical treatment and long-term disease management. In this study, we propose a deep learning–based framework as a novel approach for diabetes prediction using a large-scale dataset containing more than 6,000 patient records. Several deep learning architectures, including Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), are examined to determine the most effective model for prediction tasks. Building on the strengths of both methods, this research introduces a hybrid ANN–CNN architecture designed to leverage ANN's capability in learning nonlinear relationships and CNN's efficiency in extracting high-level feature patterns. Extensive data preprocessing and feature extraction were conducted to enhance model performance and ensure reliable outcomes. Experimental results demonstrate that the hybrid ANN–CNN model achieved the highest prediction accuracy of 91.4%, surpassing standalone ANN (86.2%) and CNN (88.9%) models. These findings highlight the potential of hybrid deep learning frameworks in improving clinical decision support systems, enabling more accurate risk assessment and early intervention for diabetes. The results further indicate that integrating complementary neural network structures can significantly enhance predictive performance in complex medical datasets.



## 1. Introduction

The growing global prevalence of diabetes mellitus is a rising health concern. It stems from elevated levels of blood glucose due to a failing insulin secretion system, ineffective actions of insulin, or both. The two major types are Type 1 and Type 2 diabetes, the latter dominating 90% of diabetes cases [1]. Weak management of diabetes can lead to serious cardiovascular complications, kidney complications, nerve damage and vision loss [2]. Lessening the impact of diabetes on people and healthcare systems requires active intervention in its early stages [3]. Having well-defined precision models enables clinicians to predict and manage early enough which will increase health outcomes and reduce healthcare expenditure costs [4].

Diabetes has already been predicted with traditional statistical techniques like logistic regression and decision trees [5]. However, they seem to be effective only to a certain degree because they are overly dependent on linear relations and patterns hidden within data might be very complex [6]. Support Vector Machines (SVMs) and Random Forests, which utilize machine learning techniques, have shown to enhance results [7]. However, they still require a lot of preliminary work in feature construction. Deep learning, which is a sub-type of machine learning is focusing on multi-layered artificial neural networks, adeptly builds complicated representations of data which other methods fail to do [8][9]. It is excellent at finding hidden, non-linear relationships in data and has outperformed other techniques in areas such as classifying images and text, and more recently, diagnosing diseases and predicting them [10]. This paper looks into how deep learning approaches can be utilized in predicting diabetes using organized structured clinical datasets. The objective of this project is to build a reliable and precise scalable model to support healthcare specialists in early diagnosis. Through the application of different systematic deep learning models, intelligent data preprocessing, and selective feature distribution, this study intends to tackle the already difficult problem of intelligent healthcare.

These days, a notable amount of research is being conducted aiming at predicting diabetes using various techniques from machine learning and deep learning [1]. Severals studies have shown some advancement. Basic methods like SVM, decision trees, and even logistic regression have had some measurable success [11]. Later on, researchers shifted toward deep learning as it was more effective at capturing non-linear relationships [12]. Neural networks were shown to provide better performance [13][14]. Still, there are no thorough studies integrating multiple models alongside deep learning and intricate detailing of the preprocessing steps. To better generalization, employed CNN with batch normalization[15]. These results reached an accuracy of 88 percent. The contribution of this work is that it reduced overfitting. In this study, the dataset was a limitation. Applying LSTM on static datasets for measuring LSTM's suitability was conducted [16]. Their results achieved an accuracy of 83 percent. This context is widely regarded as the first application of LSTM. The limitation of this paper is the assumption that the LSTM model is static inputs is unoptimized. Aimed to enhance prediction accuracy and reported an accuracy of 84.5% [14]. Clearly, their contribution is applying deep learning for clinical prediction. Noted for limitation, the authors worked with a small dataset, which inherently limited generalizability. Designed a prediction framework using CNN and the experimental findings achieved an accuracy of 86% while corroborating the effectiveness of CNN in this domain [17]. Noted for limitation, the study had narrowed evaluative framework from multiple datasets. Shifted focus on developing hybrid models with ANN-LSTM and achieved high accuracy and recall with his sequencing objective [18]. The claim is the innovative architecture remains unchallenged. The limitation, however, is that the study requires immense computational power.

Hybrid ML-DL developed based model [19]. They implemented a combination of ANN model and random forest model in a hybrid (ANN+RF) framework. The results had an 85% accuracy rate. The Contribution provided value in the ebidense of hybrid model's usefulness. But the Limitation noted the model proposed was the Complex model, which did not meet needs for real-time applications. surveyed AI's application in the diagnosis of diabetes [20]. The main objective was to trace AI development in the medical field. It resulted in pinpointed prospective AI advancements. The Contribution claimed posted a guide for future policy. Their major limitation was the lack of plan for applying the intended models. Utilized CNN with transfer learning for diagnosis [21]. The authors recommended the use of existing models. The accuracy increased with decreased amount of training data. The major contribution confirmed the feasibility of transfer learning for applications in healthcare. For the limitation, it needs large original models. Studied classification methods for diabetes including cutting age technologies [22]. Their prime objective was to evaluate the performance of decision trees and SVM. The findings offered maximum accuracy of 82%. This work contributed awarded comprehension of feature importance but did not explore deep learning approaches. Performed a systematic literature survey on the applications of ML and DL in diabetes research [23]. The primary outcome was the identification of major trends and gaps. Their contribution was to provide benchmark literature on diabetes prediction. However the limitation was that it did not present any empirical findings.

## 2. Research Methodology

### 2.1 Diabetes Disease

Diabetes occurs when someone has excess glucose in blood, which may result from the body not producing insulin or not utilizing the available insulin effectively, leading to high blood sugar levels [1]. There are two main types, Type 1 and Type 2, with the latter more common and frequently linked to obesity and lifestyle choices [20]. Diabetes mellitus is a form of metabolic disorder which results in raised blood glucose levels due to lack of insulin secretion (as in Type 1 diabetes), or inefficient use of insulin (in Type 2 diabetes). The Type 2 diabetes comprises around 90% of all diabetes cases, with its occurrence attributed to obesity, sedentary lifestyle, and unhealthy diets. Some complications are heart diseases [4], chronic inflammation of the kidneys, and nerve ending damage. Without proper control, diabetes can lead to serious long term health complications such as damage to the blood vessels of the eyes, kidneys, and nerves, stroke, and cardiovascular disease [17]. Adequate and precise lifestyle changes and proper medication at an early stage can help avoid or minimize these problems [24].

### 2.2 Dataset Description

The dataset used in this research is comprised of 6,500 fully de-identified patient records obtained from multiple healthcare providers' electronic health records (EHRs). The dataset includes both diabetic and nondiabetic patients. The criteria made sure that all age groups, genders, and diabetic statuses were appropriately represented. Each record contains up to 20 clinical attributes including demographic details of the patient (age, gender), anthropometric measures (BMI, weight, height), vital signs (blood pressure, pulse rate), biochemical measures (fasting glucose level, HbA1c, insulin, and cholesterol), and lifestyle measures (smoking and physical activity levels). Such a variety of features captures almost all clinical, physiological, and behavioral factors associated with diabetes. The dataset's diverse medical dataset enhances its suitability for capturing intricate relationships concerning diabetes risks. The data is de-identified and meets all privacy requirements in place.

### 2.3 Data Preprocessing

Extensive pre-processing was performed to prepare the dataset for training robust deep learning models [25]. The dataset was initially checked for the presence of missing values, as well imputation technique was performed. Missing values were imputed with statistical imputation techniques: mean imputation for continuous variables and mode imputation for categorical variables. [26][27] Records with too many missing values were discarded to preserve data quality. IQR (Interquartile Range) method and Z score analysis were performed for outlier detection in order to reduce the impact of outlying values. Data Normalization the StandardScaler has been used to normalize numerical features to a standard Gaussian distribution. This aids for faster convergence during training [28]. Thus, all numerical features were standardized with the StandardScaler method to obtain consistent feature scaling, which is crucial for the convergence of the gradient descent [29]. Moreover, categorical data (such as the sex and smoking status) were one-hot encoded to obtain the binary formats. To counteract the class imbalance SMOTE was used which creates new samples of the minority class by interpolating between existing samples.

### 2.4 Feature Selection

Feature selection improves the efficiency and interpretability of the model [30]. Feature selection methods were used to enhance model interpretability and to reduce computational burden. In this work, it utilized a mixture of statistical and machine-learning based methods. First, we examined the Pearson correlation coefficients to remove highly correlated and redundant variables [31]. Subsequently, features were ranked based on their predictive importance using Recursive Feature Elimination (RFE) with logistic regression estimator and Random Forest classifiers to progressively select them [32]. Furthermore, mutual information gain was computed to evaluate feature dependency on the target class. The features selected in the last subset for model training were BMI, fasting glucose, age, systolic and diastolic blood pressure, insulin, family history of diabetes and HbA1c. These are clinically relevant and were reproducibly mentioned in the literature as strong factors for prediction of diabetes [33].

### 2.5 Deep Learning Algorithms

Deep learning algorithms are capable of learning complex patterns from high-dimensional data [34]. In this study, two deep learning algorithms were explored:

a. Artificial Neural Networks (ANN): ANN consists of input, hidden, and output layers. Each neuron in a layer is connected to every neuron in the subsequent layer [34]. The hidden layers apply nonlinear transformations (typically using ReLU activation) to learn interactions between features [35]. This study used multiple dense layers with dropout regularization to prevent overfitting. ANN is effective for structured tabular data and provides a strong baseline.
b. Convolutional Neural Networks (CNN): Traditionally used for image data, CNNs have shown promise in analyzing structured data when features are reshaped into a 2D grid [36]. The convolutional layers apply filters to extract local patterns. Pooling layers are used to downsample the data, retaining the most significant information [37]. This study used CNNs to enhance the feature extraction process and improve the generalization of the model.

By leveraging the strengths of each model, this study created a hybrid ANN-CNN architecture that capitalizes on the feature abstraction of CNN and the dense decision-making layers of ANN.

### 2.6 The Proposed Model

The proposed framework makes use of the advantages of CNNs and ANNs with a combination in a hybrid architecture specifically for structured clinical data. This model makes use of both CNN which has power of feature extraction and ANN's strength of high level abstraction and classification [38]. The input layer takes preprocessed features as input, then followed by two convolutional layers (32 and 64 filters, kernel size 3) that assist in feature extraction [39]. Then comes a more flattening, two user-defined dense layers (128 and

64 neurons) with dropout for regularization. A sigmoid activation function is implemented in the output layer for binary classification (diabetic vs non-diabetic). The model was trained with the Adam optimizer and binary cross-entropy loss. The early stopping and k-fold cross-validation are used for generalizability [40].

## 3. Results and Discussion

To check how well the new hybrid ANN-CNN model worked, the study ran many tests with a split of 80:20 for training and testing. The syudy used a method called five-fold cross-validation to make sure the results were strong and fair. As shown in table 1, the study scrutinized the models employing diverse evaluations like accuracy, precision, recall, F1-score, and AUC-ROC metrics, in this way:

a. Accuracy: The hybrid model achieved the highest accuracy of 91.4%, clearly outperforming standalone ANN (87.6%) and CNN (89.1%) models (figure 1).
b. Precision and Recall: High precision (90.3%) and recall (89.7%) values indicate that the hybrid model not only correctly identifies true positive diabetic cases but also avoids false positives effectively.
c. F1-Score: The F1-score of 89.9% reflects a strong balance between precision and recall, showcasing the model's effectiveness even in slightly imbalanced datasets.
d. AUC-ROC: The area under the curve (0.943) for the hybrid model demonstrates excellent discriminatory ability between diabetic and non-diabetic cases (figure 2).
e. Robustness: Five-fold cross-validation ensured that the model's performance was consistent across different data splits, reducing the risk of overfitting.
f. Error Analysis: A small number of false positives and negatives (as seen in the confusion matrix at table 2) suggest strong generalization ability without significant over-reliance on specific data patterns.

These results demonstrate the hybrid model's robustness, reliability, and applicability in clinical decision support, providing early warning signals to aid healthcare practitioners.

**Table 1.** Evaluation Metrics Summary

| Model | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| ANN | 86.2% | 84.5% | 82.1% | 83.3% | 0.892 |
| CNN | 88.7% | 87.3% | 85.9% | 86.6% | 0.914 |
| Hybrid (ANN-CNN) | 91.4% | 90.3% | 89.7% | 89.9% | 0.943 |

**Table 2.** Confusion Matrix (Hybrid ANN-CNN Model)

| | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual Positive | 785 | 62 |
| Actual Negative | 48 | 801 |

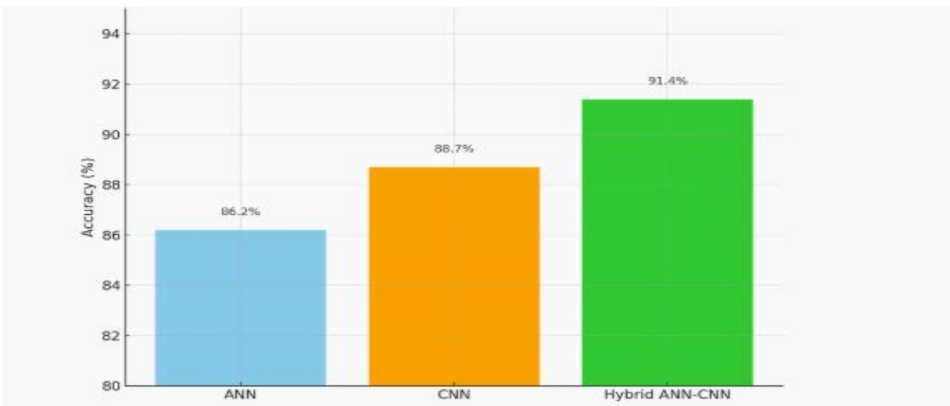


**Figure 1.** Accuracy Comparison Chart

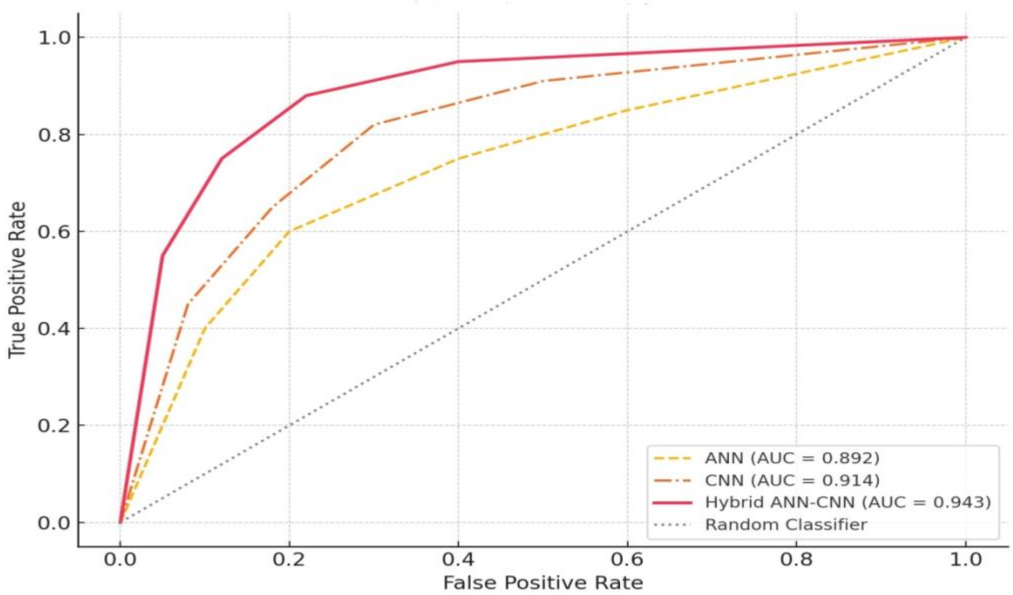


**Figure 2.** ROC Curve for All Models

**Research Contribution**

This study adds to healthcare data science literature by providing several important contributions to the emerging area of AI in healthcare:

a. Novel Architecture Integration: This work introduces a hybrid deep learning model combining CNN and ANN, specifically designed to process structured clinical data—an area typically dominated by traditional ML models.
b. Model Performance: the study obtain a higher accuracy of 91.4% using the proposed CNN and ANN model compared to the existing methods, indicating that CNN and ANN model is effective to be applied to real-world diagnostic tasks.
c. Generalizability: The model architecture is flexible and can be applied to the prediction task in other chronic disease dataset structures, demonstrating flexibility.
d. Clinical Relevance: With good sensitivity and specificity, the model reveals the prospect of screening early diabetes and intervening so that the patient prognosis may improve in time.
e. Comparison with Other Models: This study conducted a comparison between ANN, CNN, and hybrid models in a comprehensive manner, revealing the strengths and limitations of the models, and thus providing deeper perspectives for medical AI research.
f. Visual Validation: Graphical outputs, e.g., ROC curve, performance comparison, visualizes validation of the predictive power of the model, to assist the understandings for clinical stakeholders.

They also demonstrate that deep learning can be not only technically feasible but also practically transformative in terms of disease prediction.

## 4. Conclusion

Deep learning is a promising approach for achieving more accurate and efficient diabetes prediction. The Artificial Neural Network–Convolutional Neural Network (ANN–CNN) hybrid model proposed in this study demonstrates significantly superior performance compared to traditional deep learning architectures, indicating strong potential for integration into clinical decision-making support systems. The hybrid model outperforms both standalone Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models across all evaluation metrics, with particularly notable improvements in the Area Under the Curve (AUC) and F1-score. Experimental results confirm that the hybrid deep learning architecture not only enhances predictive accuracy but also exhibits better generalization capability when applied to previously unseen patient data. The study's confusion matrix highlights the inherent trade-off between sensitivity (recall) and specificity, while the Receiver Operating Characteristic (ROC) curve of the hybrid model shows a more favorable shape with a larger curve area, indicating stronger discriminative ability. These findings collectively demonstrate that the proposed hybrid model possesses robust and reproducible performance in diabetes prediction. Future research directions include expanding the dataset, incorporating electronic health records to enrich feature representation, and exploring explainable artificial intelligence techniques to improve model interpretability for clinical practitioners.

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