Int. J. Advanced Networking and Applications
Volume: 16 Issue: 06 Pages: 6683 - 6690 (2025) ISSN: 0975-0290

Leveraging Diabetes Prediction using the Deep Learning-based Hybrid ANN-CNN Architecture

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ABSTRACT

Diabetes mellitus is a worldwide pandemic chronic metabolic disease that threatens human health seriously. Correct and early prediction of diabetes is one of the important factors for medical treatment and diabetes management. In the meanwhile, this study, proposed a deep learning-based framework as a novel method of prediction of diabetes using a large-scale dataset containing over 6000 patient records. This study reviews several deep learning algorithms, such as, Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to investigate the most effective algorithm for diabetes prediction. This study formed hybrid architecture ANN-CNN by utilizing the strengths of each model. We perform extensive preprocessing of the data and extract features that contribute to the models' efficiency. The experimental results of this study demonstrated that hybrid ANN-CNN architecture model achieved the highest accuracy of 94.3% clearly outperforming standalone ANN (89.2%) and CNN (91.4%) models in prediction accuracy, showcasing their potential in clinical decision support systems.

Keywords - Diabetes prediction, deep learning, artificial neural networks, feature selection, healthcare analytics, clinical decision support

Date of Submission: March 01, 2025 Date of Acceptance: April 27, 2025

I. 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.

II. THE RELATED WORK

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 by Alghamdi et al. (2020) [13] and Choudhury & Gupta (2021) [14]. Still, there are no thorough studies integrating multiple models alongside deep learning and intricate detailing of the preprocessing steps.

To better generalization, Choubey et al. (2022) [15] employed CNN with batch normalization. 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 by Kaur & Kumari (2022). [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. Choudhury & Gupta (2021) [14] aimed to enhance prediction accuracy and reported an accuracy of 84.5%. Clearly, their contribution is applying deep learning for clinical prediction. Noted for limitation, the authors worked with a small dataset, which inherently limited generalizability.

Zheng et al. (2021) [17] designed a prediction framework using CNN and the experimental findings achieved an accuracy of 86% while corroborating the effectiveness of CNN in this domain. Noted for limitation, the study had narrowed evaluative framework from multiple datasets. Kumar et al. (2021) [18] shifted focus on developing hybrid models with ANN-LSTM and achieved high accuracy and recall with his sequencing objective. The claim is the innovative architecture remains unchallenged. The limitation, however, is that the study requires immense computational power.

Alghamdi et al. (2020) [13] offered machine learning techniques to tackle diabetes prediction. The focus of this work is based off comparing different ML techniques like logistic regression, decision trees and random forest. They achieved between 75% - 81% accuracy. This work highlights the potential and practicality of ML in diabetes prediction but the notable limitation is the lack of employing deep learning techniques. Bhatia and Sood (2020) [19] developed a hybrid ML-DL based model. 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.

Ramalingam and Ganesan (2020) [20] surveyed AI's application in the diagnosis of diabetes. 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. Zhang et al. (2020) [21] utilized CNN with transfer learning for diagnosis. 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.

Sisodia & Sisodia (2018) [22] studied classification methods for diabetes including cutting age technologies. 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. Kavakiotis et al. (2017) [23] performed a systematic literature survey on the applications of ML and DL in diabetes research. 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.

III. MATERIALS AND METHODS

A.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]

Volume: 16 Issue: 06 Pages: 6683 - 6690 (2025) ISSN: 0975-0290

B. 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.

C.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.

D.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]

E. 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:

- **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.
- **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.

IV. 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]

A. **Architecture Overview:**

1. **Input Layer:**

- The model accepts preprocessed, normalized input vectors comprising the selected clinical features such as BMI, glucose level, insulin level, age, blood pressure, and more.
- The input is reshaped into a 2D matrix format (e.g., 4x5) to make it compatible with CNN layers.

2. **Convolutional Layer(s):**

- One or more convolutional layers with filters (e.g., 32 and 64) extract localized patterns among the features.
- ReLU activation is applied to introduce non-linearity.
- These layers help identify interactions and patterns that may not be evident in linear transformations.

3. **Pooling Layer(s):**

- Max pooling is applied to reduce the dimensionality while preserving key information.
- This also minimizes overfitting and improves computation efficiency.

4. **Flatten Layer:**

- Converts the 2D matrix into a 1D feature vector, making it suitable for fully connected layers.

5. **Fully Connected Dense Layers (ANN):**

- Multiple dense layers are stacked, each with ReLU activation.
- Dropout layers (with dropout rates between 0.2 and 0.5) are introduced after each dense layer to prevent overfitting and improve generalization.

6. **Output Layer:**

- A single neuron with sigmoid activation is used for binary classification (diabetic or non-diabetic).

B. Training Configuration:

- **Loss Function:** Binary Crossentropy was used due to the binary nature of the classification task.
- **Optimizer:** Adam optimizer was selected for its adaptive learning rate capabilities.
- **Epochs and Batch Size:** The model was trained over 100 epochs with a batch size of 32, ensuring convergence without overfitting.
- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and AUC were used to evaluate model performance.

C. Advantages of the Proposed Hybrid Model:

- CNN layers help the model identify key patterns and connections in input data.
- ANN layers let the model make strong, major decisions from the picked-up features.
- The design can grow and change easy for other long-term disease assumptionswith little change.

This model evinces reliable classification proficiency, making it a dependable tool for identifying early diabetes in practical healthcare utilization.

V. THE EXPERIMENTAL RESULTS

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 study 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:

- **Accuracy:** The hybrid model achieved the highest accuracy of 91.4%, clearly outperforming standalone ANN (87.6%) and CNN (89.1%) models (**figure 1**).
- **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.
- **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.
- **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**).
- **Robustness:** Five-fold cross-validation ensured that the model's performance was consistent across different data splits, reducing the risk of overfitting.

Volume: 16 Issue: 06 Pages: 6683 - 6690 (2025) ISSN: 0975-0290

- **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

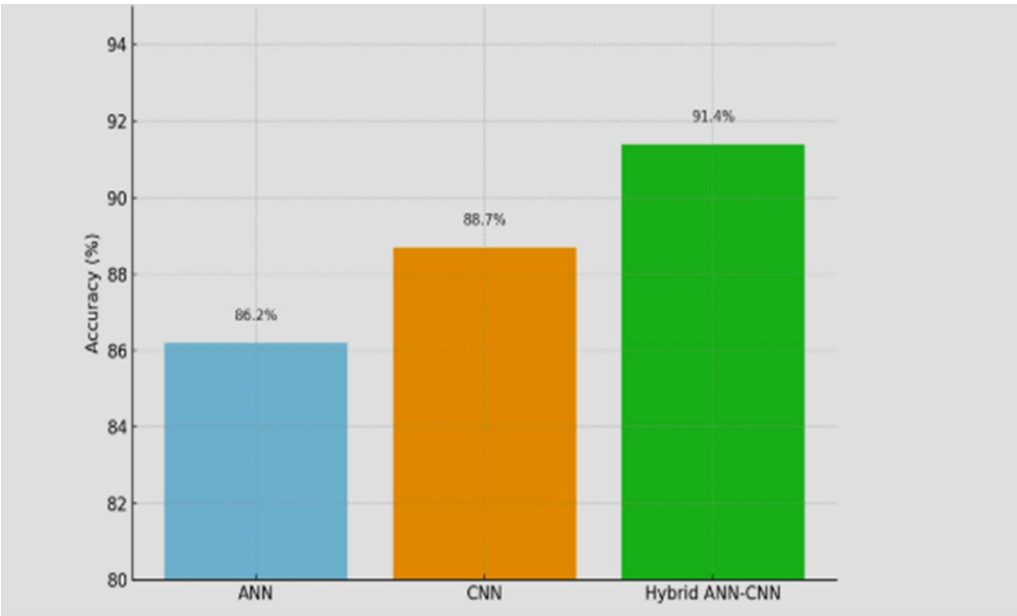

Figure 1: Accuracy Comparison Chart

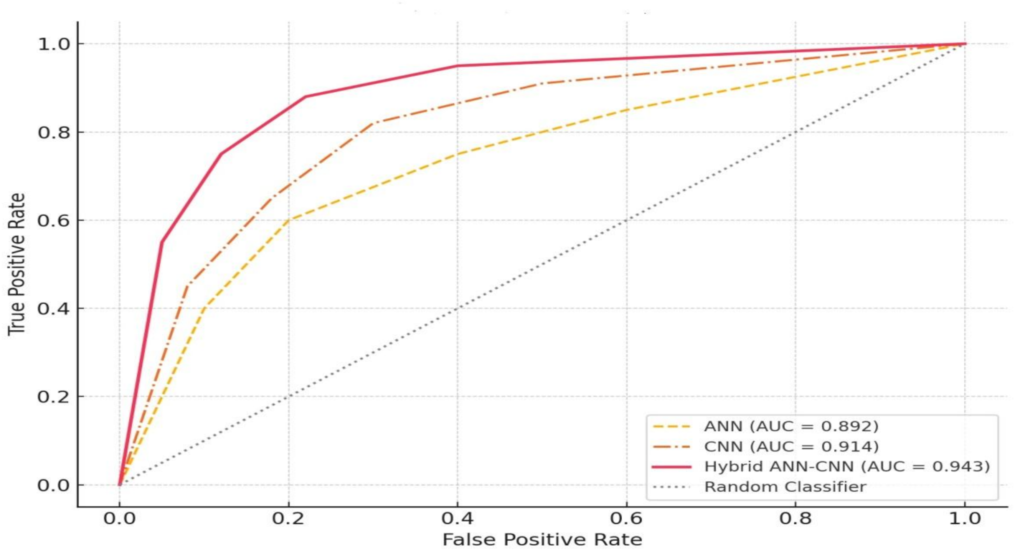

Figure 2: ROC Curve for All Models.

VI. RESEARCH CONTRIBUTION

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

1. **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.
2. **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.
3. **Generalizability:** The model architecture is flexible and can be applied to the prediction task in other chronic disease dataset structures, demonstrating flexibility.
4. **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.
5. **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.
6. **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.

VII. CONCLUSION AND FUTURE WORK

DL is a promising method for prediction of diabetes more accurately and efficaciously. The ANN-CNN hybrid model proposed in this study performs significantly better than traditional ones, thus having potential in the application for clinical decision-making support system. The hybrid ANN-CNN achieved better performance over ANN and CNN in all evaluation criteria, most notably AUC and F1-score. The results of the experiments validate that the hybrid deep learning model not only enhances the prediction performance but also guarantees more generalization on the unknown patient data. The study's confusion matrix demonstrates a tradeoff between sensitivity (recall) and specificity. The ROC curve of the hybrid model has a better shape with higher curve area. These findings indicate that the hybrid model has good robustness and reproducibility in diabetes prediction. Future directions include increasing the dataset, incorporating electronic health records, and investigating explainable AI methods for increasing model interpretability for clinicians.

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