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Hybrid Models in Diabetes Prediction: A Review of Techniques, Performance, and Potential

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ABSTRACT

This review focuses on the versatility of hybrid models in diabetes prediction, for which early and accurate diagnosis is crucial for patients. Hybrid models have an advantage over traditional approaches since they utilize a combination of machine learning and deep learning to overcome several restrictions inherent in conventional techniques in terms of feature extraction, accuracy, and robustness. Among the structures discussed in this paper, Combine Convolutional Neural Networks and Long Short Term Memory (CNN-LSTM), Support Vector Machine (SVM) with clustering or Decision Tree, and ensemble methods all show high capabilities of capturing the patterns in the diabetes datasets. Analyses state that current typical implementations of hybrid models, intense machine learning, and machine learning achieve the finest steadiness and predictability. However, the following challenges are still experienced: high computational demand, data demands, and interpretability. The subsequent studies should enhance the clinical relevance of these models, including efforts to interpret these models, combine electronic health records, and improve models' ability to work in real-time before contributing to more effective healthcare solutions for diabetes.

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1. Introduction

Diabetes is a long-term condition caused by high blood sugar levels due to inadequate insulin production or utilization. Presently, more than 537 million adults, including the US population, have diabetes as per the International Diabetes Federation (IDF) [1], and this number is expected to increase further in the future based on causes such as poor nutrition, lack of physical activity as well as an enhanced life span. This continually increasing prevalence has put pressure heavily on health systems around the world, and complications of diabetes like cardiovascular diseases, kidney problems, blindness and nerve damage present serious threatening health problems that require long-term, costly care. These complications are best managed when diagnosed at an early stage of diabetes because early diagnosis leads to prevention or slowdown of the disease [2]. Research has turned out that

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with some essential changes in patients' lifestyles, diet regimens, and, in some cases, medication, the risk of patients moving from prediabetes to diabetes can be minimized greatly, enhancing the quality of life. Also, early detection means that the caregivers can track the patient carefully for any changes, and, in this process, they will ensure that the patient gets the right information about their disease [3]. In this regard, the dispersion of predictive models for diabetes management has emerged as vital medical assets [4]. With the use of patient demographics, lifestyle, and genetic characteristics incorporated in the model, high-risk patients are easily pointed out, and measures are taken to prevent susceptibility. Of all the AI techniques, machine learning (ML) and deep learning (DL) have specific potentiality in this field since; by comparing the different pieces of data, they can detect patterns that the other ordinary methods cannot [5]. The main problem here is that single-model strategies need to achieve an appropriate, effective balance between accuracy, stability, and interpretability. Conventional approaches like Support Vector Machines (SVM) or Artificial Neural Networks (ANN), higher predictive performance on such a heterogenic data structure or coupled to the challenge of modeling temporal structures of the data can take time to achieve. In addition, the partial overlapping of complementary techniques reduces their efficacy in combating the polyfactorial nature of diabetes prediction. Integrating both ML and DL forms hybrid models and improves the performance and reliability of the new models in enhancing accurate predictions [6]. Therefore, constructing robust diabetes prediction models is central to helping healthcare facilities tackle the diabetes crisis and alleviate the suffering of patients and healthcare providers. Previous approaches for diabetic prediction are beneficial, but there are several drawbacks to these classical models, which may limit their practical applicability [7]. However, one major drawback is the relatively low predictive power of these models, sometimes as simple as a statistic or rule-based. These models might not give the right representation of interaction to the risk factors for diabetes and may have less accurate predictions. However, traditional models are mostly non-explanatory, which implies that little can be understood about how certain parameters develop the risk level for an individual patient [8]. This lack of transparency can be a disadvantage, as clinical practitioners must understand the rationale of a specific model to make the right clinical decisions. Another severe restriction is the requirement for big, accurate data sets. Several conventional approaches involve a set of detailed and varied attribute data to work better with different populations [9]. However, acquisition and maintenance of such datasets are not easy as there are privacy issues in data collection, data quality is not always excellent, and there is restricted access to medical records. Additionally, the conventional approaches cannot perform as well on the unseen or signaling datasets or provide more practical consequences when using different patient samples. These significant limitations suggest that other higher-order methods are required to enhance predictive capability, model readability and flexibility in other data environments. Hybrid models are considered a more refined approach to diabetes prediction, involving multiple ML and DL technologies embedded together. By combining these two approaches, hybrid models can overcome some of the disadvantages characteristic of the conventional prediction models. For instance, a hybrid model can be associated with a classy machine learning algorithm like a support vector machine (SVM) for classification and a deep learning model like Long Short-Term Memory (LSTM), that works as a great temporal pattern detector. This combination allows the model to process and analyze structural and temporal characteristics in the data and improve prediction. Many authors have considered hybrid models because they are flexible models that can accommodate many forms of data [10]. They can be built to consider different aspects of the data; they can capture nonlinearity and announce time components, which are important in chronic disease prediction, including diabetic prediction [11]. Due to the ensemble ideas or model stacking or deep learning structures, hybrid models give a more extensive guideline about the risk facets and patterns of diabetes. The proposed methodology has not only enhanced the accuracy of the prediction but also aided in attaining a more interpretable and stable prediction model. This paper aims to review hybrid models for diabetes prediction, emphasizing their techniques, performance and suitability in clinical practice. More constructively, this paper will seek to discuss different hybrid models about the system architecture layout and the advantages and disadvantages associated with the different modes of operation in predicting diabetes. This review considers the performance of these models and how hybrid approaches open new ground to enhanced predictions over traditional models while examining how they improve the accuracy of predictions and their interpretability. Furthermore, the paper outlines the limitations of research data. It reveals avenues for future research studies by pointing out ways of enhancing and improving the hybrid models and applying them to effective models of the healthcare system. This review is therefore intended to help researchers and practitioners choose and improve better prediction models to reduce the increasing incidences of diabetes globally; also, the proposed solution is encapsulated within the framework for a systematic assessment of hybrid models with regard to the types of models themselves, the appropriate metrics for evaluation, and the contexts in which such models are applicable. This review aims to highlight the Made-based CNN-LSTM for temporal prediction and show critical challenges and potential research in this area. In summing up the paper and integrating the results, the authors help to use hybrid methodologies for improving diabetes prediction and provide a reference for further investigation. This paper provides a systematic comparison of hybrid models for the diagnosis of diabetes regarding their methodologies, performances and implementations. It also highlights the various approaches like CNN-LSTM architecture and classifies other methods like SVM with clustering and ensemble methods giving insights on Advantages and Disadvantages info. Besides, the review presents the evaluation framework that provides the foundation for evaluating hybrid models: accuracy, type of hybridization, computational efficiency, and application contexts. Thus, the paper provides practical solutions for the limitations associated with landscape analysis, including computational complexity, data demands, and interpretability. Therefore, the study also discusses the research avenues for further work, such as investigating new combinations of hybrid structures, including the implementation of real-time predictive functionality and improving usability and understanding of the model. This review will, therefore, act as a repository of past knowledge and a helpful roadmap for future work on the use of hybrid models for diabetic prediction.

2. Overview of Hybrid Models for Diabetes Prediction

Hybrid models combine multiple algorithms, often using mathematical frameworks to leverage the complementary strengths of each technique [12]. In diabetes prediction, a hybrid model can be represented mathematically as a function:

$$f(x) = g1(x) + g2(x) + \ldots + gn(x) \quad (1)$$

where f(x) is the final prediction function and gi(x) represents each component model contributing to the overall prediction. Hybrid models are often constructed using approaches like ensemble methods (bagging, boosting, stacking), model stacking (layered combination of algorithms), and hybrid deep learning networks (merging CNNs with RNNs such as LSTM or GRU).

The advantages of hybrid models are improved prediction through several vital benefits such as enhanced feature extraction [13], the capture of diverse patterns in data, helpful in identifying nonlinear relationships in diabetes risk factors [14], higher accuracy by integrating multiple methods [15], hybrid models reduce the error associated with single models and robustness against data variability; it generalize better to different patient demographics and medical conditions, which helps avoid overfitting [16].

2.1 Hybrid Machine Learning Models

Hybrid machine learning models combine classical ML algorithms to improve performance. For instance:

$$f(x) = \alpha 1 \,.\, SVM(x) + \alpha 2 \,.\, Decision\ Tree(x) \quad (2)$$

Here, α1 and α2 are weight coefficients that balance contributions from a Support Vector Machine (SVM) and a Decision Tree. Another example is K-means clustering combined with SVM, where K-means groups data into clusters first:

$$C_k = \{x: ||x - \mu_k||^2 \le ||x - \mu_j||^2, \forall j \ne k\} \quad (3)$$

where $C_k$is the kth cluster and $\mu_k$is centroid. Then, SVM performs classification within each cluster, allowing for enhanced accuracy; Fig. 1 explains hybrid SVM with a decision tree.

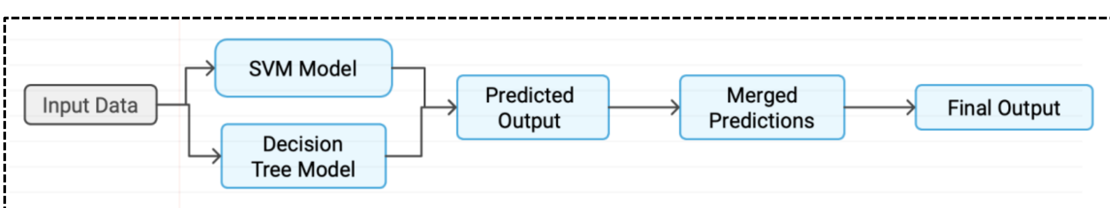

Fig. 1 - Structure of Hybrid SVM with Decision Trees

2.2 Hybrid Deep Learning Models

Hybrid deep learning models combine deep learning architectures to handle complex data. For instance, CNN-LSTM models help process both spatial and temporal features in sequential data; Fig. 2 explains hybrid CNN with LSTM, such as time-series glucose levels:

$$h_t = LSTM(CNN(x_t) \quad (4)$$

where x_t is the input at time t, CNN (x_t) Extracts spatial features, and LSTM $(\cdot)$ captures temporal patterns. Other models, like CNN-SVM, use CNN for feature extraction.

$$f(x) = SVM(CNN(x)) \quad (5)$$

Here, the CNN layer learns spatial features from images or time-series signals, and the SVM performs classification, yielding a hybrid model that excels at feature extraction and classification.

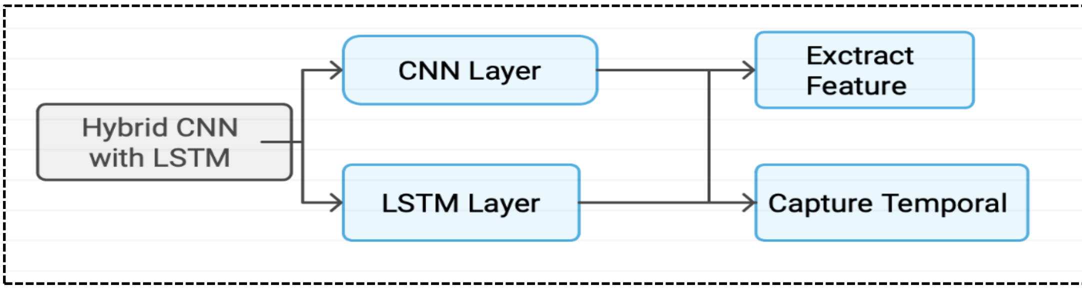

Fig. 2 - Structure of Hybrid CNN with LSTM

2.3 Ensemble Methods

Ensemble methods combine the outputs of multiple models to improve prediction performance; Fig. 3 explains Ensemble Methods. Standard ensemble techniques in hybrid models include:

1. Bagging: this technique creates multiple models, each trained on a random subset of the data. The final prediction is the average (for regression) or majority vote (for classification) of individual models:

$$f(x) = \frac{1}{n}\Sigma_{i=2}^{n} gi(x) \quad (6)$$

2. Boosting: It builds models sequentially, where each model corrects errors of the previous one. The final prediction is a weighted sum of individual models,

$$f(x) = \Sigma_{i=}^{n} \alpha igi(x) \quad (7)$$

where αi represents the weight assigned to a model g_i (x) based on its accuracy.

3. Stacking: In stacking, multiple base models are combined by training a meta-model to integrate their predictions. Mathematically, $g1(x) + g2(x) + \cdots + gn(x)$ these are the base models, then the final prediction is

$$f(x) = g1(x) + g2(x) + \cdots + gn(x) \quad (8)$$

where h(.) is the meta-model that combines the predictions from the base models, often trained on the outputs of these models.

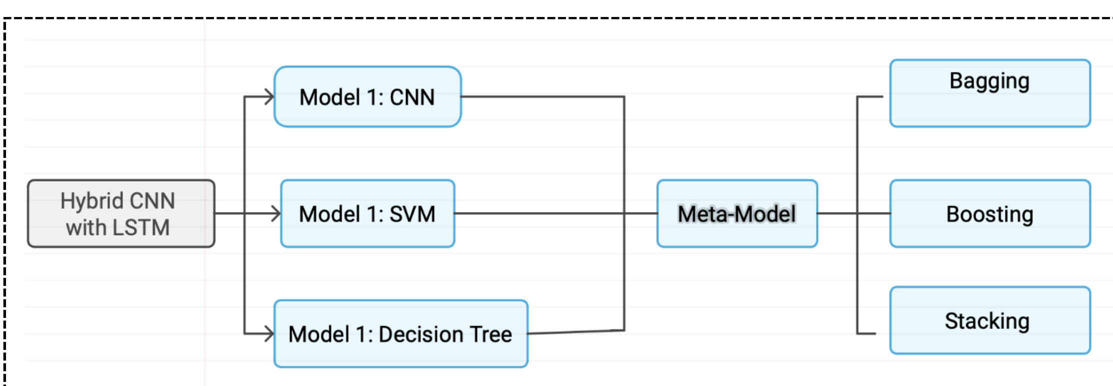

Fig. 3 - Structure of Ensemble Methods

3. Techniques of Prepare Data

We will show a set of Techniques to prepare data before feeding it to models

3.1 Data Preprocessing

Effective data preprocessing is crucial for accurate diabetes prediction. Typical preprocessing steps [17] include:

1. Feature Selection: Feature selection helps isolate the most relevant factors for diabetes prediction, which improves model interpretability and efficiency [18]. Techniques such as mutual information and correlation analysis identify significant variables from datasets with numerous attributes.

2. Normalization: To ensure consistent scale across features, normalization methods like Min-Max Scaling and Z-score normalization are frequently applied [19]. For a feature x, Min-Max Scaling can be represented as

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (9)$$

normalization is essential in hybrid models where models with different architectures (e.g., SVM and CNN) benefit from data being on the same scale.

3. Handling Imbalanced Data: Diabetes datasets often contain imbalanced classes (e.g., fewer cases of diabetes compared to non-diabetic instances). Techniques like oversampling (e.g., SMOTE) or under sampling can be applied to balance the dataset [20]. SMOTE (Synthetic Minority Over-sampling Technique) generates synthetic instances to enhance the minority class and improve model learning.

3.2 Feature Selection and Dimensionality Reduction

In high-dimensional datasets, feature selection and dimensionality reduction methods are applied to optimize the input space for hybrid models:

1- Principal Component Analysis (PCA): PCA reduced dimensionality by transforming correlated variables into uncorrelated principal components [21]. For a data matrix X, the PCA transformation to a new coordinate system can be represented as

$$X' = X\,W \quad (10)$$

where W is the matrix of eigenvectors of X' covariance matrix. This transformation helps hybrid models by reducing redundancy and enhancing computational efficiency.

2. Linear Discriminant Analysis (LDA): LDA maximizes class separation by projecting data onto a lower-dimensional space that best discriminates between classes [22]. For two classes, a projection matrix W is sought to maximize the between-class and within-class variance ratio.

By applying PCA or LDA, hybrid models can focus on the most informative features, which helps improve both model training time and prediction accuracy.

3.3 Hyperparameter Optimization

To improve hybrid model performance, it is essential to optimize hyperparameters for each component model [23]. Standard optimization techniques include:

1. Grid Search: Grid search exhaustively evaluates all possible combinations of specified hyperparameters within a defined search space. Although computationally expensive, grid search is adequate for smaller parameter spaces [24].

2. Random Search: Random search samples random combinations of hyperparameters from a predefined distribution [25]. This approach is less computationally intensive than grid search and is practical for high-dimensional parameter spaces.

3. Genetic Algorithms (GA): GAs use evolutionary principles to refine hyperparameters iteratively. With an initial population of hyperparameter settings, GA applies selection, crossover, and mutation operators to evolve toward optimal configurations [26]. For example, in a CNN-SVM hybrid model, GA could optimize the kernel type in SVM and filter sizes in CNN.

4. Performance Evaluation of Hybrid Models

In this chapter, we will show datasets, evaluation metrics and related works that are used for diabetes prediction using hybrid models

4.1 Datasets of Diabetes

Several key datasets are commonly used for diabetes prediction, providing a standardized basis for comparing model performance:

1. Pima Indians Diabetes Database (PIDD): Collected by the National Institute of Diabetes and Digestive and Kidney Diseases, PIDD is widely used in diabetes research. It contains 768 samples with eight features, including glucose level, BMI, and age [27]. Due to its relatively small size, researchers often enhance it with data augmentation techniques.

2. Diabetes 130-US Hospitals Dataset: This dataset, sourced from U.S. hospitals, contains over 100,000 records of diabetic patients, with features on demographics, lab tests, and medications [28]. Its size and diversity make it ideal for deep learning models, but it requires significant preprocessing.

3. Early-Stage Diabetes Risk Prediction Dataset: This dataset includes information on early diabetes symptoms, with 520 instances and 16 attributes [29]. It allows for predictive modeling focused on early detection of diabetes.

4.2 Evaluation Metrics

To assess the effectiveness of hybrid models in diabetes prediction, the following evaluation metrics are commonly used:

1. Accuracy: The proportion of correct predictions to the total predictions. While widely used, accuracy can be misleading for imbalanced datasets [30].

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Sanples} \quad (11)$$

2. Precision: The ratio of true positives to the sum of true positives and false positives, indicating the model's accuracy in predicting positive cases [31].

$$\Pr e\ cision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (12)$$

3. Recall: The ratio of true positives to the sum of true positives and false negatives highlights the model's ability to identify positive cases [32].

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (13)$$

4. F1 Score: The harmonic mean of precision and recall provides a balanced measure that accounts for false positives and false negatives [33].

$$F1 - score = 2 \cdot \frac{\Pr ecision \cdot Recall}{\Pr ecision + Recall} \quad (14)$$

5. Area Under the ROC Curve (AUC): AUC represents the probability that a model ranks a randomly chosen positive instance higher than a random negative one [34]. An AUC close to 1.0 indicates excellent performance.

4.3 Comparative Performance Analysis

We will show and summarize performance results from recent studies on different hybrid models applied to diabetes prediction. These comparisons are based on accuracy, F1 score, and AUC, providing a clear view of each model's strengths.

The paper presents a new AI-based method for diabetes risk prediction that makes use of machine learning algorithms and a database including demographic, clinical, and lifestyle information. This model's high level of accuracy makes tailored intervention possible and lessens the strain on healthcare systems and people caused by diabetes [35]. A CNN-Bi-LSTM hybrid deep learning model was developed to detect and predict the occurrence of type 2 diabetes mellitus using the PIMA Indian diabetes database. With an improvement of 1.1% over existing methods, the model outperforms prior deep learning algorithms regarding accuracy, sensitivity, and specificity. Health care providers may access detailed patient records and evaluate critical metrics in real-time with this monitoring gadget [36].

The Pima Indian Diabetes dataset is used in this research to examine machine learning approaches for diabetes datasets. The dataset has 768 people, 268 of whom have diabetes and 500 of whom have it under control. The purpose of the research is to assess various methods based on their features and performance metrics [37].

The processing power and availability of electronic health records have expanded. The accuracy of readmission predictions increased to 78% when Convolutional Neural Networks (CNN) and Support Vector Machines (SVMs) were used together for prediction. The topic of feature engineering and the hinge loss function is covered in this paper [38].

The authors of this paper provide a clinical decision-support system for diabetes prediction using Ensemble Deep Learning (EDL). The system uses an ensemble learning-based stacking model, which incorporates Deep Learning architectures such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), etc. An evaluation is conducted on the model using metrics such as accuracy, precision, sensitivity, specificity, F-score, Matthews Correlation Coefficient (MCC), and ROC/AUC. The model is trained using three diabetes datasets. When it comes to diabetes prediction, the stack-ANN model is superior to earlier research [39].

This research presents a deep learning framework for early diabetes prediction and complication reduction that combines long-term memory and convolution neural networks. Nearly half of all people will have diabetes by the year 2045, making it a rapidly increasing health concern. When forecasting the likelihood of diabetes, the suggested model performs better than competing machine learning and traditional deep learning methods [40].

Table 1 - Hybrid Models for Diabetes Prediction in Previous Studies

Study	Dataset	Model	Evaluation Metrics	Result

[35]	PIDD	logistic regression and a random forest	Accuracy	100%
[36]	PIDD	CNN-Bi-LSTM	Accuracy	98%
			sensitivity	97%
			specificity	98%
[37]	PIDD	CNN with LSTM	Accuracy	89.3%
			Precision	87.8%
			Recall	84.1%
			F1	85.5%
[38]	Clinical Dataset	CNN-SVM	Accuracy	78%
[39]	PIDD	Stack-ANN, Stack-LSTM, Stack CNN	Accuracy	98.8%, 97.23%, 94.81%
	DDFH-G	Stack-ANN, Stack-LSTM, Stack CNN		99.51%, 98.36%, 97.44%
	IDPD-I	Stack-ANN, Stack-LSTM, Stack CNN		98.45%, 97.88%, 96.89%
[40]	-	CNN with LSTM	Accuracy	99.12%
[41]	Frankfurt Hospital in Germany	K-means-Random Forest	Accuracy	97.6%
	PIDD	K-means-SVM		83.1%
[42]	PIDD	stacked ensemble-genetic algorithms	Accuracy	98.8%- 99%
[43]	PIDD	ANN-Genetic algorithm	Accuracy	80%

There are several takeaways from comparing hybrid models:

1. Top Models: CNN–LSTM-based models are more suitable for big data sets containing sequential data as they provide high accuracy in F1 score and AUC rate. The key feature in these models when it comes to forecasting the risk of diabetes in time is the ability of the model to learn in a space-time context.

2. Supervised Learning Hybrids' Benefits: For other small data sets such as PIDD and Early-Stage Diabetes, the integration of SVM with Decision Tree and K-means with SVM are good performers. To enhance the interpretability of those models, decision trees are used and for the classification of patient subgroups, K-means clustering is incorporated; these models employ SVM since it can construct multi-layered decision boundaries.

3. Ensemble Models' Limitations: Thus, although ensemble methods such as bagging are quite stable to data peculiarities regarding their robustness to data unpredictability, relatively simple hybrids can sometimes be slightly worse than more complex hybrids on small sets like PIDD to some extent. For class imbalance situations, ensembles perform well; for a particular problem, they need a little tuning to achieve optimum accuracy and generalization.

In the diabetes prediction tasks, hybrid models also outperform single-method models. They describe complex interactions more accurately, are less sensitive to noise, and are more accurate when used with different data sets. This means that the hybrid strategy that will be implemented will depend on the properties of the dataset and the computing power of the computing equipment available.

5. Challenges and Limitations of Hybrid Models

However, as it will probably be seen when the reader tries to implement any of the models in practice, hybrid models are not devoid of problems and limitations. Computational complexity is the biggest issue here. As the layers increase with depth in the model and as the model gets complex, the computational requirement to run these models, which include deep learning with machine learning, depends on different techniques and may be rather large. The problem with applying hybrids or semi-hybrid models in areas of low computational support is the big and fast GPU and high and sometimes huge memory usage requirements of deep learning layers like CNNs or LSTMs.

Another area for improvement is the amount of data required to train hybrid models effectively. These models need big data and could contain many attributes for them to capture complex and diverse relationships. Lack of privacy, restricted data sharing and summarized high costs of labeled medical data make such datasets hard to come by, especially within the healthcare domain. Consequently, models trained from small or homogeneously labeled data may not be very helpful when used on large amounts of clinical data.

The last difficulty is that the model is hard to explain. The emergent structures, which are frequently convoluted, are inherently complex and are the result of employing multiple algorithms. Often, hybrid models can offer poor interpretability of the result, which means that physicians cannot put faith in the outcome or understand how such a decision was made, whereas simpler models, such as logistic regression, will provide tangible and easily understandable results. In healthcare, where clinical acceptability directly depends on the logic of logical reasoning of the forecast, this is particularly disadvantageous for this model.

The final consideration is generalizability, again a factor that is environment-dependent to a great extent. In particular, ordinary hybrid models that achieve good results when applied to a certain data set may perform worse when applied to new, unused or previously unseen data. This is especially so because it manifests itself uniquely depending on the population, and as such, data from one location cannot be directly compared with another. For any such models attempted at this high level of complexity to generalize well and give statistically reliable predictions across a broad range of clinical scenarios, they must be thoroughly validated on several different data sets. Therefore, this is an obstacle that, if not surmounted, can slow the application of hybrid models for diabetes prediction in general.

6. Conclusion and Future Works

In comparing the hybrid models to the more traditional models for this review, it has been realized that they have far more accuracy, robustness and flexibility regarding diabetes prediction. Techniques which have been employed to achieve this include ensemble methods, model stacking and CNN-LSTM, SVM with clustering hybrid deep learning architecture., Hybrid models are successful in the identification of complex patterns of health data. In diabetes prediction, these combinations are crucial due to the feature extraction, accuracy, and data unpredictability needed for the task complexity. We use crucial datasets and efficient data preprocessing to support these models' accurate predictions. In general, it is proved that hybrid models can reshape diabetes prediction. He believes that these provide accurate information that is good for the early identification of the condition, developing a tailor-made treatment plan, and improving the result for the patient. However, several challenges remain regarding computational demands, data availability, and analysis and translation across studies. More work must be done to bypass these limitations and enhance hybrid models for therapeutic use. These challenges remain significant as great expectations regarding hybrid models as a tool for diabetes control and predictive healthcare can be true only if these obstacles are solved.

To overcome important challenges and discover new opportunities, focused work is necessary for developing advanced hybrid solutions for diabetes prediction. Diving into the following clinical usability aspects indicated clinical model presentational improvement is needed for model interpretability. To increase the interpretability of hybrid models, such as SHAP or LIME, these approaches may detract each feature's contribution in the model's final decision. Future works can also offer novel interpretability methods developed for intricate MH models to assist HC professionals in improving trust in the predictions.

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