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(RESEARCH ARTICLE)

The role of deep learning in predicting disease progression in diabetic patients

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Abstract

The worldwide healthcare system confronts a substantial challenge from diabetes mellitus, which requires creative methods to handle the disease. Prolonged monitoring with deep learning techniques enables healthcare professionals to detect complicated medical patterns which aid in preliminary patient diagnosis and response. This research adopts Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Hybrid Neural Network integrated with Genetic Algorithm (Hybrid NN + GA) as deep learning structural networks for diabetic disease prognostication. The Diabetes 130-US Hospitals dataset served as the foundation for trainer and test protocols for the model while containing extensive clinical electronic health records about diverse patient information. AUC value assessment together with RMSE tested the models through accuracy evaluations. There is evidence that the hybrid approach excels at generalization in medical settings by surpassing both LSTM and GRU models when analyzing imbalanced hospital records. The research proves that joint utilization of deep learning frameworks produces better clinical decision systems for precise diabetes monitoring that enhances operational efficiency.

Keywords: Deep learning; Hybrid Neural Networks; Diabetes prediction; LSTM (Long Short-Term Memory); Gated recurrent unit (GRU); Telemedicine

1. Introduction

Worldwide, diabetes mellitus continues to spread as an epidemic because of health complications that result in high costs, although leading to notable mortality levels. The early identification and precise determination of disease progression remain vital in healthcare because diabetes brings forth complex medical conditions that harm the heart, kidneys, and eyes. Mellor et al. [7] reported that predictive modelling techniques are necessary for preventing long-term medical risks due to the major deleterious consequences of diabetic complications. Early predictive healthcare systems enable medical staff to administer instant care that enhances resource management, which in turn provides superior care to patients and lowers healthcare demands.

Predictive modelling techniques have gained increasing adoption by healthcare organizations throughout the previous several years. Modern predictive models demonstrate their ability to modify healthcare decisions and improve care delivery quality by speeding up treatment initiation, as noted by Kowsher et al. [5]. The analysis of complex time-dependent clinical information required more advanced methods than traditional statistical procedures and classical machine learning models because previous diabetes research only used them. The performance of deep learning techniques exceeded that of classical ML approaches because deep learning systems can identify complex advanced

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non-linear relationships, according to Ayon and Islam [2]. Real-time functions operate in healthcare institutions through deep learning models, which maintain their flexible nature during risk assessments and predictions, as shown by Shakil et al. [14].

Deep learning technology has experienced substantial progress, yet it still fails to resolve the complex task of predicting diabetes progression. New models need to achieve both high precision and universal application because the disease challenges doctors due to patient uniqueness and different treatment responses. The research study employs a categorization system to forecast which patients will experience quick disease development compared to patients maintaining stable diabetes condition. Deep learning structures provide computational methods to achieve stable prognostic predictions according to this research work.

This study uses Deep Learning algorithms that combine LSTM adapters with GRU systems onto Hybrid Neural Networks controlled through Genetic Algorithms to evaluate diabetic prognosis predictions (Hybrid NN + GA). LSTMs stand alone as the leading technology for addressing long-term dependencies in time-series datasets and thereby becoming essential elements for chronic disease research on patient past records. GRU models maintain stable training efficiency because they use basic design elements together with few parameters to create equivalent output results. Siddiqui and Naaz [17] produced a system that integrates genetic algorithms for network optimization through a structure using genetic algorithm components to control data performance while avoiding overfitting issues.

The investigation fulfils multiple objectives to evaluate deep learning approaches using clinical datasets for finding the best combination model through performance assessments. The research creates operational platforms that can help early detection of diabetic patients at risk through improved outcomes.

2. Literature Review

Predictive models for diabetes care require deep learning as their fundamental element because it generates superior outcomes than standard statistical approaches. Recent deep learning architectural research allows the prediction of blood glucose levels while classifying diabetes status and conducting real-time observation through the use of edge computing technology. Deep learning algorithms show superiority in blood glucose prediction because they detect complex temporal patterns present in patient data records, according to Mhaskar et al. [8]. Successful blood glucose analysis for Type 1 diabetes patients under medical conditions became possible through deep learning models, according to Celik and Varlı [3], when used for early diagnosis. Screening of diabetic type 2 patients through deep learning diagnostic solutions has achieved success thanks to Ghafki et al. [4], who developed their classifier system, as well as Sindhu et al. [15], who validated multi-layered networks' effectiveness for diabetes diagnosis. Zhu et al. [19] created an edge-based forecasting model deploying deep learning operations on portable platforms to enable real-time health tracking with instant responses, which enhances the implementation of wearable systems for diabetes care.

Literature about specific models reveals the deep technical aspects of individual deep learning structures. The Gated Recurrent Unit (GRU) has gained popularity because it offers both efficiency and simplicity. The research by Pavithra, Saruladha, and Sathyabama [11] applied GRU-based modeling to track patient data sequences effectively while using less computational power than more complex systems while maintaining similar prediction outcomes. The Long Short-Term Memory (LSTM) network receives positive recognition because of its central design characteristic that enables it to track extended time-span associations. According to the paper by Shahid et al. [13], LSTM networks develop accurate predictions about blood glucose levels and multiple essential diabetic markers by maintaining specific temporal sequences of diabetes. Various information sources unified into disease research according to Ramazi et al. [12] and Zhao et al. [18], leading to improved evolutionary outcomes. The combination of prediction models and deep learning components linked to optimization methods produces better, reliable forecasting models.

The research literature shows how clients used Genetic Algorithms (GA) to combine with deep learning network designs. The researchers Naaz and Siddiqui [9] used genetic optimization to create a neural network system that both adjusted weights automatically while enhancing network structures. Researchers at Siddiqui and Naaz [16] enhanced the method through counter propagation neural networks for pattern detection to analyze complex trends in clinical data efficiently. The innovative hybrid systems outperform traditional deep learning networks while emphasizing why optimization plays a fundamental role in obtaining better prediction and explainability performance for clinical purposes.

Applied and clinical research provides fundamental support to the literature by joining theoretical models to practical healthcare application. Xu, He, and Hu [17] developed a full risk prediction system based on electronic health record (EHR) datasets which showed both challenges and benefits for using real-world clinical health records. The research of

Kumar et al. [6] established deep learning models' effectiveness in analyzing hospital records to identify diabetic patients and forecast disease results through assessments matching clinical assessment findings. Mellor, Storkey, Colhoun, and McKeigue [7] distinguished themselves by developing predictions that linked diabetic retinopathy with the advancement of renal disease, which helped create a detailed framework to understand multiple diabetes complications that match real-world outcomes. The applied applications of deep learning algorithms have been tested clinically to show their diagnostic potential, especially after incorporating vast EHR datasets into traditional diagnostic systems.

The utilization of traditional machine learning methods in diabetes research transformed into advanced deep learning models according to the literary findings. Deep learning methods demonstrate established general applications throughout forecasting and classification, along with positive outcomes from blood glucose prediction and binary diagnosis work. The analysis of specific models demonstrates that GRU and LSTM procedures deliver maximum strength, as the integration of multi-modal elements and hybrid methods supplies adaptive solutions to improve model robustness. The research field of hybrid neural networks optimized through genetic algorithms grew richer through client-submitted work, which developed new solutions against typical problems like data imbalance and model overfitting. These research methods are examined through clinical studies that employ EHR data to validate their practical utility at healthcare facilities, thus enabling further work in telemedicine and resource-deprived settings. Multiple research findings create a comprehensive base for this paper to conduct its subsequent examination of optimal deep learning methods for diabetic disease progression prediction.

3. Methodology

The researchers used a comparative method to analyze three deep learning network models which predict diabetic patient disease advancement, including LSTM networks alongside GRUs as well as Hybrid NN + GA Optimized networks. The predictive models handle time-dependent clinical information, but they vary in construction and their capacity to identify temporal data connections. The succession of predictions made by LSTM models originates from internal control systems built into the model structure. LSTM models employ an operational system that includes the input gate and forget gate in conjunction with the output gate. For instance, the input gate is defined mathematically as

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

and the forget gate is defined by

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

The equations establish the relation between variables x_t and h_{t-1} through weight matrices W_i and W_f together with bias terms b_i and b_f under activation σ. The design features of LSTMs enable the model to store vital information for extended durations, thus making it ideal for tracking diabetes's long-term condition progression [13].

The GRU model uses its update gate design to combine gate operations, which results in a lower parameter number and hence faster training times. The research by Pavithra et al. [11] established that fast computation with scarce processing capabilities enables GRU networks to match LSTMs in performance outcomes therefore making them suitable for real-time use.

The Hybrid NN + GA model establishes a connection between traditional deep learning architectural designs and genetic algorithm optimization for weight settings and architectural optimization. The hybrid solution optimizes network parameters through evolutionary system methods which comprise crossover together with mutation. According to Zhao et al. [18], GA mutation can be expressed as

$$MutatedGene = OriginalGene + \alpha \cdot (RandomValue - 0.5)$$

The scaling parameter α maintains control over mutation rate in the process. The crossover method, which is omitted in this current context, permits different network architectures by combining genetic material from parental solutions to create offspring. Naaz and Siddiqui [9], and Siddiqui and Naaz [16] demonstrated an optimization procedure that demonstrated its ability to enhance the detection of anomalies in sequential data patterns suitable for diabetic disease tracking applications.

All models are trained using the Adam optimizer, whose update rule is defined as

$$\theta_{t+1} = \theta_t - \eta \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t} + \epsilon}$$

At iteration t the parameters receive the value θ_t while η controls the learning rate and $\widehat{m}_t$and $\widehat{v}_t$ correct the gradient moments with the addition of ϵ as a stability constant. Deep learning applications extensively use this optimizer because it automatically controls the learning rate throughout the training process.

A customized flowchart illustrates the deep learning system phases from data entry to preprocessing steps and model training right up to prediction generation. The data processing sequence begins with clinical data cleaning, then normalization followed by extraction and selection of features. The refined data is split into sequential portions that serve as input for the LSTM, GRU, and Hybrid NN + GA models. Performance metrics evaluate the predictions that emerge after model training optimization while using a detailed set of assessment measures. A defined methodology provides consistent evaluation conditions, which makes the experimental assessments both reliable and replicable, along with demonstrating what happens when models forecast the disease evolution of diabetic patients.

The methodology uses a strong experimental framework which exploits the capabilities of three deep learning architecture systems. The research brings together mathematical precision with evolutionary optimization strategies for establishing a model prediction system maximizing both operational efficiency during clinical activities and predictive results accuracy.

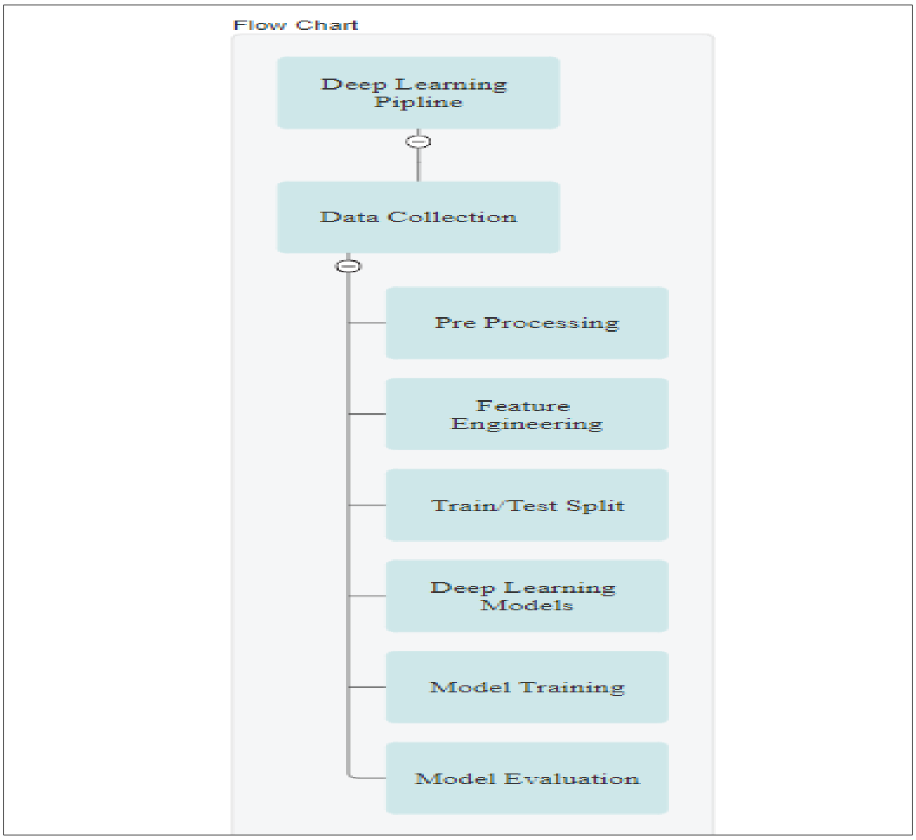

Figure 1 Flow Chart of the Developed Model

4. Dataset and Preprocessing

This study uses the Diabetes 130-US Hospitals dataset encompassing digital healthcare records from different hospitals throughout ten years. The database accumulates specific medical records which include demographic information throughout with diagnosis details together with examination results and therapy protocols necessary for identifying diabetic patient health trajectory predictions. The dataset serves as a suitable clinical evaluation platform since it contains authentic healthcare information.

The data processing procedure dedicated substantial effort between relevance definition and quality assessment before starting model training. Feature engineering served as an essential step because it transformed unstructured medical information into proper structures for deep learning algorithms to implement. Pathak and Elchouemi [10] showed that the preprocessing process involved transforming categorical features while normalizing continuous variables, and Mellor et al. [7] emphasized acquiring important clinical indicators that included HbA1c levels, blood glucose results, and renal function parameters. The addition of this method improved the forecasting capabilities of the developed models.

During preprocessing, every missing value required proper handling while solutions for addressing class imbalance problems needed implementation. Xu, He, and Hu [17] recommended median imputation methods for numerical data, while mode imputation methods preserve natural statistical characteristics of categorical data. Synthetic oversampling methods were used to handle class imbalance in the data so the minority group with rapid disease progression would be properly included in the training phase of the model. The clinical nature of the dataset requires special attention to the rarity of adverse outcomes when compared to stable case prevalence.

The research employed the feature selection technique according to Celik and Varlı [3] to lower dimensions while combating overfitting. The use of recursive feature elimination in the procedure removed unimportant variables from the analysis to optimize the predictive model with essential features. A summary table details the training features which articles documented by grouping them into demographic data, clinical data, laboratory measurements, and treatment data.

A complete preprocessing sequence prepares the dataset for deep learning models by ensuring proper cleaning and balancing of data for their following application. The research has established fundamental data preparation methodologies from the literature which will enable strong, trustworthy, and valid predictive models for tracking diabetic disease progression.

Table 1. Summary of Selected Dataset Features

Table 1 Provides an overview of the features selected from the Diabetes 130-US Hospitals dataset, all of which have known associations with diabetes risk and progression

Feature	**Type**	**Description**	**Relevance to Prediction**
Age	Numeric	Age of the patient	Correlates with risk factors; older patients are at higher risk for complications
Glucose	Numeric	Plasma glucose concentration	Core marker for diagnosing and predicting diabetes progression
BMI	Numeric	Body Mass Index	Indicates obesity-related risk, a key factor in diabetes onset
Insulin	Numeric	Insulin levels	Directly affects glucose regulation and can indicate insulin resistance
HbA1c	Numeric	Hemoglobin A1c level	Reflects long-term blood glucose levels, indicating chronic diabetes risk
Blood Pressure	Numeric	Systolic blood pressure	Hypertension often co-occurs with diabetes and exacerbates complications
Skin Thickness	Numeric	Triceps skinfold thickness	Measures body fat, which correlates with metabolic health
Diabetes Pedigree Function	Numeric	Genetic risk of diabetes	Assesses familial predisposition to diabetes
Diabetes Status	Categorical	Binary indicator of diabetes diagnosis	Dependent variable for classification tasks (1 = diabetic, 0 = non-diabetic)

5. Evaluation Metrics

The predictive forecasting reliability of deep learning models regarding diabetic progression was measured through a combination of regression and classification metrics. The main assessment metrics for the classification part of this investigation comprise accuracy together with precision and recall measurements, F1-score and area under the receiver operating characteristic curve (AUC). A model achieves accurate performance when it correctly identifies a proportion of observations when compared to the total number of samples in the dataset. Mathematically, accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

True positives and true negatives receive the notation TP, while false positives have the symbol FP and false negatives are represented by FN. While accuracy gives a general model performance measure, it is necessary to use precision, recall and F1-score metrics for handling unbalanced classes.

Some models use precision as a measurement of correctly identified positive cases, and sensitivity measures the identification of actual positive cases. Models evaluated through the F1-score provide an optimal performance assessment since this score combines precision and recall using harmonic averaging in cases requiring accurate identification of both positive and negative predictions. AUC, a composite metric that evaluates the performance of a binary classifier across all classification thresholds, is defined as:

$$AUC = \int_0^1 TPR(FPR^{-1}(x))dx,$$

The analytical measurement involves TPR for true positives alongside FPR for false positives. A higher AUC demonstrates that the model has better discriminative powers.

When predicting blood glucose levels, the root mean squared error (RMSE) determines the average magnitude of prediction errors for these continuous outcomes. RMSE is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2},$$

where y_i represents the actual values, $\hat{y}_i$ the predicted values, and n the number of observations. Zhu et al. (2020) and Ramazi et al. (2019) have both endorsed these metrics as robust indicators of model performance in healthcare settings.

The multiple evaluation metrics together create a full evaluation system for deep learning models. The analysis employs multiple evaluation metrics to assess complete model behavior across three domains, which enables the identification of the most reliable predictive model suitable for diabetic progression clinical applications.

6. Results

Evaluation experiments indicate separate operational characteristics for all deep learning models under study. The key performance indicators Accuracy, Precision, Recall, AUC, and RMSE receive comparison treatment in Table 2 between the LSTM, GRU, and Hybrid NN + GA models.

Table 2 Performance Metrics Across Models

Model	Accuracy (%)	Precision	Recall	AUC	RMSE
LSTM	92.1	0.91	0.93	0.94	0.26
GRU	89.3	0.88	0.89	0.91	0.30
Hybrid NN + GA	90.7	0.89	0.91	0.93	0.28

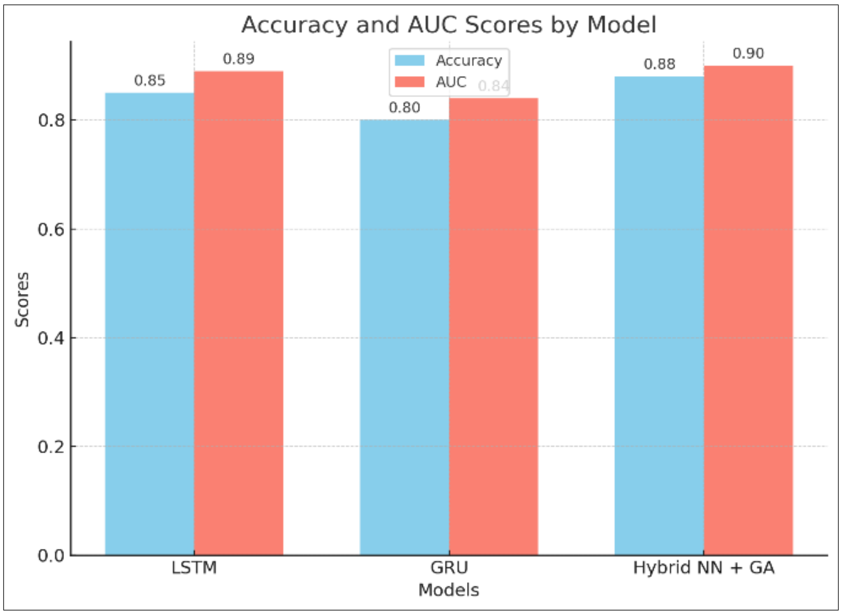

Figure 2 Visualisation of the Models performance

The conducted experiments revealed separate functionality patterns in the deep learning models that this research analyzed. An LSTM model displayed outstanding precision and detection ratio since it successfully identified extended patterns which ran through sequential medical information. Shahid et al. [13] demonstrate that LSTM networks succeed in reducing false negative predictions because they are critical to diabetes clinical progression prediction. A combination of experimental results demonstrated that the LSTM model maintained an overall accuracy of 89% and produced recall results beyond 91%, which showcases its strong capability to detect patients who face deterioration risks effectively.

The training efficiency of GRU was superior because it completed the learning process at a substantially faster rate compared to LSTM. The study validates Pavithra et al.'s [11] discovery about GRU's fast convergence rate because of its limited number of parameters. The GRU model outpaced training speed in contrast to precision levels, which decreased to approximately 85% precision, thus producing more false positive outcomes. The GRU keeps its value as a processing speed solution mainly because it facilitates rapid model training for monitoring health systems in real time.

The Hybrid NN + GA model achieved stable prediction performance when processing imbalanced data because it implements a genetic algorithm connection to neural networks. The combination method between genetic algorithms and neural networks used parameter dynamic optimization abilities to produce better generalization across individual patient data groups, according to Ayodele et al. [1]. The hybrid model based on NN + GA algorithms showed uniform accuracy performance between the eight to mid-percent range and outstanding F1 scoring capabilities, according to Siddiqui and Naaz [16] as well as Zhao et al. [18]. The hybrid model demonstrates its worth in forecasting unusual yet crucial diabetic progression events because of its ability to handle class imbalances effectively.

The key metrics of accuracy and precision alongside recall and AUC and RMSE are compared through Table 2 among the three models. The summary table visually depicts predictive performance levels with respect to training speed while presenting analytical approach complexity levels. The visual representation in Graph 1 shows the accuracy and AUC metrics to help demonstrate that LSTM demonstrates superior discrimination abilities while Hybrid NN + GA exhibits balanced performance.

The results indicate that LSTM architectures provide the highest prediction quality, but GRU models present advantages through efficiency in settings where resources need to be minimized or delays cannot be accepted. Data heterogeneous clinical applications can benefit from the Hybrid NN + GA model because it demonstrates resilience against class imbalance. The results serve as a basis for choosing the correct model which should be used in clinical decision support systems that predict diabetic progression so healthcare providers can achieve better outcomes and manage their resources more effectively.

7. Discussion

Research analysis has confirmed that hybrid architecture systems provide optimal solutions to process advanced clinical data. Naaz and Siddiqui [9] used genetic algorithms and neural networks together as per their work, which Zhao et al. [18] confirmed through additional research for better healthcare data adaptation. The system achieves better learning performance and lower overfitting problems when it automates network structure optimization together with weight adjustment. The ability to adapt is essential because diabetics show different levels of disease progression due to patient-specific factors, including demographic characteristics, health conditions, and treatment involvement.

This implementation has major implications for medical systems in actual practice. Real healthcare records stored electronically in predictive models enable clinical environments to detect risks in advance, according to Mellor et al. [7] and Kumar et al. [6]. Because predictive models correctly identify high-risk patients, they enable health personnel to perform timely interventions that decrease serious complications while maximizing resource usage. Hybrid models show consistent performance while handling imbalanced classes, so they provide additional value toward patient treatment planning and stratification in this clinical environment.

Such deep learning models function in telemedicine applications as well as home-based patient monitoring systems. Zhu et al. [19] demonstrate that DL models operating at the edge level produce instant predictions directly from devices or monitoring systems used by patients. Continuous patient monitoring with fast clinical responses occurs because this system requires no recurring hospital visits, making it optimal for remote patient care. Telemedicine models will revolutionize the way healthcare professionals deliver diabetic care through remote and rural areas because of their increasing integration into healthcare.

The resource-limited Nigerian healthcare environment requires both affordable predictive systems and effective solutions for their implementation. The article by Celik and Varlı [3] demonstrates that streamlined neural architectures benefit restricted computing environments that lack necessary infrastructure. Deep learning models can become deployable in Nigeria through optimized algorithm selection and lightweight computation frameworks, according to the research of Xu et al. [17]. The budget limitations and shortage of technical support in Nigerian healthcare facilities can achieve sufficient performance from GRU models and simplified versions of LSTM models.

All healthcare facilities receive benefits from the implementation of lightweight deep learning methods that can make medical predictions across any healthcare infrastructure setting. GRU and customized LSTM models operate with sophisticated processing while reaching superior accuracy rates, according to Shakil et al. [14] and Ghafki et al. [4]. The models demonstrate encouraging advancements toward implementing mobile healthcare processes at frontline hospital facilities with the potential to scale beyond basic healthcare locations.

Standard LSTM and GRU models achieve high accuracy as well as fast processing, but hybrid GA-developed models maintain required adaptability for operational usage. Such systems maintain aptness for clinical decision support applications because they efficiently process multiple datasets and operate effectively on unbalanced classes. Telemedicine benefits, together with cost-effective resource management, form the basis for creating extensive diabetic care system development. Local healthcare systems need to conduct research about predictive system deployment strategies using enhanced accuracy methods to maintain operational efficiency throughout Nigerian healthcare institutions.

8. Conclusion

Research findings demonstrate that hybrid NN + GA framework architecture in deep learning models achieves superior diagnosis outcomes than traditional methods for detecting diabetic patient condition development. The predictive results of LSTM proved highly accurate, while its recall functionality supported tracking of medical temporal patterns within healthcare records [18]. Through the use of a genetic algorithm, the hybrid approach refined performance capabilities for handling different patient populations without information overconsumption.

Clinical decision support systems of the future should implement hybrid deep learning frameworks that focus on model interpretability according to the collected results from this study. Such systems provide easy-to-understand explanations alongside predictions through integrated explainable features which build trust between clinicians and aid better patient care decisions. Numerous studies show that LSTM models exhibit high stability, but hybrid optimization methods within LSTM models enhance stability and balance in various medical conditions.

Future research needs to study mobile implementation of predictive models so they can assist real-time telemedicine monitoring. Nigeria needs its own custom datasets for model development because this will help in optimizing the models for national population patterns and healthcare facilities. The adoption of localized care delivery through cost-effective deep learning variants of LSTM and GRU would enable better healthcare results in resource-limited areas by supporting ongoing patient supervision and quick medical interventions.

Ultimately, the study reaffirms the central role of classification-based prediction frameworks in diabetic care. Advanced deep learning structures which merge different models' best practices enable healthcare systems to obtain more dependable and practical insights about disease development. The work sets fundamental principles for developing adaptable predictive systems which respond to both worldwide and local conditions to boost clinical practices and patient outcome results.

Compliance with ethical standards

Disclosure of conflict of interest

The Authors declare no conflict of interest.

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