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Original Article

A Survey of AI-Driven Techniques for Enhancing Clinical Decision Support in Modern Healthcare Systems

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Abstract - *Modern healthcare would not be possible without clinical decision support systems (CDSS), which aid doctors in making quick and accurate choices. By incorporating AI, CDSS has evolved into a sophisticated system that can sift through mountains of patient data, spot trends that might not be immediately obvious, and soffer recommendations supported by evidence. AI-powered CDSS can enhance diagnostic precision, facilitate early disease forecasting, and aid in individual treatment plans. This study suggests a model that combines a Recurrent Neural Network with a Gated Recurrent Unit (RNN+GRU) to improve the accuracy (ACC) of clinical predictions. The model tested on the MIMIC-IV dataset. The proposed hybrid model is successful in capturing the sequential clinical patterns and is able to learn without overfitting. The proposed model showed to be more accurate than the other models used, with a value of 99.71% ACC, which is higher than the ACC of the LSTM model with 82% ACC, Adaboost model with 92.9% ACC, and XGboost model with 95.8% ACC. The comparison shows that the proposed framework has higher prediction performance, reliability and generalization ability. The developed model has the potential to be a powerful tool in the era of modern healthcare, enabling intelligent healthcare analytics, patient risk assessment, and effective clinical decision-making.*

Keywords - *Healthcare, Clinical Decision Support Systems, Machine Learning, Predictive Analytics, Diagnosis, Deep Learning, Electronic Health Records.*

1. Introduction

Healthcare systems have changed significantly, as digital technologies and data-driven medicine were introduced [1]. Intelligent computation tools are necessary for the successful analysis of the vast quantities of healthcare data generated by recent technology advancements such as genetic technologies, wearable sensors, medical imaging systems, and EHRs [2]. Clinical decision support systems (CDSS) have become essential resources for healthcare clinicians in order to facilitate the quick, precise, and evidence-based decision-making process [3]. Healthcare quality and safety are supported by these systems, which offer patient-specific suggestions, reminders, and diagnostics for better patient outcomes, lower medical error rates and healthcare quality improvements [4][5][6][7]. Originally, CDSS were structured as rule-based systems, which were based on clinical guidelines, expert knowledge and deterministic decision rules [8][9]. As healthcare information systems have developed and large datasets have become more prevalent, Artificial Intelligence (AI) techniques have become crucial for enhancing the efficiency and intelligence of CDSS [10][11][12].

The use of ML techniques allowed modern CDSS to learn from their mistakes and make predictions about future outcomes using clinical data. Modern CDSS were greatly enhanced by ML methods, which enabled systems to learn from previous clinical data and forecast future outcomes [13][14]. The use of various ML techniques has been successful in predicting disease, assessing risk, early diagnosis, and recommending treatments [15]. The development of CDSS based on AI has been significantly enhanced by DL, a subfield of ML that makes use of multi-layered neural architectures [16][17]. DL models have demonstrated exceptional capability in medical image interpretation, disease classification, predictive analytics, and complex pattern recognition by learning directly from large-scale healthcare datasets.

1.1. Motivation and Contribution

The exponential expansion of healthcare data created by EHRs, MRIs, and wearable devices has led to an increase in the expectations for intelligent systems to aid in precise clinical decision-making. This study aims to dive into the key causes behind its inception. Clinicians receive real-time support from AI-powered CDSS, which aids in preventing diagnostic errors, improving treatment efficiency, and enabling patients to receive tailored care. These developments inspire investigations into ML and DL algorithms to improve the current healthcare systems. This study provides a number of important contributions as follows. The

following are a few of the most important contributions made by this study:

- Proposes an efficient Hybrid RNN+GRU framework for enhancing CDSS.
- Achieves highly accurate and reliable prediction performance with strong generalization capability.
- Demonstrates superior performance compared with existing models such as LSTM, AdaBoost, and XGBoost.
- Reduces prediction bias and minimizes overfitting for stable clinical predictions.
- Supports accurate patient risk assessment and intelligent healthcare decision-making.

- Contributes to improving AI-driven healthcare analytics and modern clinical management systems.

1.2. Justification and Novelty

The novelty of this research is that it successfully captures complex clinical pattern and enhances prediction consistency to provide a highly accurate and reliable hybrid DL framework for CDSS. The proposed approach proves to be more effective than the current approaches, including LSTM, AdaBoost and XGBoost in terms of generalization and overfitting. The study's importance lies in the growing demand for intelligent healthcare systems that can aid in early risk assessment, accurate diagnosis, and efficient clinical decision-making. The suggested framework not only makes healthcare more efficient and high-quality but also reduces mispredictions and helps in medical analysis through data in modern healthcare environments.

1.3. Organization of the Paper

The paper is organized as follows: In Section II, the pertinent literature on CDSS is reviewed. In Section III, present the proposed technique; in Section IV, gives the experimental data and compare them; and in Section V, talks about the results, the important findings, and where the research could go from here.

2. Literature Review

A comprehensive review and analysis of the key research studies on improving CDSS was conducted to inform and improve the development of this study. Bhuvaneswari et al. (2026) development of a heart disease detection predictive model using the XGBoost algorithm in the field of medicine for attributes such as age, sex, BP) Cholesterol, Max HR, smoking, and diabetes. The model performance was enhanced by normalizing and encoding features of the dataset. The normalization and feature encoding of the dataset resulted in an enhanced performance of the model. It attained ACC of 97.00% which is higher than the ACC of LR Classification, DT Classification, SVM Classification and KNN Classification [18].

Kumar et al. (2025) employ Markov Chain Monte Carlo methods for posterior inference and integrates uncertainty quantification into operational decisions. Experimental results show significant improvements in bed utilization efficiency (increased by 18.2%) and reduction in patient waiting times (decreased by 31.5%). Findings highlight the practical applicability of Bayesian methods in managing healthcare operations under uncertainty [19].

Lalithadevi, Likitha and Harini (2025) focus on a new CDSS based on AI techniques to provide reliable diagnoses and treatment recommendations. LR yielded a testing ACC of 89% for predicting diabetes, while RF classified heart disease with 99% ACC. ResNet50 outperformed other ML models, achieving an 86% testing ACC in identifying bone cancer. The overall testing ACC for the system is 91.33%. The outcomes point to the potential of the proposed CDSS in enhancing diagnostic ACC, streamlining clinical workflows, enabling evidence-based medical practices, and reducing diagnostic errors [20].

S. C. Reddy et al. (2025) creation of an intelligent AI system that helps healthcare professionals make precise medical decisions through diagnosis support for diabetes prediction from structured medical data. Experiments demonstrated that XGBoost outperformed the other baselines, such as LR, RF, and SVM, with an AUC-ROC value of 0.87 and a classification ACC of 81.3%. The predictive features detected by SHAP analysis included glucose along with BMI and age, which confirmed clinical assumptions about diagnosis [21].

Jayasingh et al. (2024) focus on the use of a dataset that includes patient medical information, such as their demographics, medical history, and test results. In order to forecast ACC, PRE, and REC where the XGBoost algorithm performed well. Treatment of cardiac illnesses becomes easier with the system's outstanding performance and promising major breakthroughs in detection. Its ACC is 93.24%, its PRE is 94.2%, its sensitivity is 93.4%, its specificity is 92.9%, and its F1 is 93.8%, which is higher than any other model [22].

Chandrakala et al. (2024) delve into the possibilities of libraries housing open-source machine-learning models to aid designers and provide a framework outlining the specifics of ML-generated analogue circuits. Creating neural network designs has traditionally relied on commercialized CMOS or software simulations; however, these approaches don't guarantee optimal performance. The proposed approach is validated using a three-stage device design. In the first stage, the type is accurately predicted with a PRE of 89.75% utilizing a machine learning approach called the decision tree [23].

Table 1: Comparative Analysis of Recent Machine Learning-Based Clinical Decision Support Systems

Author	Objectives	Source	Empirical Analysis	Challenges
Bhuvaneswari et al. (2026)	To develop a heart disease detection predictive model using the XGBoost algorithm with medical attributes such as age, sex, BP, cholesterol, Max HR, smoking, and diabetes.	Heart disease dataset containing demographic and clinical attributes.	Data normalization and feature encoding improved model performance. XGBoost achieved 97.00% accuracy, outperforming Logistic Regression, Decision Tree, SVM, and KNN classifiers.	Managing heterogeneous medical data, feature preprocessing, and improving predictive accuracy across different classifiers.
Kumar et al. (2025)	Optimizing healthcare operations using the use of	Healthcare operational and	Bayesian methods increased bed utilization efficiency by	Handling uncertainty in healthcare systems

	Bayesian inference and Markov Chain Monte Carlo (MCMC) methods when dealing with uncertainty.	patient flow datasets.	18.2% and reduced patient waiting time by 31.5%.	and integrating probabilistic decision-making into operational management.
Lalithadevi, Likitha and Harini (2025)	To develop a CDSS for disease diagnosis and therapy recommendation based on AI.	Diabetes, heart disease, and bone cancer datasets.	The accuracy rates for diabetes prediction, heart disease categorization, and bone cancer diagnosis were 89% for LR, 99% for RF, and 86% for ResNet50, respectively. There was a 91.33% overall accuracy rate.	Integrating multiple AI models for different diseases and ensuring reliable diagnosis across medical domains.
Shiva Charan Reddy et al. (2025)	To create an intelligent AI-based diagnosis support system for diabetes prediction using structured medical data.	Structured diabetes medical dataset.	XGBoost achieved 81.3% classification accuracy with 0.87 AUC-ROC. SHAP analysis identified glucose, BMI, and age as significant features.	Interpreting AI predictions and identifying clinically relevant features for reliable diagnosis.
Jayasingh et al. (2024)	Use ML algorithms to forecast heart illnesses based on patient demographics, medical history, and test findings.	Cardiac disease dataset with demographic and clinical information.	XGBoost achieved 93.24% accuracy, 94.2% precision, 93.4% sensitivity, 92.9% specificity, and 93.8% F1-score, outperforming other models.	Improving early cardiac disease detection and maintaining balanced performance metrics.
Chandrakala et al. (2024)	To explore open-source machine learning models for analogue circuit design and provide a framework for ML-generated analogue circuits.	Three-stage analogue circuit design dataset and simulation data.	Decision Tree achieved 89.75% precision in predicting circuit design types.	Achieving optimal neural network-based analogue circuit designs and reducing dependency on commercial simulation tools.

2.1. Research Gap Summary

AI and ML considerably improve the ACC of disease predictions (ACC), according to Table I. There are still a number of research gaps, though. Model interpretability, scalability, real-time implementation, and connection with clinical workflows receive minimal consideration in most research, which mainly emphasizes achieving high ACC. Additionally, many models are trained on specific or limited datasets, reducing their generalizability across diverse healthcare environments. Few studies address issues related to data imbalance, computational complexity, uncertainty handling, and explainable AI for medical decision-making. Thus, there is a need for a more powerful, interpretable and scalable prediction framework that can offer reliable health prediction and facilitate clinical practices.

3. Research Methodology

The proposed solution is based upon the MIMIC-IV data set with demographic, clinical and medication data. Data visualization, outlier detection, normalization, missing value imputation, and class balancing using SMOTE are some of the preprocessing approaches used to enhance the data's quality and distribution. The dataset is partitioned into a training set and a testing set to assist with clinical prediction and decision-making. One subsequent step is the development of a deep learning model that combines RNN and GRU. The model's performance is then evaluated using the ACC, REC, PRE, and F1. The proposed steps for enhanced CDES using machine learning are displayed in flowchart, as shown in Fig. 1.

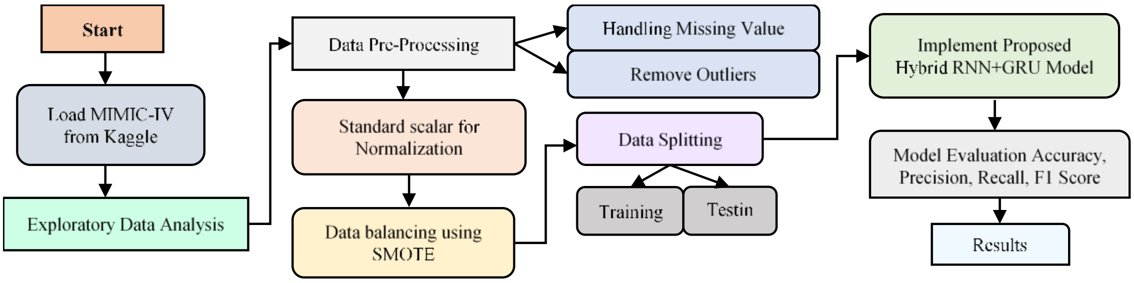

Fig 1: Proposed flowchart for Improving Clinical Decision Support Systems.

The following section presents a detailed description of each stage involved in the proposed methodology:

3.1. Data Gathering and Analysis

MIMIC-IV Electronic Health Record (EHR) Data Set from Kaggle public source. Patient demographic, clinical severity measures, variables relating to medication, mortality and care unit data. It includes input from intravenous infusion, patient output, notes of observations and ongoing documentation of the process. The data is analyzed using the visualization techniques which are shown below to understand the distribution of each feature, check for patterns and test for correlation between the variables:

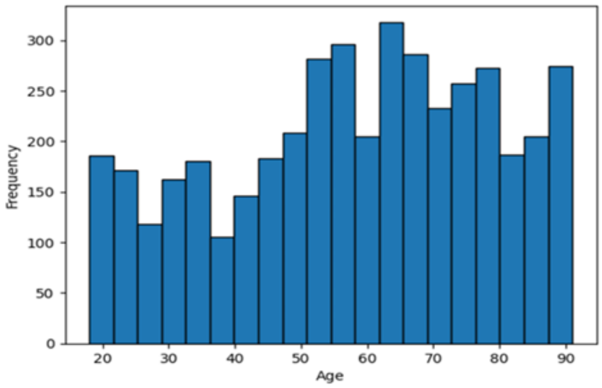

Fig 2: Histogram for Distribution of Ages

The frequency distribution of ages in a set of data is displayed in Fig. 2. The number of people in each age range, from 20-90 years, is displayed as a bar chart. The histogram shows that there are more people in the middle age groups (50 to 70 years), indicating a clustering of people in these age ranges. This visualization is an effective way to show demographic trends and age variance within a society.

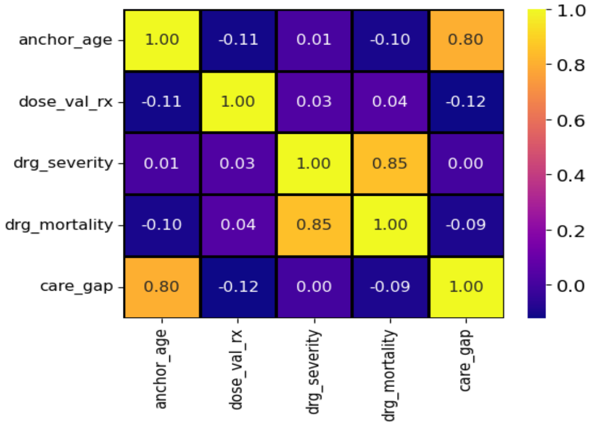

Fig 3: Correlation Heatmap of Numerical Features

The pairwise correlation among five numerical variables: anchor_age, dose_val_rx, drg_severity, drg_mortality, and care_gap are shown in Fig. 3. The cells display the value of the correlation coefficient: strong positive correlation appears in red cells, weak or negative correlation appears in blue cells. It is noteworthy that the correlation between drg_severity and drg_mortality is high (0.85) and similarly the correlation between anchor_age and care_gap is also high (0.80) with a positive link. The heatmap can be used to identify interdependencies between features, which can then be leveraged to inform the selection of the appropriate model and/or feature engineering.

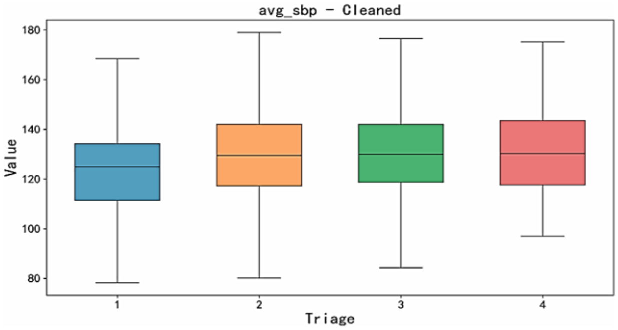

Fig 4: Box plots Distribution of Average Systolic Blood Pressure

Fig. 4 displays box plots from four different triage groups showing the distribution of average systolic blood pressure (avg_sbp). Each shaded box shows the median, interquartile range and variability of blood pressure measurements in a triage. Medians are similar across categories and there is moderate variation among patients based on the spread seen. This visualization can be used to evaluate the blood pressure stability and the discrepancies of clinical triage classifications.

3.2. Data Pre-Processing

Identifying and addressing anomalies is an essential component of preparing data for processing. Detected data outliers using the IQR approach. Missing values are filled in using means when the proportion of characteristics without data is low. A total of 14,717 data points were used to choose 14 characteristics as input variables and 1 characteristic, high_risk_flag, as the target variable.

3.3. Standard scalar () Normalization

StandardScaler() is used to change the dataset so that it has an end distribution with a mean of 0 and a standard deviation of 1. The term for this procedure is standardization. The descriptions have varied scales, thus this is done. The standard deviation of each observation divided by the mean, as shown in Equation (1), is all that is needed to accomplish this transformation:

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

The variables that make up this dataset are as follows: z, which is the converted feature value, x, which are the original descriptor values, μ, representing the mean, and σ, representing the standard deviation.

3.4. Data balancing using SMOTE

The class imbalance problem is addressed with data balancing, ensuring an equal distribution of samples across all classes. This process resulted in a better-balanced model performance, minimized bias and increased model classification ACC. To solve class imbalance problem in the data, the SMOTE is used. This method is used to create synthetic samples for minority classes, thus producing a more balanced class distribution.

Fig. 5 shows both the pre and post-SMOTE sample counts for each class. The large variation is indicated by the stark contrast between the sample sizes of class 0 and class 1, which are 130,000 and 50,000 samples, respectively. Both classes are balanced to near equal size (SMOTE samples adjusted to 130,000) to achieve near-equal representation. The visualization is clear with synthetic instances created for the minority class that is used to balance the data overall, increasing the fairness and stability of the model.

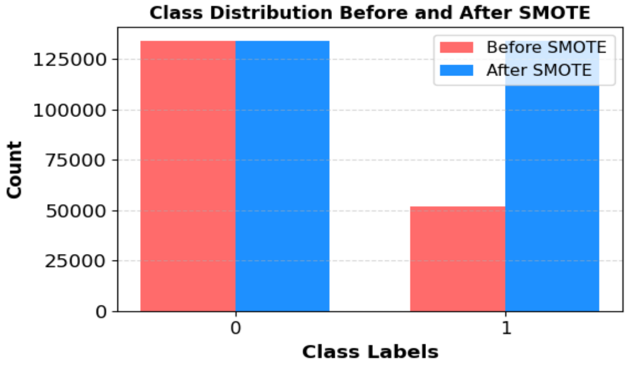

Fig 5: Class Distribution Before and After Applying SMOTE

3.5. Data Splitting

The dataset is divided into training and testing sets using a stratified 70:30 split. The two sets of data keep the same original distribution of classes.

3.6. Proposed Hybrid RNN+GRU Model

A proposed Hybrid RNN and Gated Recurrent Unit (Hybrid RNN+GRU) model is developed for enhancing clinical decision support in healthcare systems through accurate analysis and prediction of clinical data.

3.6.1. Recurrent Neural Network (RNN)

RNN models excel at handling sequential data because RNN units are designed to recall previous states. In order to calculate the current state, this memory attribute is used [24]. This is why RNN units allow both the current and past output values as inputs. To better understand how RNN units work, consider the following Equation (2).

$$y(t) = f\big(x(t) + y(t-1)\big) \quad (2)$$

The input at the moment is denoted by $x(t)$, the result is represented by $y(t)$, and $y(t-1)$ is the output from one period before. The $f(x)$ graph shows this relationship. An RNN's nonlinearity arises from the function $f(x)$, a basic hyperbolic tangent function, and its unstable gradient tendency. See gradients grow to limitless sizes when using the rectified linear unit function or another non-saturating activation function.

3.6.2. Gated Recurrent Unit (GRU) Model

The more complex internal structure of an LSTM neural network, as well as the difficulty in modifying its parameters, causes the train time to be larger. A GRU variation of LSTM [25]. The GRU model trains faster than the LSTM model while yet achieving comparable predictive ACC. The number of gating components needed for the memory module was reduced from three to two by GRU, who combined the input and forget gates of an LSTM into an update gate. An update gate controls the amount of data used in the current state from prior states; it is denoted as Z_t. The memory REC of the current neuron is better than that of its predecessor if the value of the update gate is larger. The primary purpose of clearing the memory via the update gate is to allow the observation of patterns in the sequence of water quality data over a long period of time. Equation (3) shows the formula for the update gate to capture information:

$$Z_t = \sigma(W_Z * [h_{t-1}, X_t]) \quad (3)$$

The reset gate, abbreviated as R_t, is a crucial component in determining the amount of data stored. Lowering the reset gate value allow for better retention of earlier data, making it easier to detect short-term patterns in the water quality parametric data. In order for the reset gate to acquire data, as shown in Equation (4),

$$R_t = \sigma(W_r * [h_{t-1}, X_t]) \quad (4)$$

where the expected value of the unit's output state at time b is denoted by $\bar{h}_t$ and h_t is the actual state at that time. The current unit's data is saved and transferred to the next unit using this value. Using Equation (5), the output from the earlier time may be estimated.

$$\bar{h}_t = tanh(W_{\bar{h}} * [r_t * h_{t-1}, X_t]) \quad (5)$$

The outcomes that are expected based on the data on water quality characteristics can be shown by Equation (6).

$$h_t = (1 - Z_t) * h_{t-1} + Z_t * \bar{h}_t (6)$$

A memory cell's output value of the water quality parameters at moment $t-1$ is denoted by h_(t-1), while X_t represents the current value of the input data at moment t_t. In this cell, can finds the weight matrices W_Z, W_r, and $W_{\bar{h}}$. The symbol "[]" denotes the union of two matrices, "$*$" represents the product of the matrices, σ stands for the activation function, and tanh denotes the bisecting curve of that function.

The Hybrid RNN+GRU architecture proves to be an effective model in cloud environments where dynamics and resources are important, offering the potential to improve convergence speed, reduce vanishing gradients, and boost prediction ACC. The suggested Hybrid RNN+GRU model begins with a single RNN layer that has 128 hidden units, then two GRU layers that have 64 and 32 units, respectively. Adam optimizer is used to prepare the model through eight training iterations with 32 batch size and 0.001 learning rate. Tanh and sigmoid activation functions, along with categorical cross-entropy loss, are employed to enhance classification and generalization performance, with a dropout rate of 0.3.

3.7. Evaluation Metrics

A number of performance metrics for the proposed model's classification efficacy are evaluated. In order to see which predictions were right and which were wrong for each class, generate a confusion matrix. Then, take the values of TP, FP, TN, and FN from the confusion matrix. The important metrics, including REC, ACC, PRE, and F1, are then calculated using the aforementioned values in line with Equations (7)-(10).

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (10)$$

The ACC is the proportion of instances correctly classified relative to the total cases. To test the efficacy of several classifiers, it can be utilized. PRE measures how well the model predicts good outcomes relative to all positive outcomes. The F1 examines the model's ability to properly identify TP examples by integrating REC and PRE in a harmonic mean, while REC measures the model's ACC in a more balanced method.

4. Results and Discussion

The experimental setup and evaluation of the suggested model's training and testing performance are explained in this section. A robust system comprised of a 3.0 GHz Intel Core i9-13900K CPU, 64 GB of DDR5 RAM, and a 24 GB GDDR6 VRAM NVIDIA RTX 4090 GPU is utilized to conduct the testing. Data is processed and the model is built using Python libraries such as Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn, and it runs on Windows 11 Pro. The suggested model was tested on the clinical dataset to determine its accuracy, consistency, and predictive power in classification tasks. Table II displays the outcomes of the model's examination. The RNN+GRU model achieved 99.7% across all evaluation metrics. The model is dependable for assisting healthcare systems with clinical decision-making, and it performs admirably with great generalization (high ACC and little overfitting).

Table 2: Experimental results of the proposed model for Clinical Decision Support Systems

Matrix	Testing	Training
Accuracy	99.71	100
Precision	99.73	100
Recall	99.72	100
F1-score	99.74	100

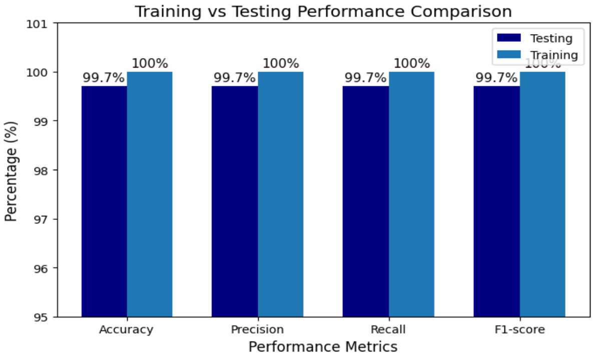

Fig 6: Bar Graph for comparison of Train and Test performance

The performance metrics of the proposed model are illustrated in Fig. 6 through a bar chart. The model's ACC was excellent across all datasets, including training and testing. across the board, demonstrating high prediction ACC and learning efficiency for the model. The strong generalization, model stability, and limited overfitting are evidenced by the similarity between the results obtained from the training and testing sets.

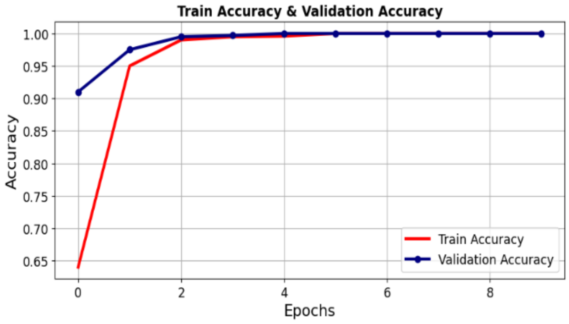

Fig 7: Accuracy Curve For For RNN+GRU Model

Fig. 7 presents the ACC plot of the proposed model demonstrates rapid learning capability and stable performance during training. The training ACC rose from about 65.5% to 100% in just a few epochs, and the validation ACC also rapidly converged to perfect ACC, and kept on the training curve. Both curves are very close, suggesting that there is not much difference between learning and overfitting, and good generalization.

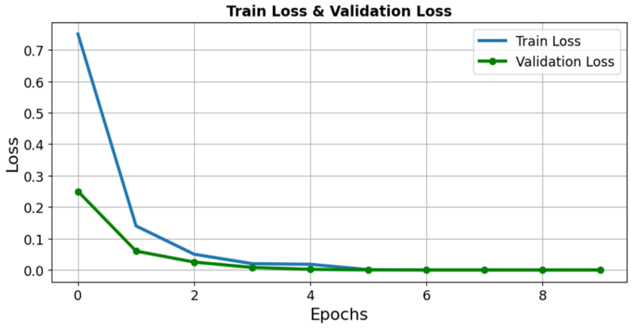

Fig 8: Loss Curve for Hybrid RNN+GRU Model

Fig. 8 shows efficient convergence with a rapid reduction in error during the initial training epochs. The training loss dropped precipitously from about 0.75 to near 0.00, and the validation loss is also gradually reduced and tracked the training loss curve very closely. Both curves are decreasing smoothly and synchronously, thus showing a stable learning process, effective error minimization and no significant overfitting.

4.1. Comparative Analysis

The suggested model is evaluated in comparison to current machine learning models in Table III. Outperforming LSTM, AdaBoost, and XGBoost models, the suggested model achieved the highest ACC of 99.71%. When it comes to balanced classification measures, the LSTM model achieved an ACC of 82% and AdaBoost 92.9%. Reduced prediction consistency lowers the value of F1, REC, and PRE compared to XGBoost. The findings demonstrate that the suggested model is the best option for CDSS using clinical data due to its high efficacy, dependability, and generalizability.

Table 2: Comparison of Different Machine Learning Models for Improving Clinical Decision Support Systems

Model	Accuracy	Precision	Recall	F1-score
LSTM[26]	82	-	-	-
AdaBoost[27]	92.9	89.3	94.2	91.6
XGBoost[28]	95.8	16.5	37	22.8
Propose	99.71	99.73	99.71	99.74

The proposed Hybrid RNN+GRU model has high ACC and reliability in clinical prediction, good generalization ability, and is relatively light in training. The model demonstrates powerful temporal representation learning by integrating RNN and GRU architectures, and excels over conventional models like LSTM, AdaBoost, and XGBoost. Patients' privacy is protected with anonymized public health data, and SMOTE balancing minimizes prediction bias and helps achieve equitable clinical decisions. In summary, the framework enhances the diagnostic support, predictive ACC, and efficiency of healthcare decisions.

5. Conclusion and Future Study

The integration of AI with CDSS is causing a sea change in the healthcare industry. Doctors are able to develop better diagnoses and treatment plans with the use of data-driven insights provided by these platforms. To improve CDSS in the MIMIC-IV healthcare dataset, a new DL method called Hybrid RNN+GRU is introduced. The use of preprocessing techniques enhances the model, leading to better prediction performance. The proposed model demonstrated consistent convergence during training and validation without overfitting, and experimental results demonstrated that it provides outstanding classification results with 99.7% ACC, PRE, REC, and F1. Comparative investigation also revealed that the suggested technique performed better than competing methods, such as LSTM, AdaBoost, and XGBoost. The results of this research show that the presented framework is efficient, reliable and applicable to effectively predict patients' risk accurately and to support intelligent clinical decision making in healthcare systems.

The proposed Hybrid RNN+GRU model is able to attain high predictive performance but there are certain shortcomings in the study. This model has been tested with one publicly available healthcare dataset, potentially reducing the generalizability of the model across various clinical settings and to real-time hospital systems. Besides that, the deep learning architecture is also computationally expensive and is not interpretable in the clinical decision-making process. The model could be further developed and validated with more extensive, multi-center healthcare datasets, incorporating explainable AI methods to enhance transparency, and fine-tuning the model for real-time use in clinical settings.

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