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Hybrid Deep Learning Models For Predicting Gestational Diabetes Mellitus

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Abstract
Diabetes Mellitus forms part of our nation's serious public health concerns. It could be a clutter of the digestion system in thousands of the individuals emerging from a statement of extra glucose inside the body. If diabetes is not diagnosed rather soon on human creatures there will continuously be serious wellbeing complications for example cardiac conditions, renal problems, nerve complications and damage to the eyes. Gestational diabetes is a pathological increase of blood glucose during pregnancy with high risk to mother and child including preeclampsia, neonatal hypoglycemia and future complications. As a result, early interventions for better maternal and fetal outcomes benefit from the accurate prediction and early diagnosis of GDM. Current models usually underperformed in predicting GDM with adequate accuracy more so with imbalanced datasets and lack of supportive mechanisms to handle them. Diabetes mellitus among lactating women is the topic of this research and it intends to predict the same by utilizing Deep learning Algorithms viz GRU+LSTM, GRU, LSTM, RNN, and also different Machine learning algorithms namely Random Forest and XG-Boost classifiers on a real–time diabetes dataset. Considerable effort is therefore put to work-including new techniques such as SMOTE-to obtain the best solution in forecasting of diabetes mellitus. The Pima Indian Diabetes Dataset from the National Institute of Diabetes and Digestive and Kidney Diseases provided the data—all female patients, 768 in all, above the age of 21. One target variable and eight predictor variables are available. In this research, after using the SMOTE algorithm, accuracies were achieved and achieved in whose sequence were GRU+LSTM- 99%, RNN-96%, Random Forest-85%, XG-BOOST-86%, GRU-90%, LSTM-82% are better than those of rest of models covered in the research. The accuracy of existing model [3] comparing the proposed model with respect to XG Boost, (84%), Random Forest (83%), Decision Tree (79%); these proposed models gave the accuracy of GRU+LSTM-99%, RNN- 96%, XG-Boost-86%, Random Forest-85%.
Keywords
Gestational Diabetes Mellitus (GDM), Hybrid Deep Learning, GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory), RNN (Recurrent Neural Network), SMOTE (Synthetic Minority Oversampling Technique), Pima Indian Diabetes Dataset, Machine Learning, Random Forest, XGBoost, Model Accuracy, Pregnancy Health Prediction.

INTRODUCTION
Diabetes is a long-term illness that alters the approach the body uses food for fuel. It is still going to be among the most prevalent and deadly diseases, though.Women appear to be more vulnerable than men to this disease; this relates to their body structure and, to a certain degree, hormonal shifts that occur in their life.Women are usually at twice the risk of experiencing a heart attack when compared to male peers. Women are at risk of developing a variety of issues that are diabetes-related; these range from depression, to kidney disease, and issues with eyesight. Furthermore, diabetes has been recognize to provide unique obstacles in the specific scenarios confronted by women, such as pregnancy, menopause, menstrual cycle, and urinary tract infection.
Diabetes is one of three main types.Type 1 diabetes is insulin-dependent.In this case, there is an absence of insulin production because of a decrease in the number of pancreatic beta cells. Type 2 diabetes, however, is characterized as non- insulin-dependent. The faulty action or secretion of insulin is the cause of the condition known as glucose tolerance. Here the given body fails to effectively utilize the available insulin. Type-3 diabetes is also called gestational diabetes. It affects only women, and occurs during amniotic periods.In the case of type 3, normal diabetes is not diagnosed during the period of pregnancy: Arising from an increase of blood sugar during pregnancy and other times of gestation.

Class imbalance has been a problem for many previous methods of predicting GDM, resulting in lower accuracy and higher false-negative rates.Due to these limitations, advanced solutions like hybrid deep learning models are required for prompt diagnosis and efficient treatment. Predictive analysis uses information from the past and the present to find trends and predict events in the future. These involve a range of deep learning and machine learning models, data mining techniques, and statistical analysis. It is possible to make significant recommendations and decisions according to the patient files and predictive modeling. Diabetes has been demonstrated to be brought on by a variety of factors, including obesity, genetics, hormone imbalance, and poor lifestyle choices. Hence, data containing this information can be employed to detect the pattern of attacks of diabetes. Diabetes, as of now, has been diagnosed by laboratory procedures involving fasting blood glucose measurements and oral glucose tolerance tests. This process takes a huge amount of time and money. Consequently, the application of machine and deep learning methods to anticipate illnesses early on getting more popularity in recent years. A diligent review of literature discovered that all previous studies employed unbalanced and untreated datasets, lacked proper data scaling, and used only fundamental methodologies.To solve all these issues, the current project aims at building an ensemble deep and machine learning model for diabetes early prediction.In addition, the Explainable Artificial Intelligence feature gives complete details of how different features impact the model.In a hybrid deep learning algorithm, the interaction between the Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) is frequently used to use the strengths of both architectures and improve model performance in particular tasks. GRU and LSTM are recurrent neural networks that maintain long-term dependencies in sequential data.

LSTS are more complex with separate memory cells and gating mechanisms, whereas GRUs are superior in simpler structures where memory and gating unit are captured. About the effective model made, combinations of both. Then comes a model with fewer parameters to train quickly: while GRU can be faster in convergence, LSTM might have to get involved with the memory part.Such hybrid architectures could, therefore, help obtain a better trade-off position when exposed to larger datasets or when operating in resource-constrained environments. The main flow involves importing python packages into an IDE, loading the dataset into a data frame, preprocessing, which includes SMOTE into an imbalanced dataset; consequently, this means SMOTE balancing it and storing it as a certain dataset, both datasets analyzed and validated, and followed by data visualization and the scaling of the data. Thus, the division of testing and training is transferred to the model, then testing and training of the model, which generates the matching accuracy of every model, and finally, the comparison and accuracy announcement is done.

LITERATURE REVIEW

[1] Kirti Kangra and Jaswinder Singh emphasized that diabetes mellitus (DM) is a serious issue for world health, causing problems like neuropathy and retinopathy. They proposed using machine learning (ML) for early Identification and observation of diabetes. Various ML methods, including Naïve Bayes, KNN, SVM, Random Forest, Logistic Regression, and Decision Tree, were tested using the WEKA tool on the Germany Diabetes and Pima Indian Diabetes datasets. Results showed SVM performed best for Pima Indian data (74% accuracy), while KNN and Random Forest achieved 98.7% accuracy for the German dataset.

[2]Akkur E and Turk F proposed using machine learning (ML) to predict diabetes mellitus. They tested algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT) and K-Nearest Neighbour (KNN) on the PIMA Indian dataset. Random Forest showed the topmost accuracy (89.06%), with strong precision, sensitivity, and AUC scores. Using SHAP analysis, significant variables like insulin, age, and glucose were identified as the most significant predictors.

[3] F. Muntasir et al. studied diabetes, a prevalent condition affecting women, using the Pima Indians Diabetes Dataset. They addressed dataset imbalance with SMOTE and applied a majority voting ensemble method, combining XGBoost, KNN, and Random Forest. In predicting diabetes, the method was successful with an accuracy of 86% and good precision, recall, and F1 scores.

[4] Semonti Banik et al. aimed to improve early detection of diabetes using a machine learning-based system. They collected data from Sylhet Diabetic Hospital patients, focusing on symptoms and risk

factors.The Gradient Boosting Machine (GBM) outperformed 14 other algorithms, achieving high F1 (99.37%) and ROC (99.92%) scores, making it the most effective for diabetes prediction.
[5] S.Diabetes, particularly Type 1, Type 2, and gestational diabetes, was emphasized by Mahajan et al. With global diabetes cases expected to rise from 382 million in 2022 to 592 million by 2035, early detection is crucial. The study applied Random Forest and Logistic Regression for diabetes prediction, with Random Forest achieving the topmost accuracy of 99.03%.
[6] Laila et al. proposed that diabetes is a chronic illness characterized by elevated blood sugar levels, which, if uncontrolled, can lead to serious complications such as blindness, kidney issues, nerve damage, and heart disease. Early diagnosis is crucial for effective treatment and saving lives. The study utilized 17 diabetes-related factors from the UCI dataset and explored automated prediction methods through group learning, which blends several techniques for optimal predictions.They evaluated AdaBoost, , Random Forest and Bagging models based on precision, recall, classification accuracy, and F1-score.The results showed that the Random Forest Ensemble Method achieved the highest accuracy at 97%, while AdaBoost and Bagging performed significantly worse.
[7] Siddhartha Suprasad Mohanty and Babita Majh developed different methods for machine learning for predicting diabetes, introducing a deep neural network into their research.Their dataset comprised 130,157 records with 181 characteristics to determine whether a patient had diabetes.To handle the significant number of missing values, they employed K-nearest neighbors (K-NN) imputation.The dataset was resampled using oversampling, with 80% allocated for training and 20% for testing.
[8] Houri, O. et al. developed a machine learning system to predict the development of type-2 diabetes mellitus (T2DM) in women based on glucose screening test outcomes during pregnancy, in addition to additional maternal and fetal elements. Age, parity, gravidity, and the outcomes of the three-hour oral glucose tolerance test using 100 grams and the one-hour 50-gram glucose challenge test (GCT) were all incorporated into the model. test (OGTT) results, gestational age at delivery, and birthweight. Using the XGBoost algorithm, which employs decision trees to analyze training data, they achieved a prediction accuracy of 91%, with sensitivity and specificity both at 74%. The model's area under the curve (AUC) was 0.85, highlighting the effectiveness of age and neonatal birthweight as key predictors. This approach presents an opportunity to identify individuals at risk, allowing for early evaluation and intervention.[8] Houri, O. et al. developed a machine learning system to forecast the development of type-2 diabetes mellitus (T2DM) in women based on glucose screening test results during pregnancy, in addition to additional maternal and fetal elements. The model incorporated data such as age, parity, gravidity, 1-hour 50-gram glucose challenge test (GCT) results, 3-hour 100 gram oral glucose tolerance test (OGTT) results, gestational age at delivery, and birthweight.Using the XGBoost algorithm, which employs decision trees to analyze training data, they achieved a prediction accuracy of 91%, with sensitivity and specificity both at 74%. The area under the curve (AUC) for the model was 0.85, highlighting the effectiveness of age and neonatal birthweight as key predictors.This approach presents an opportunity to identify individuals at risk, allowing for early evaluation and intervention

METHODOLOGY

To obtain precise results, this study emphasizes the creation and execution of diabetes prediction models that integrate machine and deep learning methods. The job of prediction takes into account the following variables: age, blood pressure, glucose, diabetes pedigree function, insulin, skin thickness, BMI (body mass index), and pregnancy. To guarantee higher accuracy in prediction and less bias, this research applies the SMOTE technique, which uses synthetic minority oversampling to balance the dataset before deploying hybrid GRU-LSTM models. Diabetes prediction models are tested and trained based on these features as the basis. Two well-known machine learning algorithms and one hybrid deep learning model are employed in the methodology of this paper. This paper methodology involves the utilizing a single hybrid deep learning approach and two known Machine Learning algorithms. The following algorithms were selected for comparison: Random Forest, XG Boost, GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory), and RNN (Recurrent Neural Network). One important aspect of the article is the dataset split, which divides the entire dataset in a 75:25 ratio. This partitioning strategy uses 75% of the data to train the models, allowing them to learn patterns and relationships from the features provided. The remaining 25% of the dataset acts as the testing set, containing previous unknown data against which the models will be assessed. This careful data separation provides a thorough evaluation of the models' prediction accuracy and generalization capabilities.

XG-Boost Algorithm:
XB is an enhanced type of GB that is very powerful and can be employed for regression and classification. This is accomplished by the iterative construction of consecutive decision trees, each of which corrects the errors of the others to make a robust model. Depending on the kind of work that must be completed., an objective function that seeks to minimize mean squared error or some other loss function propels XGBoost's training. MSE is utilized for regression.
For Regression,
$Mean\ Squared\ Error(MSE)= \frac{1}{num}\Sigma(x_j - \hat{x}_y)2$ (1)
$\hat{x}_y$ $=value\ of\ jth\ data\ point$
x_j = $Actucal\ Target\ Value\ of\ jth\ data\ point$
num = $total\ no.\ of\ data\ points$
For Classification,
$Log\ Loss$ = -(xj log aj+ $(1 - xj)$ log(1 − aj)) (2)
xj = $Actucal\ Target\ Value\ of\ jth\ data\ point$
aj = $Predicted\ probability\ that\ jth\ data\ point\ belongs\ to\ class$ – 1

Random Forest Algorithm:
It is among the strongest ML methods utilizing MDT to estimate reliable and stable predictions possessing high prediction capacity and outperforming in classification, regression, HDM, in addition to feature selection. Among the scores that are applied for measuring possible impurities of child node, is called Gini Impurity that is part of random forest algorithm. For the best class separation, it selects split with the lowest Gini impurity.
Gini Impurity (I)= Σ(aj $* (1 - aj)$)
aj = $proportion\ of\ instances\ belonging\ to\ class\ j$

GRU Model:
A type of Recurrent Neural Network (RNN) architecture called a Gated Recurrent Unit (GRU) makes use of gating mechanisms to control the flow of input throughout the network.

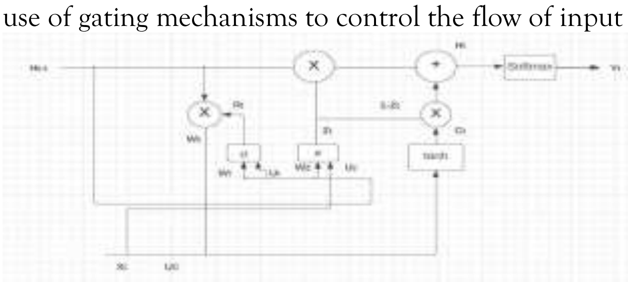

Figure1: GRU Model Architecture
Equations:
At time step t, given xt as the input, $ht{-}1$ as the prior hidden state, and γt (the reset gate), and zt (the update gate) being the reset and update gates, the GRU equations take shape as follows:
Update Gate (zt):
This gate tells the model how much of the data from the past it keeps to inform the future.
$zt = \sigma(Wz \cdot [ht{-}1, xt\ ]\ bz)$
Reset Gate (γt):
This block tells the model how much of the past information to forget.
$\gamma t = \sigma(Wr \cdot [ht{-}1, xt]\ br)$
Candidate Hidden state:

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Some candidate hidden state $\tilde{h}t$ is calculated. This candidate hidden state $\tilde{h}t$ is a new hidden state composed of parts of the current input xt and the past hidden state $ht-1$, with contributions controlled via the reset gate.

$\tilde{h}t = tanh(W \cdot [\gamma t \odot ht-1, xt] + b)$

Final Hidden State Update:

The final hidden state is a weighted combination of the past hidden state $ht-1$ and the new candidate hidden state $\tilde{h}t$, again with contributions controlled by the update gate.

$ht = (1 - zt) \odot ht-1\ zt \odot \tilde{h}t$

Where:

- Wz, Wr, and W are matrices of weights for the update gate, reset gate, and new memory content respectively.
- bz, br, and b are bias terms
- σ is the sigmoid activation function
- $\odot$ denotes element-wise multiplication
- $[ht-1, xt]$ means concatenating $ht-1$and xt. SoftMax block represents the SoftMax function. The network's output is transformed into a probability distribution across all potential outputs using this function.

<u>LSTM Model:</u> Recurrent neural networks called LSTM networks use a sophisticated structure and mechanisms for remembering and forgetting information to control distant dependencies in sequential information.

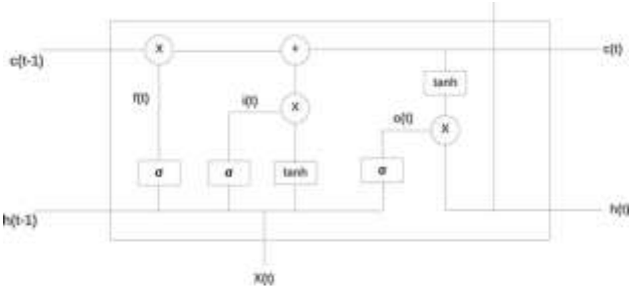

Figure 2: LSTM Model Architecture

Equations:

Input Gate ($\boldsymbol{it}$):

The input gate accepts input into the cell state.

- $\boldsymbol{it} = \sigma(Wi \cdot [ht-1, xt] + bi)$

Forget Gate ($\boldsymbol{ft}$):

The forget gate determines information is not retained into the cell state. $ft = \sigma(Wf \cdot [ht-1, xt] + bf)$

Cell State Update ($\boldsymbol{ct}$):

A candidate cell state ct is calculated using the previous hidden state and using $ct = tanh(Wc[ht-1, xt] + bc)$.

- $\tilde{Ct} = tanh(Wc \cdot [ht-1, xt] + bc)$

Update Cell State ($\boldsymbol{ct}$):

The candidate cell state is calculated, and the candidate gate and the forget gate are employed to determine the cell state.

- $ct = ft \odot Ct-1 + it \odot ct$

Output Gate ($\boldsymbol{Ot}$):

The next hidden state is calculated out of the previous hidden state based on the output gate ht.

• $Ot = \sigma(W0 \cdot [ht - 1, xt] + b0)$

RNN Model:
Recurrent Neural Networks (RNNs) are specifically used for processing sequential data. RNNs, in contrast to regular feedforward neural networks, contain connections that create internal loops, allowing them to keep information about past inputs in the sequence in a hidden state.

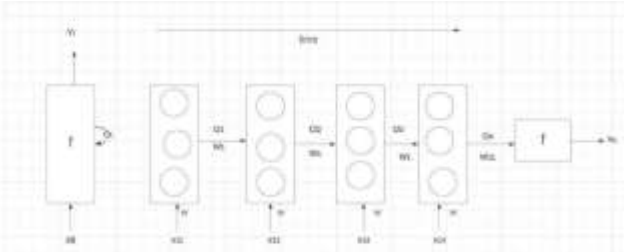

Figure 3: RNN Model Architecture
Equations:
1.Hidden State Update:
$ht = tanh(Whh.\ ht{-}1 + Wxh.\ xt + bh)$
Here,
At time t, the state that is hidden is ht.
The input at time t is xt.
Whh is the weight matrix for the hidden state,
Wxh is the weight matrix for the input,
bh is the bias term,
tanh is the hyperbolic tangent activation function
2.Output Calculation:
$\boldsymbol{yt = Why.\ ht + by}$
Here,
The result at time t is yt
Why is the weight matrix for the output,
by is the bias term.
The diagram's components include
X(t), which represents the network's input at time stamp t.
h(t): This is the hidden state of the network at time stamp t.
W(ih): This is the weight matrix that connects the input layer and hidden layer.
W(hh): Each hidden layer is connected to itself by this weight matrix.
B(h): This is hidden layer's bias vector.
O(t): This is network's output at time stamp t.
Hybrid GRU-LSTM Model:
A hybrid GRU (Gradient Recurrent Unit) and LSTM (Long Short-Term Memory) model blends components from the LSTM and GRU architectures. This hybrid approach seeks to capitalize on the advantages of both types of recurrent neural networks. GRU and LSTM both attempt to solve the issue of the disappearing gradient and obtain long-term relationships from sequential data, but their fundamental strategies are different. The computational equations will include calculations for the GRU and LSTM units and then a classification output layer. Here is an abbreviated version:
• **GRU Equations:**
$h^{GRU}_{t} = GRU(h^{GRU}_{t-1}, xt)$
For Computations the same equations of the GRU Model can be used.

• **LSTM Equations:**
$c_t^{LSTM}, h_t^{LSTM} = LSTM\left(c_{t-1}^{LSTM}, h_{t-1}^{LSTM}, x_t\right)$

For Computations the same equations of the LSTM Model can be used.

- **Hybrid Output for classification:**

Output=Output Layer (h_t^{GRU}, h_t^{LSTM})

The hidden states from the GRU and LSTM components are combined in the Output Layer function.

Sigmoid Activation Function:

Output=$\sigma(w_{out}.[h_t^{GRU}, h_t^{LSTM}] + b_{out})$

Here,$[h_t^{GRU}, h_t^{LSTM}]$ represents the concatenation of the GRU and LSTM hidden states, w_{out} is the weight matrix,b_{out} is the bias term.

PROPOSED WORK

Step 1 (Modular Importing): Necessary libraries such as seaborn, matplotlib for plotting; scikit-learn for splitting into training and testing; NumPy for numerical computing; and finally, pandas for data manipulation were imported.

Step 2 (Dataset Loading): The UCI dataset was loaded into memory at runtime.

Step 3 (Feature Selection): Following the check for missing values (there were none) and correlation matrix there were no features removed. Outliers were found though, and were retained for better performance.

Step 4 (Oversampling Using SMOTE): The SMOTE method was employed for oversampling the minority class. The minority instances were raised from 768 to 1000 to yield a diabetic to non-diabetic ratio of 1.86:1 to a 1:1 ratio.

Step 5 (Data Visualization): The patterns and relationships were presented in pie charts, heatmaps, bar plots, and pair plots.

Step 6 (Standardization): In maximizing the model's performance (specifically the methods used in a gradient descent), the variables were standardized to minimize the influence of extraneous variables.

Step 6 (Standardization): To optimize the model's performance, particularly the gradient descent techniques, the variables were normalized to reduce the impact of outside factors.

Step 7 (Distribution of Training and Testing Data): The train_test_split function divides the data into 25% for testing and 75% for training.

Step 8 (Model Development): Random Forest, XG-Boost, GRU, LSTM, and RNN models for machine learning created for training.

Step 9 (Model Training): Models were created through training in order to forecast the training data's outcome.

Step 10 (Model Testing): To generate predictions, trained models were tested with unseen data.

Step 11 (Results Calculation - Accuracy): The forecast results' accuracy was assessed using an accuracy calculation such as confusion matrix in which actual outcomes were compared against predicted values.

Step 12 (Accuracy Comparison): After comparing each model's accuracy, the models were selected for usage in the future based on their greatest scores.

RESULT AND DISCUSSION

The advantages of both GRUs and LSTMs, two powerful recurrent neural network models, are incorporated into the GRU LSTM hybrid model. LSTMs are capable of modeling long-lived relationships due to their complex gated mechanisms and specially designed memory cells, whereas GRUs are computationally cheaper and particularly suitable for modeling short-to-medium-lived relationships in sequential input. The hybrid model exploits the best of both architectures, balancing efficiency and capabilities to enhance memory usage and achieve a faster convergence rate during training. This interaction better handles complex patterns and data dependencies. An example of this type of neural network with regard to diabetes mellitus predicting for pregnant women was able to accomplish a 99% accuracy rate, better than both GRU, LSTM, XGBoost, and even Random Forest models working independently. Additionally, techniques like SMOTE was applied to balance the dataset in order to

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train the model on a properly distributed dataset, which enhanced its predictive capability. This blend of efficiency, accuracy, and flexibility makes GRU+LSTM models perfect for sequential data jobs. XG-BOOST had an 86% accuracy rate along with precision, recall, and F1-score values of approximately 0.86. Within diabetes mellitus prediction for pregnant females, the GRU+LSTM model reported 99% accuracy compared to individual models including GRU, LSTM, XGBoost, and Random Forest. Additionally, approaches such asThis attests to performance balance over various evaluation parameters for the credibility of XG-BOOST prediction against diabetes. RANDOM FOREST obtained an accuracy value of 85%, precision, recall, and F1-score all equalling 0.85. The model's performance being quite consistent over several metrics gives rise to its dependability in predicting cases of diabetes. With an accuracy of 90%, the GRU, an RNN, outperformed all other models. Its precision, recall, and F1-score remained consistently at 0.8930, 0.8933, and 0.8933, respectively. This means GRU did extremely well in detecting positive situations and in minimizing false positives. Another RNN, LSTM's 82% accuracy was poorer than that of most of the other models; its precision fell to 0.7630, and it generated more false alarms. Nonetheless, LSTM demonstrated a good balance, with a recall of 0.8443 and an F1 of 0.8016, which showed that it was effective in catching common true positives. RNN, the most basic type of RNN, predicted its class correctly with 96% accuracy. It accounted for an F1- score of 0.9678, owing to its very high precision of 0.9554 and recall of 0.9678. This performance shows that RNN has done well in positively forecasting while abstaining from negative results. The combination of GRU and LSTM with 99% accuracy is singular in alternative thinking. Achieving almost a perfect score in respect to precision, recall, and F1-score of 0.997 and 0.998 respectively shows its extremely good prediction ability. The combination effect of GRU and LSTM is found to have enhanced the overall effectiveness of the model considerably. The below diagram shows the contrast between accuracy and execution time for each model.

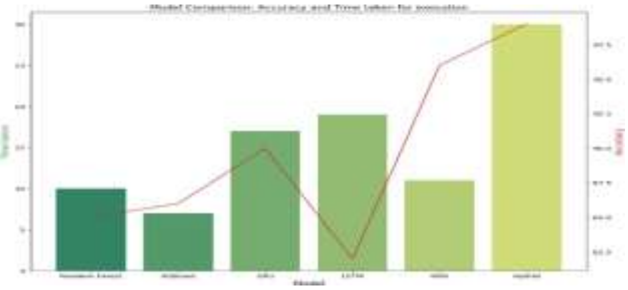

Figure 4: Comparison between Accuracy and time taken for execution

The visual appearance makes the performance comparison of several model's comparative with their execution time in terms of the accuracy. The line plot represents the accuracy percentage in the execution of models such as Random Forest, XG-Boost, GRU, LSTM, and RNN, giving an idea about their relative strengths. The bar graph offers details regarding how much time, in seconds, each model needed in order to execute. While GRU+LSTM model shows the highest accuracy of 99% approximately, Random Forest and XG-Boost show comparable accuracies. The barplot offers details regarding how much each model consumed time while executing and thus helps to select the most appropriate one in accordance with both accuracy and time consumed for execution.

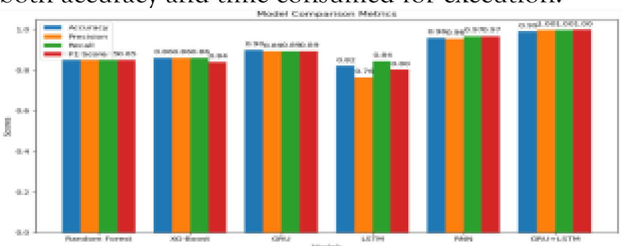

Figure 5: Model Comparison Metrics

A bar graph illustrates the various models on the basis of their performance on certain metrics. Among the models being tested corresponds to among the bars, and the height of the bars indicates the precision, recall, accuracy and F1 score. Random Forest, XG-Boost, GRU, LSTM, RNN, and GRU+LSTM were tested for different levels of success for these metrics. For instance, GRU+LSTM achieved topmost accuracy of 99%. The chart is extremely concise and clear in contrast to the chart, so it is easy to simply select a specific model based on the desired performance measure.

CONCLUSION AND FUTURE APPLICATIONS

Creating accurate diabetes prediction models combining machine and deep-learning algorithms was the aim of this project. The dataset used was the Pima Indian Diabetes Dataset, having had its distribution of diabetic and non-diabetic cases started in an unbalanced manner. In order to have balanced data, the Synthetic Minority Over-Sampling Technique (SMOTE) was implemented. In this study, XG-Boost, Random Forest, GRU, LSTM, RNN, and hybrid GRU+LSTM were tested. Performance of all the models was decided based on precision, recall, accuracy and F1-Score as calculated upon training and validating the models. The findings indicated all the models having various performances; the GRU+LSTM providing the highest accuracy at 99%. Comparison chart use aided in delineating the disparity between accuracy and execution time for a detailed explanation of the models' performance.

GRU+LSTM worked exceptionally well as regards not just accuracy but also competitive efficiency, and this has made it a promising option for diabetes prediction. Subsequent works can provide qualitative gains in model with the help an inclusion of novel ensemble methods, thereby bring about fine-tuning resulting in superior results, and validate these with different datasets. The models also have to be made comprehendible in terms of keeping pace with what's current to continue making diabetes forecasts feasible.

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