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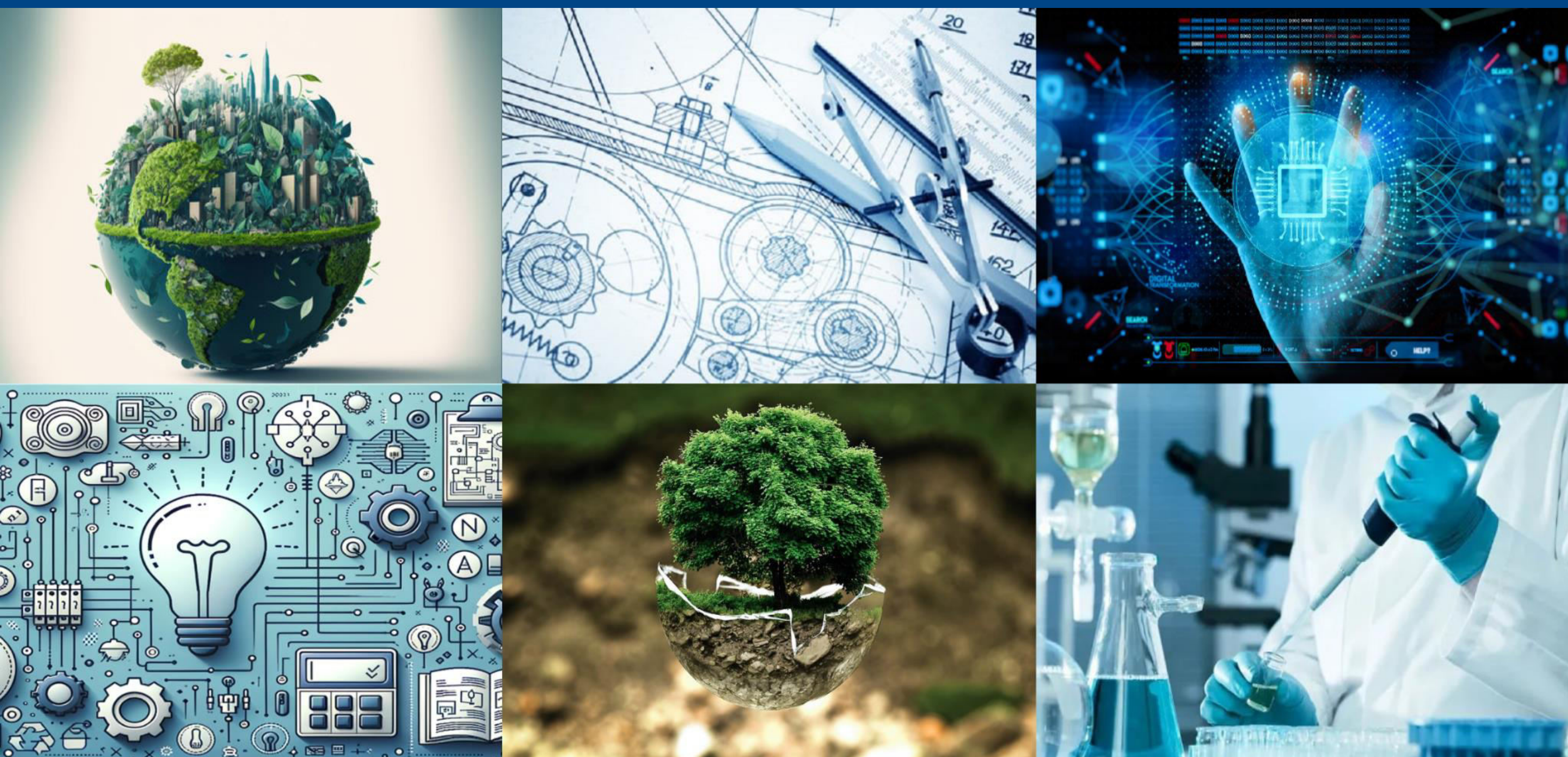

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Smart Diagnosis of Gestational Diabetes via an Optimized Deep Neural Architecture

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ABSTRACT: Pregnancy-related metabolic disorders like gestational diabetes mellitus (GDM) are common and can be harmful to both the mother and the unborn child. Timely medical intervention can mitigate consequences through early prediction. This study uses maternal health factors to predict GDM using an improved Multilayer Perceptron (MLP) model. Regularization techniques and grid search are examples of hyperparameter optimization approaches used to fine-tune the MLP. The modified MLP considerably outperforms conventional machine learning models in classification, according to experimental results on real-world healthcare datasets. Clinical decision-support applications can benefit from the model's prediction accuracy and resilience.

KEYWORDS: Gestational Diabetes Mellitus, Multilayer Perceptron, Optimization, Prediction Model, Maternal Health

I. INTRODUCTION

The management of glucose during pregnancy is impacted by gestational diabetes mellitus (GDM), which has grown in prevalence as a result of genetic susceptibility and lifestyle choices. Complications from GDM include macrosomia, neonatal hypoglycaemia, and an elevated risk of type 2 diabetes after pregnancy if untreated. Conventional screening techniques, including the oral glucose tolerance test, work well but are reactive. Through early risk identification, machine learning-based predictive modelling offers a proactive strategy. To improve accuracy, dependability, and generalization, we optimize the architecture of a Multilayer Perceptron (MLP)-based predictive model in this study.

II. BACKGROUND AND RELATED STUDY

Support Vector Machines (SVM), Decision Trees, and Naïve Bayes classifiers are examples of machine learning (ML) techniques that are frequently used in the medical field to predict disorders like gestational diabetes mellitus (GDM). These algorithms are renowned for being straightforward, easy to understand, and requiring comparatively little processing power.

For example, Decision Trees offer rule-based classification that is simple for physicians to comprehend, while SVM can produce strong decision limits. However, when used on high-dimensional, non-linearly separable datasets—which are frequently seen in clinical settings—their efficacy is constrained. Numerous interacting factors, including age, body mass index (BMI), glucose levels, insulin resistance, and more, are frequently included in medical data. These variables all have intricate and nonlinear connections with one another. These nuances are difficult for traditional machine learning models to grasp, which frequently results in poorer generalization to unknown data, increased false positives or negatives, and lower accuracy.

Deep learning methods, particularly Multilayer Perceptron (MLPs), have being used more and more for healthcare predictions in order to get over these restrictions. By transferring inputs via several hidden layers, MLPs—a kind of artificial neural network—are able to develop hierarchical representations of data. They can model nonlinear dependencies and uncover hidden patterns that traditional models might miss thanks to this feature. MLPs may accurately differentiate between high-risk and low-risk patients in the context of GDM prediction by analysing intricate relationships among maternal health markers. Despite its potential, a lot of earlier MLP implementations used default or unoptimized configurations, which led to a number of issues like sluggish training convergence, overfitting on small datasets, and less than ideal predictive performance.

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III. METHODOLOGY

Dataset Description

Clinical records of pregnant women that have been anonymized make up the dataset used in this study. There are several important aspects of maternal health that are frequently linked to the chance of getting gestational diabetes mellitus (GDM).

Table 1: Attributes related to GDM

Attribute	Description
Age	Age of the patient (in years)
BMI	Body Mass Index calculated from weight and height
Number of Pregnancies	Total number of pregnancies the patient has had
Fasting Blood Sugar Levels	Blood glucose levels after fasting (mg/dL)
Blood Pressure	Diastolic blood pressure measured in mm Hg
Family History of Diabetes	Binary indicator (Yes/No) indicating family history of diabetes
Insulin Levels	Plasma insulin levels (μU/mL)

This dataset offers a thorough understanding of the health state of the patient throughout pregnancy. These characteristics were chosen due to their clinical significance and established link to the onset of GDM. To guarantee consistency and model preparedness, the data underwent preprocessing procedures prior to model training, including managing missing values, normalization, and categorical variable encoding.

Preprocessing

To guarantee data consistency and quality, the dataset was subjected to necessary preprocessing procedures before to model training. The dataset's missing values were filled up using statistical imputation techniques; the mean was used for numerical characteristics and the mode was used for categorical attributes, if any were present. Using Min-Max normalization, which converts feature values to a standardized range between 0 and 1, all features were brought onto a common scale to avoid any one variable controlling the learning process. Furthermore, proper encoding techniques were used to convert any categorical variables in the dataset into numerical format, guaranteeing neural network architecture compatibility.

MLP Architecture

In order to efficiently learn from the pre-processed maternal health data, the Multilayer Perceptron (MLP) architecture was created for this investigation. It starts with an input layer that gets the dataset's normalized features. The model is then subjected to two or three hidden layers, each of which uses the Rectified Linear Unit (ReLU) activation function. This adds non-linearity to the model and allows it to capture intricate patterns and interactions between the input features. Using a sigmoid activation function, the output layer, the last stage, generates a probability score for binary classification, indicating whether or not a pregnant woman is likely to develop gestational diabetes mellitus (GDM).

Optimization Techniques

During training, a number of optimization techniques were used to improve the Multilayer Perceptron (MLP) model's performance. The best combination of hyperparameters, such as the number of neurons in each layer and the overall number of hidden layers, was methodically found using a grid search technique. Adaptive optimization methods like Adam, which dynamically modify learning rates during training to speed up convergence, were used to fine-tune the learning rate.

Regularization strategies including dropout, which randomly disables a portion of neurons during training, and L2 regularization, which penalizes large weights, were used to avoid overfitting and enhance the model's capacity to generalize to new data. In order to prevent overfitting to the training data, early stopping was also included to track validation performance and terminate training when no discernible improvement was seen.

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Evaluation Metrics

A number of evaluation indicators were used to evaluate the suggested MLP model's efficacy in predicting gestational diabetes mellitus (GDM). By dividing the number of accurately predicted cases by the total number of predictions, accuracy determines how accurate the model is overall. However, depending only on accuracy in medical diagnosis can be deceptive, particularly when datasets are unbalanced.

In order to determine the percentage of real positive predictions among all positive predictions the model made, precision is needed. This indicates the number of predicted GDM cases that were actually correct. Sensitivity, or recall, measures how effectively the model identifies patients who actually have GDM by evaluating its capacity to identify all true positive instances.

When false positives and false negatives must be traded off, the F1 Score is a good metric since it strikes a compromise between precision and recall. Finally, the model's capacity to differentiate between classes at different threshold settings is assessed by the ROC-AUC (Receiver Operating Characteristic – Area Under Curve) score, which provides a thorough assessment of classification performance independent of class distribution.

IV. EXPERIMENTAL RESULTS

Tools and Environment

The best Multilayer Perceptron (MLP) model for predicting gestational diabetes mellitus was developed and tested using a strong hardware and software configuration. Python was used for the implementation since it is a flexible programming language that is frequently used for machine learning tasks. TensorFlow, an open-source framework that facilitates effective model training and deployment, was utilized to construct the deep learning component, and Scikit-learn was employed for preprocessing, evaluation, and the implementation of auxiliary machine learning tools. The results were subjected to 10-fold cross-validation to guarantee their robustness and dependability.

To minimize bias and variation in model evaluation, this method splits the dataset into ten equal parts. The model is trained on nine of the parts and validated on the remaining one, repeating the process iteratively. A PC with an Intel Core i7 processor and 16GB of RAM was used for the trials, providing enough processing capability to train the neural network. To expedite the training process, GPU acceleration was optionally used where it was possible, particularly for large-batch calculations and hyperparameter adjustment.

Table 2: Performance Comparison of MLP models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	79.6%	76.5%	76.2%	76.8%	0.81
Decision Tree	81.5%	80.1%	78.7%	79.5%	0.83
Standard MLP	85.6%	83.4%	82.5%	82.8%	0.86
Optimized MLP	90.2%	88.7%	88.2%	88.4%	0.91

V. DISCUSSION

In comparison to conventional models, the improved MLP showed more predictive power. Improving performance required adjusting the number of layers, neurons, and learning parameters. Medical diagnostics depend on the model's ability to generalize well to unseen data, which was achieved by the application of regularization techniques. According to the study, when deep learning models are properly adjusted, they can produce clinically significant predictions even with a moderate quantity of input features. This strengthens the argument in favour of their use in automated health monitoring systems.

VI. CONCLUSION

In this paper, an improved Multilayer Perceptron (MLP) architecture is used to present a highly accurate predictive model for Gestational Diabetes Mellitus (GDM). The model successfully overcomes issues like overfitting and sluggish

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convergence by incorporating sophisticated optimization strategies like early halting, adaptive learning rates, dropout regularization, and hyperparameter tuning. It is quite good at identifying intricate, nonlinear patterns in maternal health data, which improves the accuracy and dependability of predictions. Strong performance across various data splits is ensured by the application of 10-fold cross-validation. The model is useful for clinical decision-making since it has high sensitivity and ROC-AUC scores, which make it suitable for identifying high-risk situations. Potential real-world implementation in healthcare systems, where it might enable early screening and intervention techniques to improve maternal and newborn outcomes, is supported by its scalability and generalizability.

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