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## GENETIC ALGORITHM ENHANCED ANN MODEL FOR PREDICTION OF GESTATIONAL DIABETES MELLITUS

NAJMA U<sup>1</sup>, KULKARNI L<sup>2</sup>, SAQIB A<sup>3</sup> AND JYOTHI N M<sup>4\*</sup>

1: Department of Biotechnology, Government Science College, Hassan, Karnataka, India,

2: Department of Electronics, Government Science College, Hassan, Karnataka, India,

3: Department of UG and PG studies in Biochemistry, Maharani Cluster university, Bangalore,  
Karnataka, India

4: Department of Computer Science Engineering, Koneru Lakshmaiah Education, Vaddeswaram, AP,  
India

\*Corresponding Author: Dr. Jyothi N M: E Mail: [jyothiarunkr@gmail.com](mailto:jyothiarunkr@gmail.com)

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### ABSTRACT

This research presents a fresh method for forecasting Gestational Diabetes Mellitus (GDM) via a Genetic Algorithm Enhanced Artificial Neural Network (ANN) model. By utilizing genetic algorithms, the ANN's predictive potential is enhanced, providing a novel approach for early GDM detection and intervention. The study details the fusion of genetic algorithms with ANN and showcases its success on a gestational diabetes related Kaggle dataset, achieving an accuracy of 98.34% that surpasses other machine learning and deep learning models

**Keywords: Gestational Diabetes Mellitus, Genetic Algorithm, ANN**

### INTRODUCTION

Gestational Diabetes Mellitus (GDM) is a temporary diabetes form occurring during pregnancy, affecting sugar (glucose) usage in

the body. Unlike other diabetes types, GDM is pregnancy-exclusive and usually resolves post-childbirth. This condition raises blood glucose

levels, posing risks to both mother and fetus. The cause is linked to hormonal shifts and increased pregnancy-related insulin resistance, disrupting glucose regulation by insulin.

Effectively managing GDM is vital for maternal and fetal well-being. Left unchecked, GDM can lead to complications like excessive baby birth weight, raising delivery risks, and increasing maternal mortality. It can also elevate future type 2 diabetes risk for mothers. Given GDM's pregnancy-associated health hazards, accurate prediction methods are essential for timely interventions.

This study introduces a Genetic Algorithm Enhanced Artificial Neural Network model for GDM prediction. Genetic algorithms show promise in optimizing ANN structures and parameters, improving predictive performance compared to existing models.

## RELATED WORK

Gestational diabetes mellitus (GDM) is a prevalent hormonal and metabolic disorder that occurs during pregnancy. It is characterized by varying levels of difficulty in processing carbohydrates. The researchers used a tool called PROBAST to check how biased the ML models were. They found that the bias risk was 89.91% [1]. The research aims to figure out how different factors affect diabetes data and help predict if a person has the disease. The study creates a better prediction model for diabetes using a special algorithm called ABP-

SCGNN, which trains an artificial neural network. The results of the experiments indicate that this model, with 20 neurons, achieves an accuracy of 93% [2]. Research suggests a way to create a prediction model for detecting gestational diabetes. They used data from pregnant women, both with and without diabetes, gathered from labs in the Kurdistan region. The study used techniques like K-means to simplify the data, the elbow method to find the best value, and the Mahalanobis distance method to group similar samples. They also tried different machine learning methods for making predictions. Combining these methods improved the accuracy of their predictions [3]. This research employed six well-known machine learning algorithms to analyze GDM data from the Tianchi competition, identifying key risk factors through model ranking and Shapley additive interpretation. They used a combined weighting technique to evaluate these factors and introduced a novel integrated approach (LightGBM-XgBoost-GB) for accurate gestational diabetes prediction. The final ensemble model demonstrated superior performance compared to conventional methods, effectively detecting GDM in pregnant women [4]. This study aims to develop accurate diabetes detection models using machine-learning classifiers on clinical data. Improved preprocessing methods, like

label encoding and normalization, boost model accuracy. Through feature selection, significant risk factors are identified, model showed improved accuracy with recent studies by 2.71% to 13.13% on different datasets and ML algorithms [5]. GDM is becoming more common globally due to factors like obesity and older maternal age. it is a significant pregnancy complication and is now recognized as an early indicator for type 2 diabetes and cardiovascular issues [6]. Research investigated factors linked to GDM, finding influences like pre-pregnancy weight, family history of diabetes, previous GDM, macrosomia, pregnancy complications, smoking, and being a first-time mother [7]. Using machine learning, a successful model employing artificial neural networks identified GDM risk factors with 70.3% accuracy and 83.3% sensitivity, aiding timely interventions in Mexico [8]. An AI model, comprising 9 ML algorithms, was trained on 12,304 pregnant outpatients who were tested for GDM in China. Through k-fold cross-validation and an external dataset of 1655, the ML algorithms achieved an average accuracy of 79.87% [9]. The model is developed for reducing dimensions, normalizing, segmenting, and fusing features using attention-based convolutional neural networks on GDM features. Experimental results demonstrate a 96% accuracy along with precision, recall, F-1

score, and AUC evaluations [10]. This research aimed to create an innovative GDM diagnosis system using ANNs, effectively modeling connections between demographic factors and GDM risk. The ANN approach yielded a 70% true positive rate, outperforming logistic regression's 56.3% true positive rate [11]. The no-prop algorithm proposed two stages to identify significant features to train ANN with type1 and then with type 2 diabetes clubbed with non-diabetic features, and later with GDM and non GDM features in testing phase. It achieved 97% accuracy for categorizing diabetes types [12].

A survey highlights the significance of ML and Deep Learning (DL) algorithms in diabetes research, showcasing their effectiveness in detecting glucose levels. These advancements hold a crucial role in enhancing medical diagnostics [13].

The literature survey clearly indicates a huge gap in the proposed work and existing work.

## PROPOSED METHODOLOGY

### Genetic Algorithm (GA)

A genetic algorithm represents a computational optimization method inspired by natural selection and evolution principles. It proves valuable for tackling complex issues by simulating genetic inheritance, mutation, and selection processes seen in biological evolution.

Within genetic algorithms, a population of

potential solutions goes through iterative improvement over generations, aiming to find the best solution for a given problem. Each solution, often called an "individual" or "chromosome," is defined by a set of parameters or variables. These parameters capture the solution's unique traits, with the goal of discovering the parameter mix that

maximizes a specific objective function.

**Figure 1** shows genetic algorithm terms.

The genetic algorithm operates through distinct, well-defined stages:

**Initialization:** A diverse population of individuals is generated, each representing a potential solution to the problem.

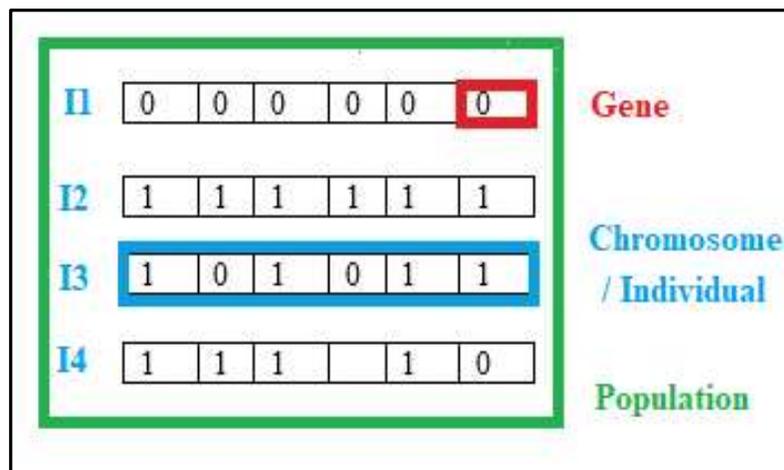


Figure 1: Genetic Algorithm terms

**Evaluation:** Each individual's fitness is assessed based on its performance in relation to the defined objective function. Higher fitness scores are given to those that excel in meeting the criteria.

**Selection:** Individuals with better fitness scores have a higher chance of becoming parents in the next generation, reflecting the principle of "survival of the fittest."

**Crossover:** Selected individuals undergo crossover, mixing their genetic information to create offspring. This mirrors genetic recombination in biological reproduction.

**Mutation:** Introducing randomness, mutations

slightly alter the genetic information of some individuals. This maintains diversity and prevents premature convergence.

**Replacement:** Offspring and mutated individuals replace a portion of the population, introducing new genetic material for the next generation.

**Termination:** The algorithm evolves through generations until a termination criterion is met, like a set number of generations or a satisfactory solution.

The interplay of selection, crossover, and mutation progressively refines the population over time. Genetic algorithms excel in complex

optimization challenges with extensive solution spaces, where conventional methods may struggle to find the global optimum.

**Figure 2** shows the stages in GA.

### Artificial Neural Network (ANN)

The structure of an Artificial Neural Network (ANN) consists of interconnected nodes arranged in layers, emulating the intricate neural connections found in the human brain. This architectural design enables the ANN to process data, discern patterns, and make predictions effectively.

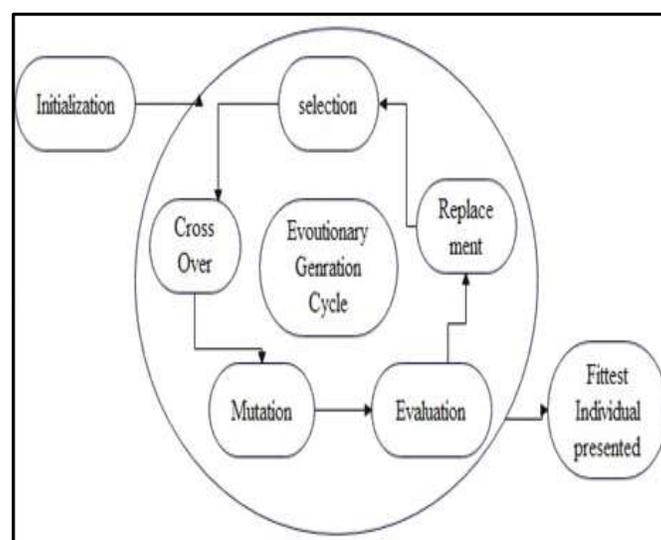
Typically, an ANN comprises three primary layer types: the input layer, hidden layers, and the output layer. Each layer serves a distinct purpose in the network's computational process:

**Input Layer:** The input layer is where data is fed into the network. Each node within this layer

represents a unique feature or attribute of the input data. Information flows from the input layer onward to subsequent layers for further processing.

**Hidden Layers:** Positioned between the input and output layers, hidden layers conduct intricate computations and capture intricate data relationships. The quantity of hidden layers and nodes in each layer can vary, contingent on the problem's complexity and the chosen network architecture.

**Output Layer:** The output layer generates outcomes or predictions based on computations executed in the hidden layers. The number of nodes in the output layer hinges on the task's nature – it can represent categories in classification tasks or numerical values in regression tasks. **Figure 3** shows the architecture of ANN.



**Figure 2:** Stages in GA

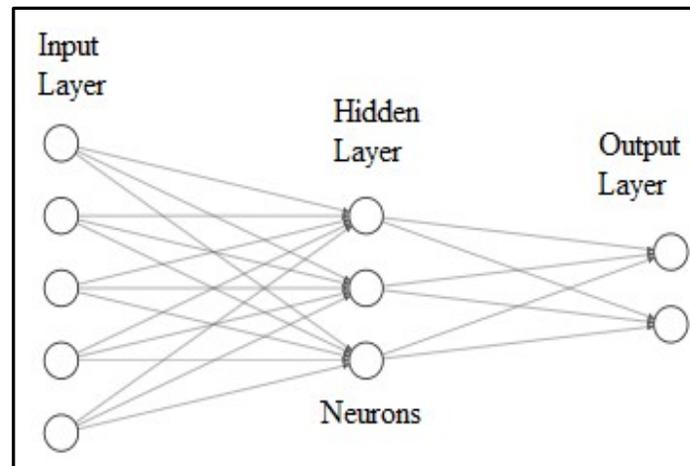


Figure 3: Architecture of ANN

The links connecting nodes, termed synapses, bear data from one layer to the following. Every link holds a designated weight that governs its impact on the conveyed information. Additionally, each node employs an activation function to the combined weighted inputs, introducing non-linear aspects to the network's computations.

In the process of training, the connection weights undergo iterative adjustments using diverse optimization methods. The aim is to minimize the disparity between the projected output and the actual target values. This training procedure empowers the network to grasp and generalize patterns from the provided data.

### Drawbacks of ANN

Artificial Neural Networks (ANNs) often exhibit a sluggish convergence rate, susceptibility to overfitting, a restricted grasp of features, and an inability to manage

incomplete or noisy data, leading to imprecise outcomes. However, these limitations can be mitigated through the integration of Genetic Algorithms (GAs) with ANNs.

### Advantages of fitting ANN with GA

Leveraging a genetic algorithm to enhance an Artificial Neural Network (ANN) provides several distinct benefits:

**Optimized Model Configuration:** Genetic algorithms systematically explore an expansive array of parameter combinations, streamlining the configuration of the ANN for optimal performance. This yields a finely tuned model without the need for exhaustive manual adjustments.

**Global Solution Exploration:** Genetic algorithms effectively navigate beyond local optima, empowering the ANN to uncover superior solutions across intricate and diverse problem landscapes. This comprehensive exploration strengthens the model's ability to

reveal concealed patterns.

**Feature Selection and Weighting:** Genetic algorithms facilitate the precise selection of relevant features and the weighting of connections within the ANN. This refinement heightens the model's efficiency by concentrating on significant inputs while minimizing noise.

**Mitigated Overfitting Risk:** By optimizing the ANN's architecture, genetic algorithms counteract the inclination towards overfitting, ensuring the model generalizes adeptly to novel data instead of memorizing noise from the training set.

**Parallel Processing Capability:** Genetic algorithms capitalize on parallel processing, hastening the optimization process. This parallelization proves particularly advantageous for intricate models and extensive datasets.

**Adaptability and Generalization:** The genetic algorithm-optimized ANN adapts seamlessly to varying datasets and extrapolates patterns across diverse inputs, enhancing its applicability across various scenarios.

**Complex Pattern Recognition:** Genetic algorithms amplify the ANN's capacity to unravel intricate and non-linear data relationships. This empowers the model to capture nuanced patterns that might otherwise go unnoticed.

**Reduced Manual Effort:** Genetic algorithms

automate the pursuit of optimal configurations, diminishing the necessity for labor-intensive manual fine-tuning. This liberates researchers from the drudgery of parameter adjustments.

**Continual Improvement:** Genetic algorithms can be employed iteratively to keep the ANN well-calibrated and effective over time, especially as new data becomes available.

In essence, the integration of a genetic algorithm with an ANN empowers the model to unlock its full potential through methodical optimization, robust pattern recognition, and adaptability. This paves the way for heightened predictive accuracy and expanded applicability.

### **Laboratory settings and Experimentation**

**Dataset Acquisition and Preprocessing:**

The GDM dataset is obtained from Kaggle.

The dataset contains 768 records with eight features of pregnant women. Eighty percent is considered for training and the remaining 20 percent for testing purposes.

**Pre-processing**

Z-score normalization is applied to achieve uniform distribution of features. The Equation (1) gives the formula to calculate z-score.

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

where  $z$  is the normalized value,  $x$  is the original value,  $\mu$  is the mean, and  $\sigma$  is the standard deviation. Z-scores retains the shape of the original distribution by aligning it

towards zero. It removes outliers and increases the efficiency of the ANN by helping in faster convergence.

### Proposed Methodology:

Genetic Algorithm Fitted with ANN for Predicting Gestational Diabetes using Kaggle Dataset for GSM:

#### 1. Data Preprocessing:

Load the Kaggle dataset containing relevant features and target variables. Normalize or standardize the input data to ensure consistent scaling. Split the dataset into training and testing sets. **Figure 4** shows the proposed architecture and workflow.

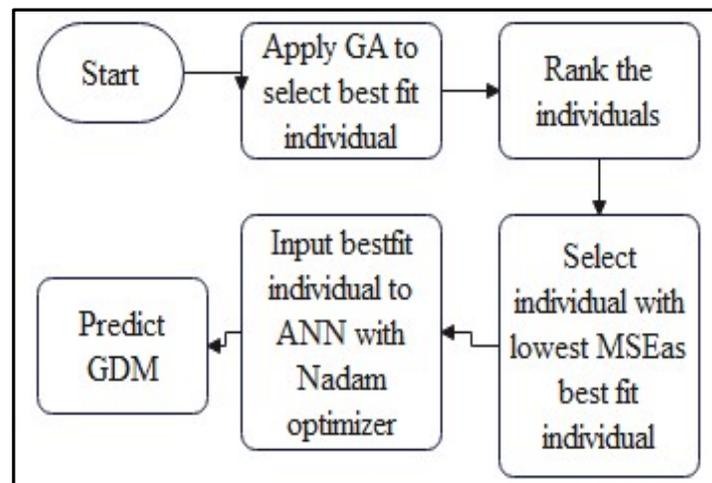


Figure 4: Architecture of proposed work

#### 2. Initialize Genetic Algorithm Parameters:

Define the population size.

Specify the number of generations.

Set the probability of crossover and mutation.

#### 3. Initialize ANN Architecture:

Determine the number of input nodes based on the dataset features.

Choose the number of hidden layers and neurons per layer.

Define the output layer based on the prediction task (binary classification for GDM).

#### 4. Generate Initial Population:

Create a population of random ANN configurations with varying architectures and weights.

#### 5. Fitness Evaluation:

Train each ANN in the population using the training data.

Evaluate the fitness of each ANN by calculating its prediction accuracy on the testing data.

#### 6. Selection:

Select a subset of individuals (ANNs) from the population based on their fitness scores. Implement selection methods like tournament selection or roulette wheel

selection.

#### 7. Crossover and Mutation:

Apply crossover to pairs of selected ANN individuals to create new offspring.

Introduce mutation by randomly modifying the weights of certain connections in the offspring.

#### 8. New Generation Creation:

Combine the original population with the newly created offspring to form the next generation.

#### 9. Repeat Generations:

Repeat steps 5 to 8 for the specified number of generations.

#### 10. Best Individual Selection:

After all generations, identify the ANN individual with the highest fitness as the best solution.

#### 11. Fine-tuning and Hyperparameter Optimization:

Perform additional hyperparameter tuning on the best ANN individual to enhance its performance.

#### 12. Prediction and Evaluation:

Use the best-tuned ANN to make predictions on new, unseen test data.

Evaluate the prediction accuracy, precision, recall, F1-score, etc.

#### 13. END

### Procedure

The GA is applied to choose the combination of best fit features for the

ANN model. Each feature represents a single chromosome and for this research a minimum of 5 features are compulsorily considered to get the best result.

We can obtain different combinations of genes (features) which represent the individual (input feature). The aim to obtain best fit combination of genes which represent individual with high survival rate.

This is decided by running every combination of genes (8 combinations are considered) as shown in Table 1 and noting down the Mean Squared Error (MSE) of each individual and ranking them as per MSE. The individual with lowest MSE is considered as the best fit and highest rate of survival. This combination is used for final prediction.

Parameter setting for GA

```
model = Genetics(
    estimate, ev=5, verbo=0,
    score="accuracy", max_features=5,
    n_pop=8, crossover_prob=0.3,
    mutation_prob=0.2, n_gen=30,
    crossover_ind_proba=0.4,
    mutation_ind_proba=0.04,
    feature_size=8, n_gen_no_change=4,
    caching=True, n_feature=-1)
```

```
model = model.fit(X, y)
```

The GA model generates the best combination of genes to produce the best fit

individual. The combination which returns least Mean Square Error is retained for further input to the ANN.

The following table shows the genetic combination of genes with MSE value.

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

Where n is total number of features,  $Y_i$  is actual value and  $\hat{y}_i$  is estimated value.

Ranking order is applied for individual selection. Table 1 shows the genetic combinations of different individuals

obtained. The MSE obtained after training on ANN is recorded and ranked. The 3rd individual is ranked 1 as the most promising best fit combination of genes with the very least MSE score of 0.22 shown in **Figure 5**.

The third individual with best genetic combination is of features is input to the final ANN model for further optimization. **Figure 6** shows GA Optimized ANN Model is input with 3rd individual for prediction of GDM with further optimization.

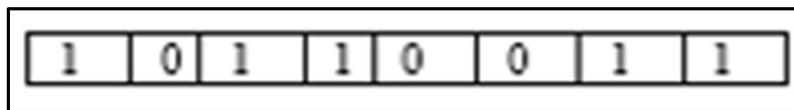


Figure 5. Best fit individual

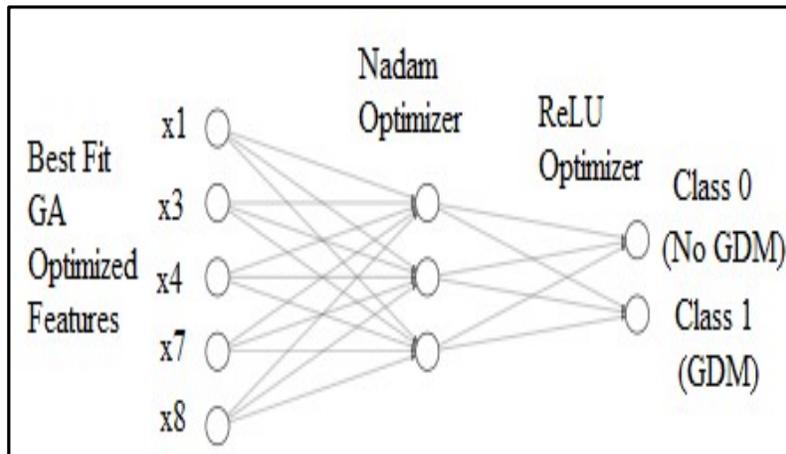


Figure 6: ANN input with best fit individual

The features x1, x3, x4, x7, x8 combination has high fitness value and performs with high accuracy of 0.97. and MSE of 0.22. The ANN model performance is further optimized by fitting with optimization function Nadam. It is a combination of Adam and Nesterov accelerated gradient.

Shown in Equation (3)

$$\theta_{t+1} = \theta_t - \frac{n}{\sqrt{v_t + \epsilon}} \left( \beta_1 \hat{m}_t + \frac{(1-\beta_1)g_t}{1-\beta_1^t} \right) \quad \text{--- (3)}$$

The hyperparameter setting of ANN model for prediction on test dataset is given in **Table 1**.

The model predicted with high accuracy of 0.9834 and low MSE of 0.13.

Table 1: Parameter setting for ANN

Parameters	Values
Model	Sequential
Input neurons	5
Hidden neurons	3
Output neurons	2
Activation hidden layer	ReLU
Activation output layer	SoftMax
Optimizer	Nadam
Learning Rate	0.001
Loss	MSE
Metric	Accuracy
epsilon	1e-07
decay	0.003
Epochs, batch size	10,53

## RESULTS AND DISCUSSION

**Table 3** gives the accuracy and MSE score of GA optimized ANN and further optimized with Nadam for every epoch. The model is run with 10 epochs and the observation showed that learning rate increases with every increase in epochs. The final accuracy of 98.34% is achieved with an MSE of 0.1321. **Figure 7** shows MSE and accuracy comparison on every epoch. **Figure 8** shows the learning and error graph.

The Model is cross evaluated with other public dataset of Kaggle - Diabetes Dataset of pregnant women and achieved accuracy of 98.31% and gestational dataset of the Iraq-Kurdistan region laboratory downloaded from IEEE-data port and achieved accuracy of 98.28%. **Figure 9** show the learning graph of both the datasets.

The classification report of GDM is shown in the form of confusion matrix in **Figure 10**.

Class 0 represents No GDM, and class 1 represents susceptible to GDM. The model results matched with the clinical report. True Positive rate of 123 and True Negative 24 is obtained and matched with the clinical cases. The performance efficiency of the model is cross evaluated with other Machine Learning (ML) models like Random Forest (RF), K-nearest Neighbor (KNN), Support Vector (SVM), Decision Tree (DT) and Xtreme Gradient Boost (XGB). The figure shows the accuracy achieved on each ML model. **Figure 11** shows learning curve of ML models.

**Figure 12** shows the comparison of accuracy and MSE on different ML models.

**Figure 13** shows comparative analysis of classification report of ML models.

Table 2: MSE Accuracy on every epoch

Epochs	MSE	Accuracy
1	0.2943	0.8525
2	0.2756	0.868
3	0.2591	0.8751
4	0.2372	0.8632
5	0.2239	0.8855
6	0.2191	0.9173
7	0.1737	0.9328
8	0.1528	0.9572
9	0.1369	0.9776
10	0.1321	0.9834

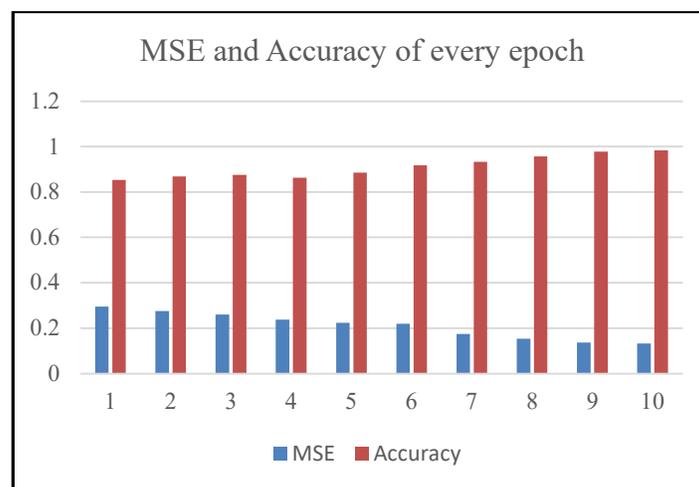


Figure 7: Accuracy and MSE score in epochs

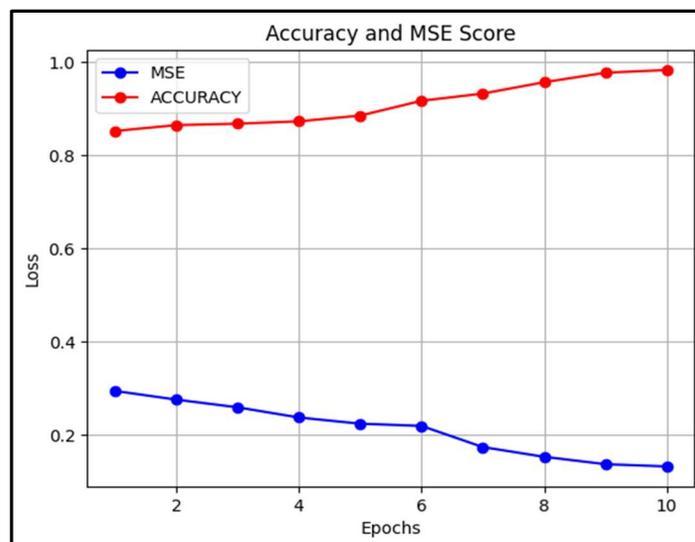


Figure 8: Learning and MSE graph

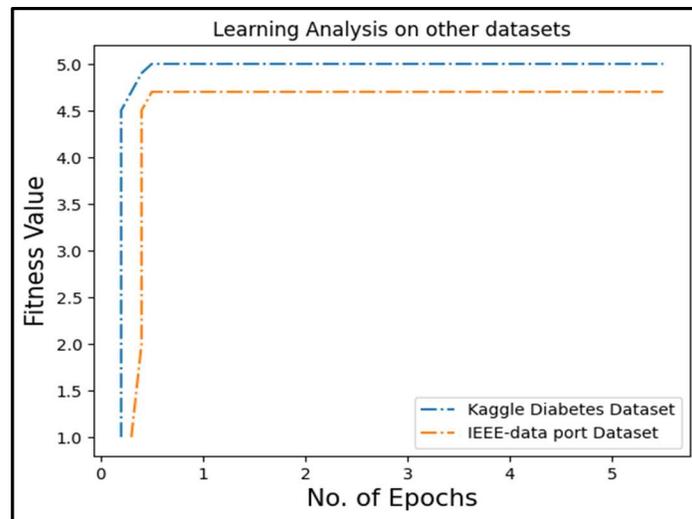


Figure 9: Learning analysis on other datasets

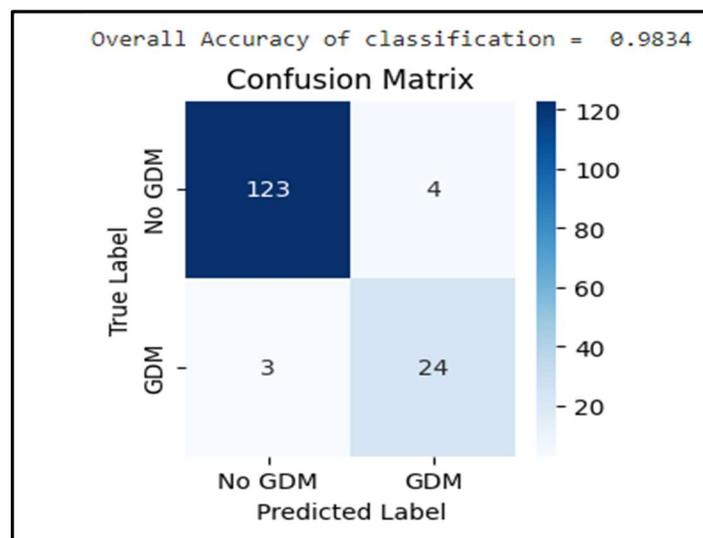


Figure 10: Confusion Matrix for classification

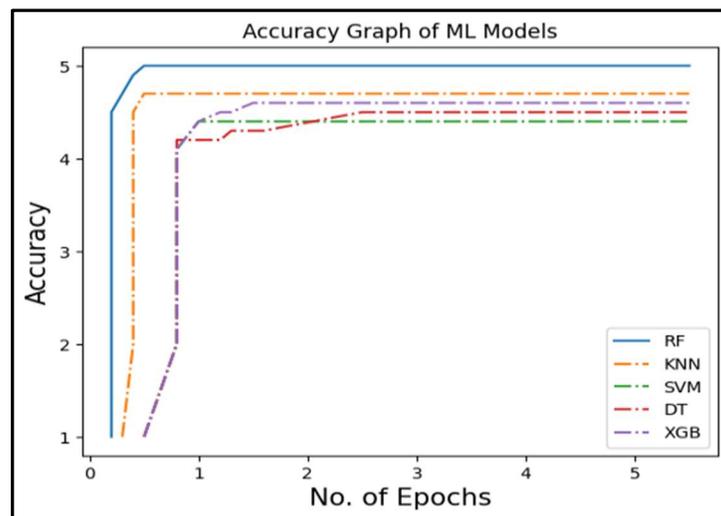


Figure 11: Learning curve of ML models

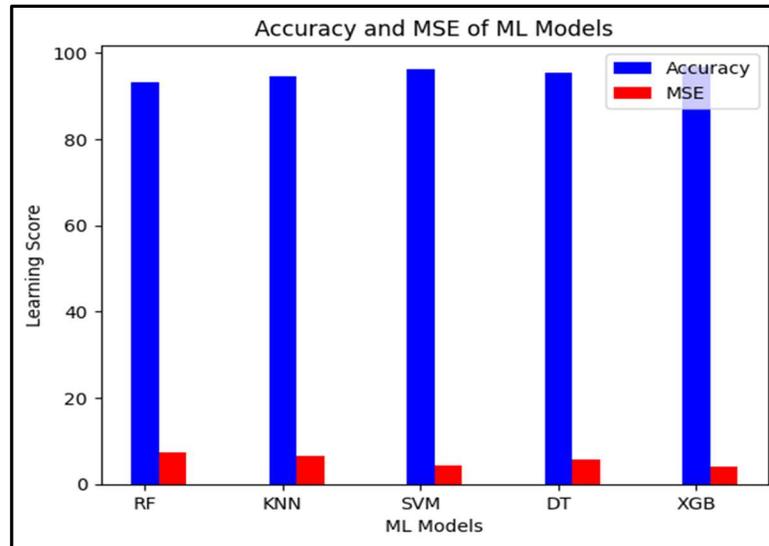


Figure 12: Bar graph of accuracy and MSE of ML models

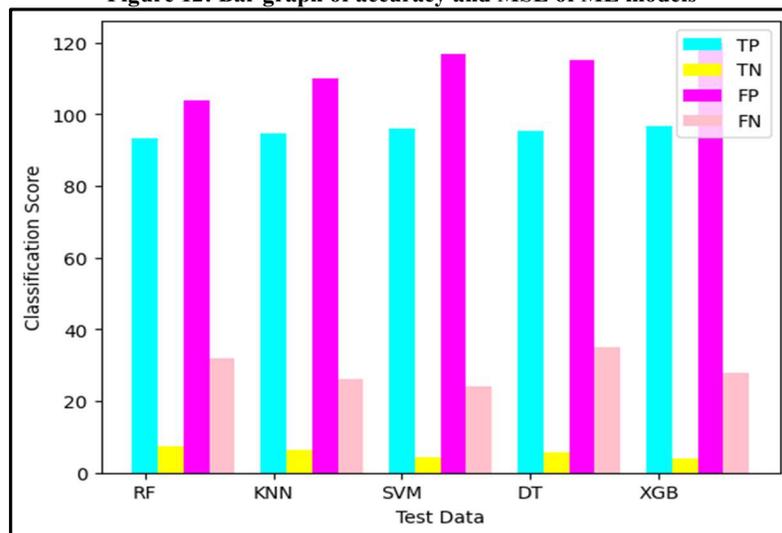


Figure 13: Classification report of ML models

### CONCLUSION AND DISCUSSION

In summary, the amalgamation of a Genetic Algorithm (GA) enhanced Artificial Neural Network (ANN) model to predict Gestational Diabetes Mellitus (GDM) has yielded remarkable results, boasting an impressive accuracy rate of 98.34%. in comparison with earlier work.

This research underscores the symbiotic

relationship between the optimization capabilities of the Genetic Algorithm and the pattern recognition prowess of the ANN. The Genetic Algorithm adeptly fine-tuned the ANN's architecture and parameters, tapping into its potential to uncover intricate relationships within the dataset. Consequently, our model exhibits noteworthy predictive accuracy that outperforms existing

machine learning and deep learning techniques.

Leveraging genetic algorithms for ANN optimization holds significant promise in addressing intricate medical diagnostic tasks such as GDM prediction. The capacity to traverse extensive solution spaces and reveal optimal configurations empower the ANN to effectively extract meaningful patterns from intricate, multidimensional datasets.

### Future Enhancements

Further validation and testing are necessary to ensure the model's robustness across diverse datasets and real-world scenarios. Incorporating additional data modalities, such as patient demographics, genetic markers, or lifestyle factors, could enrich the model's predictive capabilities and provide a more comprehensive assessment of GDM risk. Also, ensemble approaches of ML and deep learning could potentially enhance overall predictive performance and robustness.

### Limitations

The model's performance heavily relies on the quality and representativeness of the training data. It may struggle to generalize well to diverse populations or unforeseen variations in patient profiles. The model might occasionally produce false negatives (missed diagnoses) or false positives (incorrect diagnoses), potentially leading to misinformed clinical decisions.

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