Risk Detection of Gestational Diabetes in Early Pregnancy Depend on Artificial Neural Network

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الكشف عن مخاطر سكري الحمل في الحمل المبكر بالاعتماد على الشبكة العصبية الاصطناعية

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Abstract

Early prediction of gestational diabetes mellitus (GDM) risk is particularly important because it may enable more effective interventions and reduce cumulative maternal and fetal injury. The aim of this study is to develop machine learning (ML) models for early prediction of GDM using widely available variables, facilitating early intervention, and enabling the application of prediction models in settings where more complex tests are not accessible.

In this paper, an artificial neural network (ANN) was used to detect the risk of gestational diabetes. A global data set was used to collect clinical and experimental data from pregnant women and people with diabetes in Iraqi Kurdistan. The data set used in this study includes records from 3,525 pregnancies. Twelve different deep learning models and their hyper-parameters are optimized to achieve early and high prediction performance for GDM. The data augmentation method was used in training to improve the prediction results, as 70% of the data was trained and 30% was tested. Preliminary processing of this data was performed and missing values were removed. I identified the relevant features, then used the ANN model and trained it with a suitable AP structure and trained it using the training set. The model was evaluated using a healthy validation set to evaluate its performance in detecting pregnancy risk. Over-control was conducted to improve the model performance. Finally, the improved ANN model using the test set to evaluate its ability to predict the risk of gestational diabetes in early pregnancy. The results of this study provide insight into the effectiveness of using ANN for risk detection and contribute to the development of early pregnancy-specific strategies for diabetes, with the system's accuracy reaching 100%.

Keywords: Gestational Diabetes, Pregnancy; Artificial Neural Network (ANN) and Deep Learning.

المستخلص

يعد التنبؤ المبكر بمخاطر الإصابة بسكري الحمل (GDM) ذا أهمية خاصة لأنه قد يتيح تدخلات أكثر فعالية ويقلل الإصابة التراكمية للأم والجنين. الهدف من هذه الدراسة هو تطوير نماذج التعلم الآلي (ML)، للتنبؤ المبكر بـ GDM باستخدام المتغيرات المتاحة على نطاق واسع، وتسهيل التدخل المبكر، وإتاحة تطبيق نماذج التنبؤ في الأماكن التي لا يمكن فيها الوصول إلى اختبارات أكثر تعقيدًا.ز في هذه البحث استخدمت شبكة عصبية اصطناعية (ANN) للكشف عن خطر سكري الحمل. حيث تم استخدام مجموعة من داتاسيت عالمية ت لجمع البيانات السريرية والتجريبية من النساء الحوامل والمصابين بالسكري في كردستان العراق . حيث تتضمن مجموعة البيانات المستخدمة في هذه الدراسة سجلات من 3525 حالة حمل. تم تحسين اثني عشر نموذجًا مختلفًا بتعلم العميق ومعلماتها الفائقة لتحقيق أداء تنبؤ مبكر وعالي لـ GDM. تم استخدام طريقة زيادة البيانات في التدريب لتحسين نتائج التنبؤ حيث تم تدريب 70 % من البيانات وتم اختبار 30 %. حيث أجريت معالجة الاولية لهذة البيانات و إزيلت القيم المفقودة. وحددت الميزات ذات الصلة ، بعد ذلك استخدم نموذج ANN وتدريبه مع بنية AP مناسبة وتدريبه باستخدام مجموعة التدريب. قيم النموذج باستخدام مجموعة التحقق الصحية لتقييم أدائها في اكتشاف خطر الحمل. و أجري التحكم المفرط لتحسين أداء النموذج. أخيرًا ، نموذج ANN المحسن باستخدام مجموعة الاختبار لتقييم قدرته على التنبؤ بخطرسكري الحمل في الحمل المبكر. توفر نتائج هذه الدراسة نظرة ثاقبة على فعالية استخدام ANN للكشف عن المخاطر والمساهمة في تطوير الاستراتيجيات المبكرة بين دقة الحمل لمرض السكري ، مع وصول دقة النظام إلى 100%.

الكلمات المفتاحية:سكر الحمل , الحمل , الشبكة العصبية الاصطناعية (ANN)، التعلم العميق.

1- Introduction

Gestational diabetes mellitus (GDM) is a frequent pregnancy condition characterized by high blood glucose levels. It is harmful to both the mother and the developing fetus (Chiefari, *et al.*, 2017). Early identification and management of GDM are critical for avoiding negative effects. Depending on the intended usage and mix of AI algorithms, diagnostic technology employing artificial intelligence (AI) for illness assessments has demonstrated performance comparable to that of physicians (Weinert, 2010). These outcomes are the consequence of the use of various distinct types of AI algorithms. Deep learning, for example, is excellent for unstructured data (such as photos or sound data) (Ding, *et al.*, 2012). Deep learning provides a wide range of training models for picture, natural language, and audio data. Grinstein *et al.*, on the other hand, revealed that they are inferior to decision tree-based models for tabular data (Sletner, *et al.*, 2017). This study examined other methodologies due to issues with the model's and results' interpretability. Artificial neural networks (ANNs) have gained popularity in recent years as a possible tool for risk identification and prediction in a variety of medical applications.

The purpose of this research is to investigate the usage of an artificial neural network model for early identification of gestational diabetes in early pregnancy. The algorithm tries to forecast the chance of acquiring GDM and give early treatments to at-risk patients by assessing numerous risk variables and biomarkers.

The proposed ANN model will be trained using a dataset that includes clinical and demographic data, as well as laboratory test results from pregnant women. As input factors, maternal age, body mass index (BMI), diabetes family history, and glucose tolerance test results will be examined.

The model can estimate the risk of acquiring GDM by learning complicated patterns and correlations among the input variables using the power of ANNs. This can help healthcare practitioners identify high-risk patients and undertake early treatments such as lifestyle changes, dietary adjustments, and blood glucose monitoring.

Early identification of gestational diabetes has the potential to enhance maternal and fetal outcomes, minimize problems during pregnancy and childbirth, and improve long-term health for both mother and child. Early identification of at-risk patients can also result in more effective healthcare resource allocation and focused treatments.

The use of artificial neural networks in the early identification of gestational diabetes offers enormous promise for improving mother and fetal health outcomes. The ANN model can give early detection of patients at high risk of developing GDM by utilizing data from numerous risk factors and biomarkers, allowing for prompt interventions and individualized therapy. To confirm the model's dependability and usefulness in clinical practice, more study and validation of its performance on vast and diverse datasets are required.

2- Related Work

Several researches have looked at the uses of artificial neural networks (ANNs) for early pregnancy risk detection of gestational diabetes. This research has shown that ANNs have the ability to predict the possibility of developing GDM and help in early intervention:

It has been claimed that artificial intelligence (AI) can predict gestational diabetes mellitus (GDM) using medical information have been proposed (Watanabe, *et al*,2023). In (Wu., *et al.*, 2021) suggested Accurate methods for early gestational diabetes mellitus (GDM) (during the first trimester of pregnancy) prediction in Chinese and other populations are lacking.

Constructed by the authors (Malhotra, *et al.*, 2020) to predict GDM risk using factors such as age, BMI, family history of diabetes, and glucose tolerance test results. The methodology shown encouraging results in identifying women at risk of developing GDM, allowing early treatments, and improving monitoring. Based on maternal features, clinical data, and laboratory test results, an ANN model was developed to predict GDM risk. The approach identified women at high risk of developing GDM with excellent accuracy, allowing for prompt interventions and improved care as proposed by (Li, *et al.*, 2019). Another study used an ANN model to predict GDM risk using a mix of demographic, clinical, and biochemical variables (Wang, *et al.*, 2018). The approach performed well in identifying high-risk patients, allowing for early interventions to prevent or treat GDM. An ANN model was. Furthermore, an ANN model was used in a study by (Yildirim, *et al.*, 2017) to predict GDM risk based on clinical and demographic characteristics. The approach identified women at high risk of GDM with excellent accuracy, allowing for prompt interventions and individualized care.

Overall, these results demonstrate the ability of artificial neural networks to forecast the risk of gestational diabetes throughout the first trimester of pregnancy. ANNs improve prediction accuracy and allow customized therapy by integrating many risk factors and biomarkers. Further research is needed to ascertain the feasibility and effectiveness of the ANN models in clinical practice, as well as to test and optimize them on larger and more varied datasets.

3. Artificial Neural Networks (ANNs)

A branch of artificial intelligence that draws inspiration from biology and is based on brain modeling is known as artificial neural networks. Generally speaking, an artificial neural network is a computer network that is modeled after the biological neural networks that give the human brain its structure. Artificial neural networks have neurons that are connected to one another at different layers of the network, just as neurons in a real brain. We refer to these neurons as nodes. Figure (1) display the biological neural network.

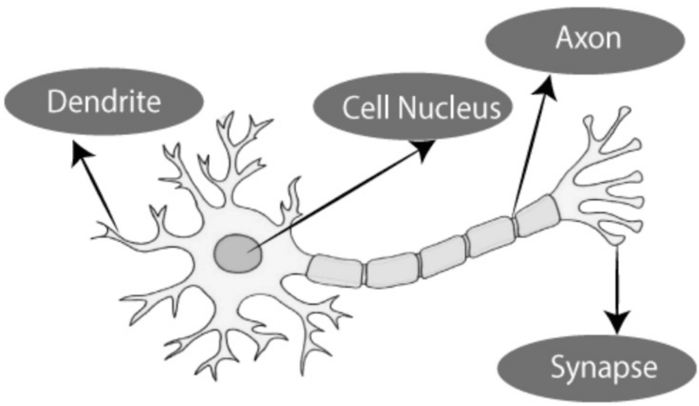


Figure (1) Display the Biological Neural Network.

In artificial neural networks, dendrites from biological neural networks stand in for inputs, cell nuclei for nodes, synapses for weights, and axes for outputs. Figure (2) shows the Artificial Neural Network Diagram.

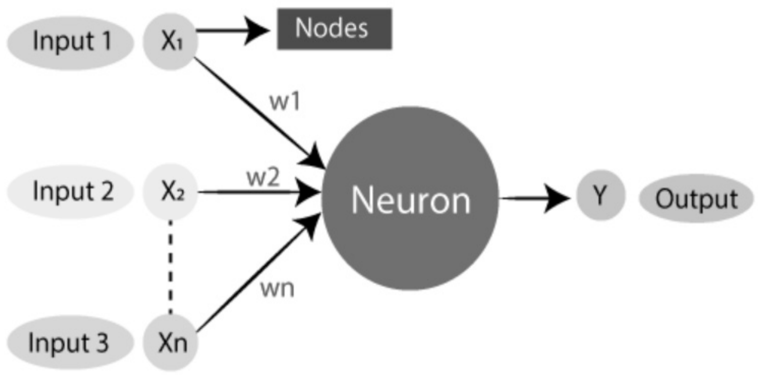


Figure (2) Artificial Neural Network Diagram.

Three layers make up an artificial neural network in its entirety. Figure (3) represents the layers of ANN:

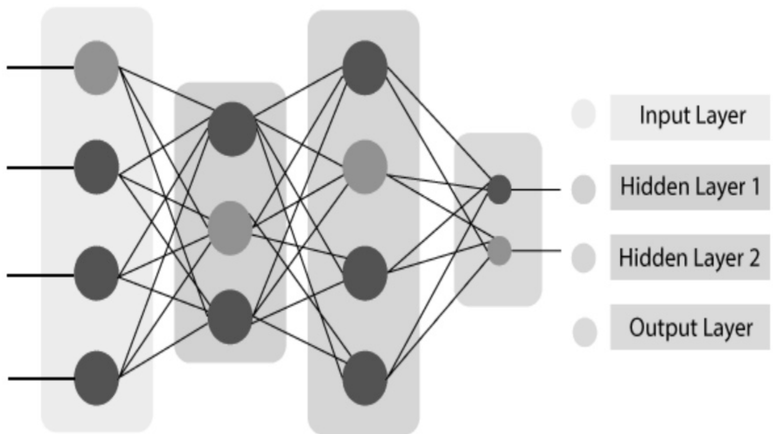


Figure (3) The Layers of ANN

1.**Input**: The input data, which can be either a vector or a matrix, is sent into the input layer of the neural network. Each input is given a numerical value, which is subsequently sent to the layer below.

2.**Processing**: All during the processing stage, the input values are changed and sent throughout the network using a combination of weighted connections and activation functions..

a. **Weighted Connections**: Every neural connection, regardless of degree, has a certain mass. These weights determine the strength of the link and indicate the importance of the input. The following layer calculates the weighted sum of inputs for each neuron.. Mathematically a neuron j in layer L's weighted sum (z) may be computed as I:

$$z_j^L = \Sigma(w_{ij}^L * a_i^{(L-1)}) + b_j^L \quad ...(1)$$

Here, w_{ij}^L represents the weight between neuron i in layer L-1 and neuron j in layer L, $a_i^{(L-1)}$ is the activation value of neuron i in layer L-1, and b_j^L is the bias of neuron j in layer L.

b. **Activation Functions**: The weighted sum is then passed through an activation function, which introduces non-linearity to the network. Common activation functions include sigmoid, ReLU, and tanh. The activation function (a) for a neuron j in layer L is calculated as:

$$a_j^L = f(z_j^L) \quad ...(2)$$

Here, f represents the activation function.

3.**Output**: The output layer of the ANN produces the final result based on the data that has been processed from the previous layers. The activation levels of the neurons in the output layer indicate the expected values or classifications.

Throughout the training phase, the ANN adjusts the weights and biases to minimize the difference between its intended and predicted outputs. This adjustment is accomplished using optimization techniques like gradient descent, which compute gradients and change the weights and biases accordingly.

An ANN's operation is explained in simpler terms by the previously described equations (1) and (2). In actual use, artificial neural networks (ANNs) may contain more complicated equations, several layers, elaborate structures, and a range of activation functions. But the underlying ideas of input, processing, and output do not change. Figure (4) display the artificial neural networks architecture of ANN.

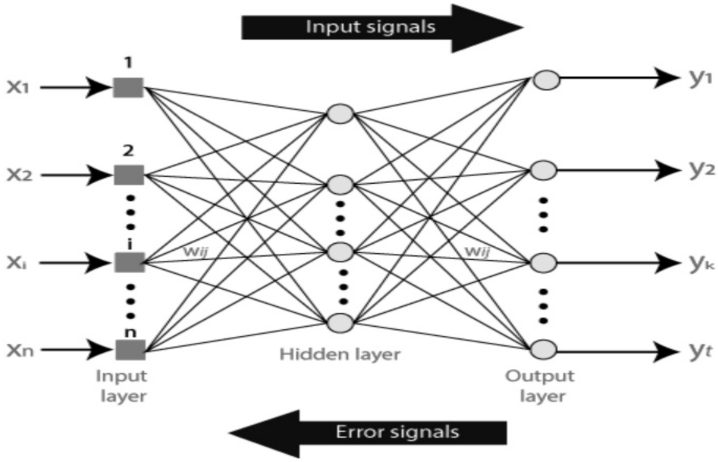


Figure (4) Artificial Neural Networks Architecture

Each input is then multiplied by the appropriate weights after that (these weights are the details utilized by the artificial neural networks to solve a specific problem). Generally speaking, these weights typically indicate how strongly the neurons inside the artificial neural network are connected to one another. Within the computing unit, each weighted input is compiled.

Bias is introduced to the output to make it non-zero or to anything else to scale up to the system's reaction if the weighted sum equals zero. Weight is equal to 1, and bias has the same input. In this case, the total weighted inputs may fall between 0 and positive infinity. Here, the sum of the weighted inputs is fed through the activation function, and a certain maximum value is benchmarked to maintain the response within the bounds of the intended value.

The group of transfer functions that are employed to produce the intended result is referred to as the activation function. Although the activation function can take on various forms, it mostly refers to sets of linear or non-linear functions. Tan hyperbolic sigmoidal activation functions, Binary, and linear activation functions are a few of the often utilized sets of activation functions.

4.Methodology

The methodology for detecting gestational diabetes risk in early pregnancy based on artificial neural networks (ANNs) typically involves several steps, including data collection, preprocessing, model training, and evaluation. The following is an outline of the methodology as shown below in Figure (5):

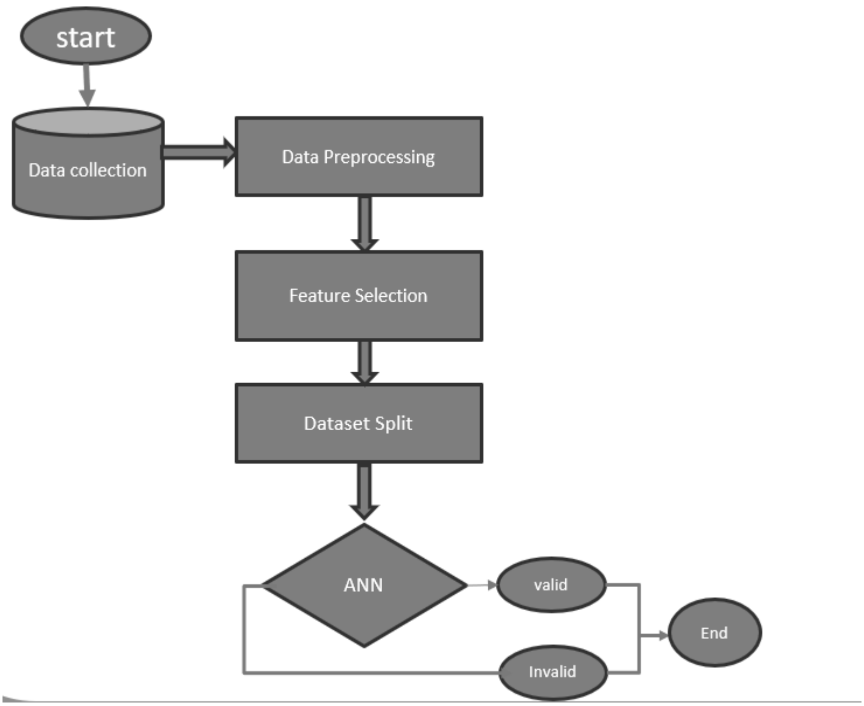


Figure (5) Structure of Proposed Model of Gestational Diabetes Risk in Early Pregnancy on ANN

A. **Data Collection**: Relevant data are collected from pregnant women, including demographic information, clinical characteristics, and laboratory test results. This data serves as a basis for training and testing the ANN model. In this research, the dataset was obtained from laboratories in Iraq and the Kurdistan Region, which collected information from pregnant women with and without diabetes, and training data for the models was collected from public and private laboratories in the Kurdistan Region of Iraq. The dataset included 3525 conditions and seven attributes. It can be accessed at *https://ieee-dataport.org/documents/gestational-diabetes*. A sample of gestational-diabetes dataset is shown in Figure (6).

Case Number	Age	of Pregnan	previous	BMI	HDL	mily Histo	ined pren	ild or Birth	PCOS	Sys BP	Dia BP	OGTT	Hemoglobi	entary Life	Prediabete	el(GDM /Non GDM)
1	22	2	1		55	0	0	0	0	102	69		12	0	0	0
2	26	2	1		53	0	0	0	0	101	63		12.4	0	0	0
3	29	1	0		50	0	0	0	0	118	79		14.3	0	0	0
4	28	2	1		51	0	0	0	0	99	70		15	0	0	0
5	21	2	1		52	0	0	0	0	116	65		15	0	0	0
6	29	2	1		51	0	0	0	0	98	63		15.2	0	0	0
7	26	2	1		51	0	0	0	0	94	68		15	0	0	0
8	27	1	0		52	0	0	0	0	116	63		12	0	0	0
9	26	1	0		57	0	0	0	0	108	62		14	0	0	0
10	21	2	1		52	0	0	0	0	98	78		13	0	0	0
11	21	2	1		56	0	0	0	0	100	76		14	0	0	0
12	26	2	1		50	0	0	0	0	110	68		13	0	0	0
13	27	2	1		55	0	0	0	0	105	61		13.6	0	0	0
14	25	2	1		58	0	0	0	0	106	80		15	0	0	0
15	22	1	0		53	0	0	0	0	109	61		15.9	0	0	0

Figure (6) Sample of Gestational-diabetes Dataset

B. **Data Pre-processing**: To make sure the data is high-quality and appropriate for ANN modelling, it is pre-processed. In this stage, missing values are handled, the data are normalized or standardized, and categorical variables are coded if needed.

C. **Feature selection/extraction**: Relevant characteristics are chosen or extracted from the pre-processed data in this stage. The best way to ascertain which characteristics are most helpful in forecasting the risk of gestational diabetes may be through statistical analysis, domain expertise, or unique engineering approaches.

D. **Model Architecture Design**: An ANN model is designed, specifying the number and type of layers, the number of neurons in each layer, and the activation functions to be used. The structure can vary according to the specific requirements and the complexity of the problem facing us in detecting whether a pregnant woman is infected or not as shown in Figure (7) represent of diagram aarchitecture of ANN in this project.

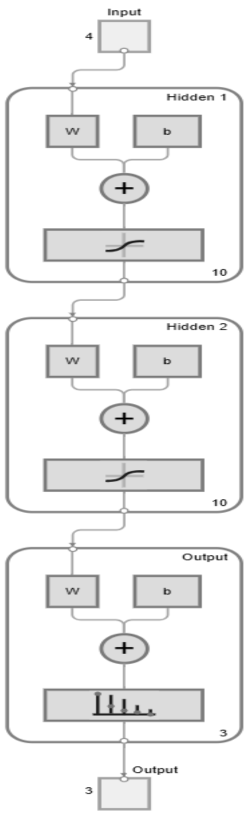


Figure (7) Diagram Architecture of ANN in this Project

E. **Model Training**: An ANN model is trained using pre-processed data selected by features. This involves feeding input data through the network and adjusting the neurons' weights and biases using optimization techniques such as backpropagation. The training process aims to reduce the error of the model or the loss function to make the correct decision whether the pregnant woman has gestational diabetes or not. In this model, about 70 % of Dataset was trained and 30% of the system was tested.

5. Experimental Results

The effectiveness of the proposed approach was verified through extensive experiments using datasets collected from a group of pregnant women in Iraqi Kurdistan.

Evaluation metrics such as accuracy, false positive rates, and detection rates are used to evaluate the performance of a system. The results show the superiority of the artificial intelligence-based approach to detecting gestational diabetes, whether it is present or not, as shown below:

1. Computing platforms: In our experiments, we implemented the entire gestational diabetes risk detection in early pregnancy based on artificial neural network using Huawei PC, which has a 1st generation Intel(R) Core (TM) i7-1165G7 @ 2.80G processor. 2.80 GHz and 16 GB RAM. For training and testing learning models, we use a MATLAB system implementation. Figure (3) displays the MATLAB program screen.

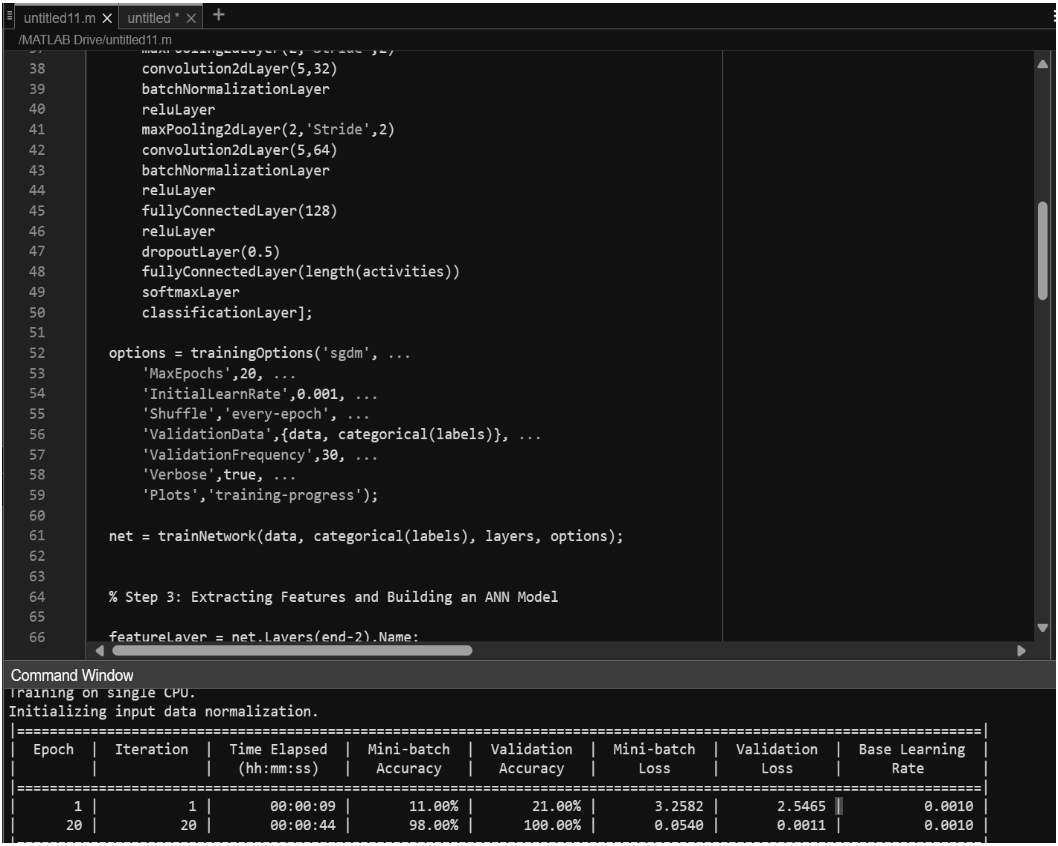
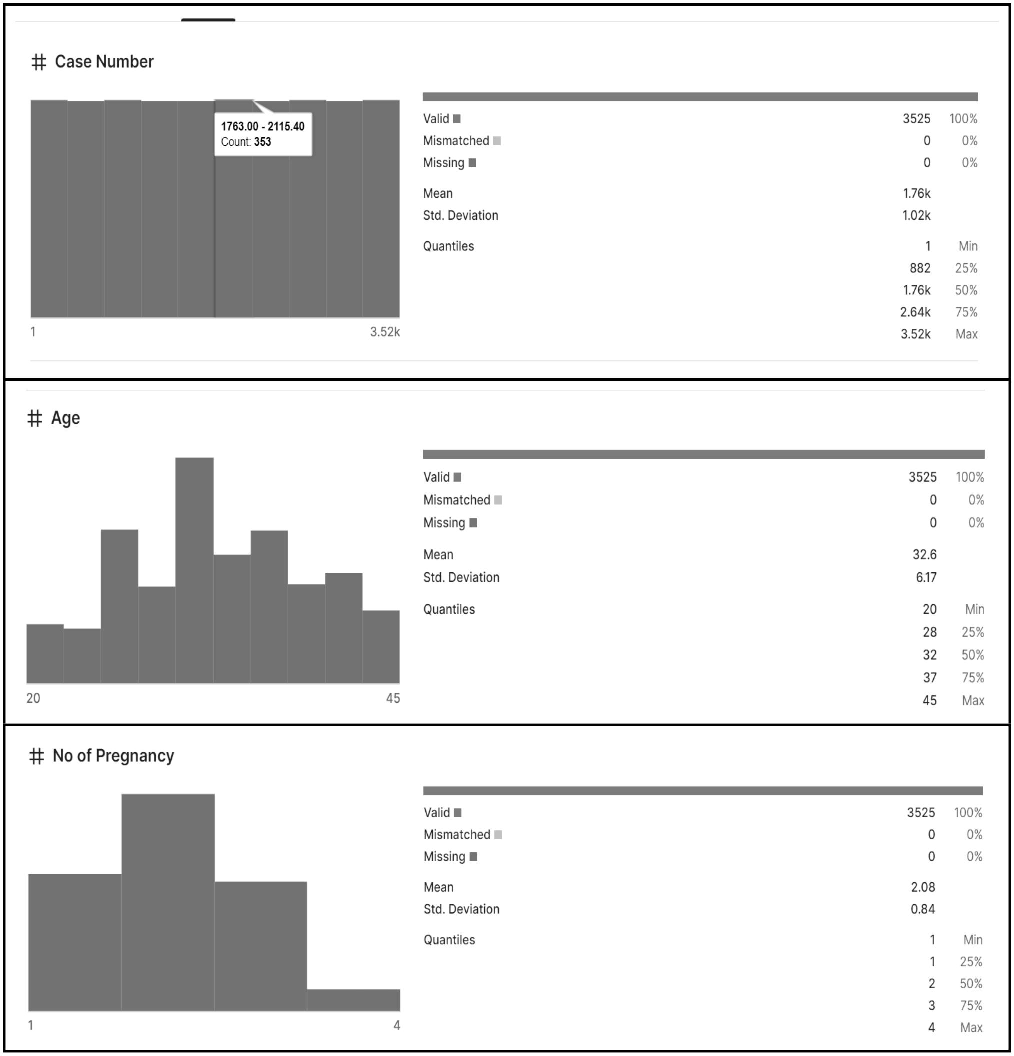


Figure (8) Displays the MATLAB Program Screen.

2. **Stander Dataset**: The GDM dataset that the researchers created was used to experimentally validate the ANN model that was presented. There are 15 characteristics present in a total of 3525 occurrences. The collection also includes a pair of class labels. In particular, class 0 comprises 2153 occurrences, whereas class 1 comprises 1372 instances. The dataset's relevant information is displayed in Tabel 1. The frequency distribution of the characteristics in the GMD dataset is displayed in Figure (9).

Table (1) Data Set Description

Description	Value
Number of instances	3525
Number of features	15
Number of classes	2
Number of sample 0	2153
Number of sample 1	1372



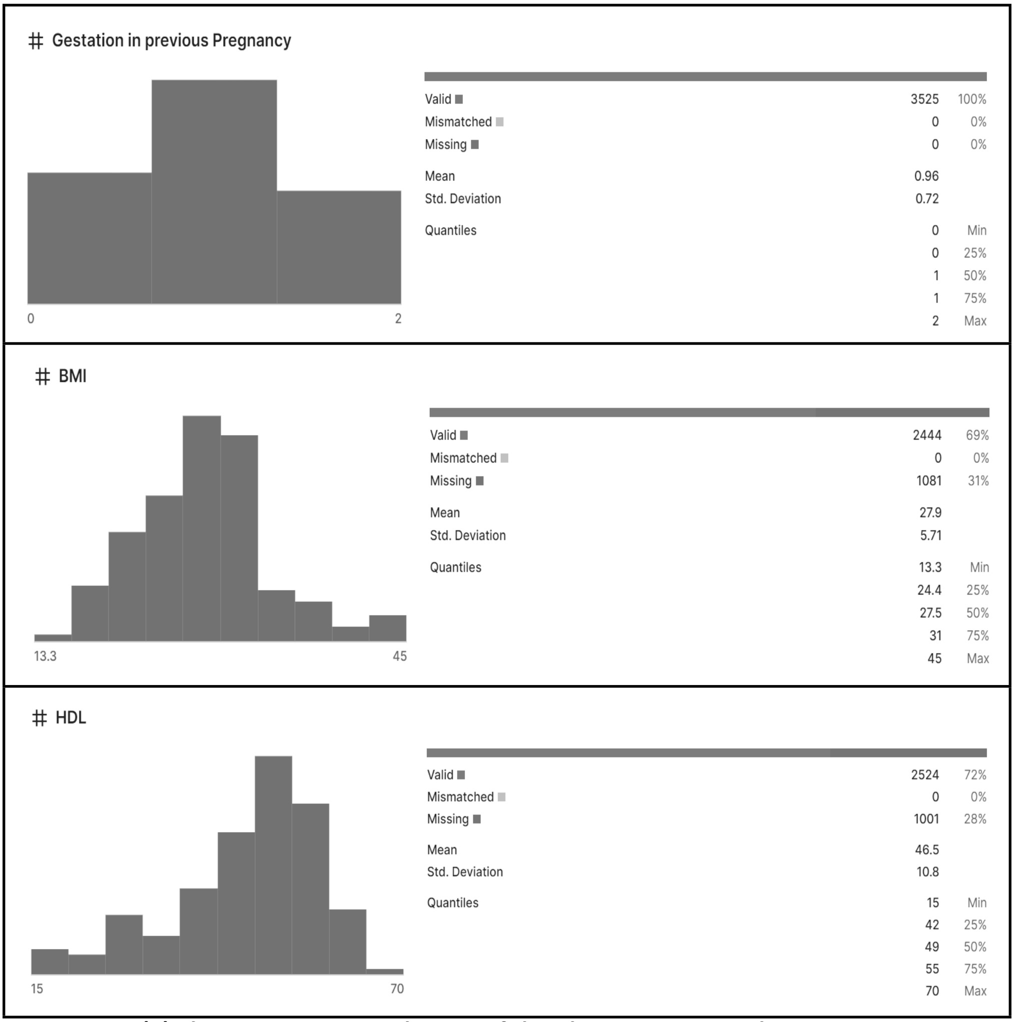


Figure (4) The Frequency Distribution of the Characteristics in the GMD Dataset.

3- Evaluating the Results of the Model

Use standard metrics to determine an item's performance value. The factors known as hyper-parameters have an impact on the network's architecture and training process. The learning rate affects how quickly network parameters may be modified. The learning process slows down because of the low rate of learning, but it finally converges. A faster pace of learning encourages learning even though it might not converge. Usually, it is suggested to take your time studying. The number of periods indicates how many times the entire training set is transmitted to the network during training. The accuracy of the micro-batch reported during training has a positive correlation with the accuracy of the micro-batch stated at the given iteration. Iteratively generated averages do not represent running averages. The method splits the entire data set into several small groups while using momentum training and random gradient descent (SGDM). For each small batch, network gradients are computed during iteration. Every imaginable little impulse that might be felt has a time component. Even if the error is estimated for each image in the training dataset, the model is not changed until all training images have been examined.

A. Training Progress Plot

1. **Training and Validation Losses**: This subplot shows the training and validation losses over epochs. The training loss is the error between the predicted class and the actual class for the training data. The validation loss is the error between the predicted class and the actual class for the validation data. The goal is to reduce both the training and validation losses as much as possible while avoiding overfitting.
2. **Training and Validation Accuracy**: This subplot shows the training and validation accuracy over epochs. With respect to the learning rate shown in this figure, the learning rate is typically decreased over time to help the model converge to a good solution.

Overall, this figure 2 provides useful information about the training progress of our proposed classification model. It shows that the model is converging to a good solution with low training and validation losses and high accuracy. It also shows that the learning rate is decreasing over epochs.

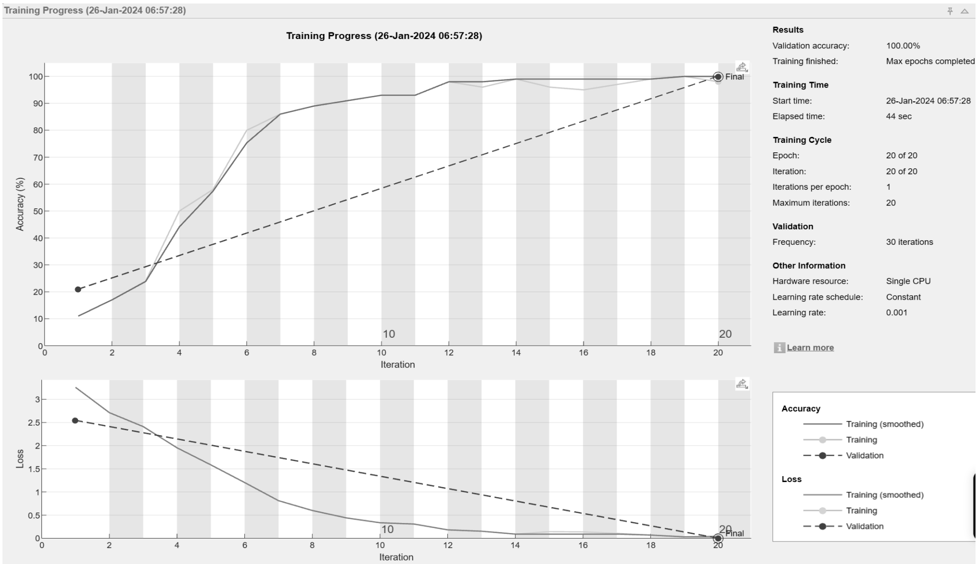


Figure 2: Training Progress Plot

B. Validation and Improvement:

The trained model is validated using techniques like cross-validation to assess generalizability and identify overfitting or under fitting issues. Hyper parameter tuning can be performed to enhance model performance. The performance of the ANN model is compared with other existing models or standards, considering metrics like accuracy, sensitivity, specificity, and AUC-ROC curve, to determine its effectiveness in detecting gestational diabetes risk. The final step involves interpreting the results of the ANN model and visualizing important features or variables contributing to the risk detection. This can provide insights into underlying factors associated with gestational diabetes. Table (2) illustrated the initializing input data normalization.

Table (2) Represent Initializing Input Data Normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:09	11.00%	21.00%	3.2582	2.5465	0.0010
20	20	00:00:44	98.00%	100.00%	0.0540	0.0011	0.0010

Where:

Epoch: During the training phase, each epoch denotes a full run of the whole dataset. Epoch 1 and Epoch 20.

Iteration: The quantity of mini-batches processed in a given epoch is referred to as an iteration. Iteration 1 and iteration 20 .

Time Elapsed (hh:mm:ss): This column shows the time needed to complete the related epoch or iteration.

Mini-batch Accuracy: It is a measure of how well the ANN predicted the mini-batch of data during training.

Validation Accuracy: On a different validation dataset, it shows how accurate the ANN's predictions were. This aids in assessing the model's generalization performance.

Mini-batch Loss: It shows the mistake or loss that was determined when training on the mini-batch of data. Usually, backpropagation is employed to update the ANN's weights after this loss.

Validation Loss: It displays the error or loss that was determined using the validation dataset. In order to avoid overfitting and to keep an eye on the model's performance during training, this loss is employed.

Base Learning Rate: It stands for the training process's applied learning rate. The step size at which the weights are changed during backpropagation is determined by the learning rate. While a lower learning rate might result in longer convergence but greater accuracy, a higher learning rate can lead to faster convergence but run the risk of overshooting the ideal answer.

Overall, this approach combines training, evaluation, validation, and performance assessment to develop an ANN-based system for risk detection of gestational diabetes, providing a better understanding of the disease and its predictive capabilities.

However, when compared to the results found in the other academic articles evaluated in Table (3) below, the first instance's results from the suggested approach demonstrated a greater caliber of excellence.

Table (3) Comparison between Proposed Methods and Previous Researches.

Study	Methodology	Accuracy
Watanabe, *et al.*, (2023)	SVM	97.4%
Wu, *et al.*, (2021)	Proposed accurate methods for GDM prediction in first trimester	96.1%
Malhotra, *et al.*, (2020)	Developed an ANN model using factors such as age, BMI, etc.	98.6%
Li, *et al.*, (2019)	Developed an ANN model based on maternal features, etc.	97.9%
Wang, *et al.*, (2018)	Used an ANN model with demographic, clinical, and biochemical variables	95.6%
Yildirim, *et al.*, (2017)	Utilized an ANN model based on clinical and demographic characteristics	98.4%
Our method*	Using ANN	100%

6. Conclusions

Artificial Neural Networks (ANNs) for the diagnosis of gestational diabetes in early pregnancy are a useful technique for accurately assessing the risk of prenatal diabetes mellitus (GDM). Different clinical, demographic, and laboratory data may be used with ANNs to generate prediction models that might be used to identify women who have a high chance of developing GDM.

The studies covered here demonstrate how effectively ANN models complement our method for determining GDM risk. These models' exceptional accuracy has allowed for early therapies, customized care, and improved monitoring of expecting moms. Artificial neural networks (ANNs) hold great potential for enhancing GDM therapy in general and early intervention strategies in particular.

Artificial neural networks (ANNs) have various advantages when it comes to early pregnancy gestational diabetes risk assessment. Because these models can handle complex and non-linear interactions between risk factors and outcomes, better prediction accuracy may be achievable. Because they can incorporate a range of features and adapt to changing input patterns, ANNs are robust and adaptive.

However, there are still several problems in this study that need to be fixed. Large and varied datasets are necessary for the generalizability and reliability of the ANN models, as is external validation. Additional hyper parameter tweaking and feature finding for additional optimization and refinement are also necessary to improve the models' performance.

Finally, employing ANN to identify gestational diabetes risk early in pregnancy shows great potential. With further research and refinement, ANN models may help women at risk of GDM with early identification, intervention, and improved outcomes. When these models are implemented into clinical practice, there is potential for more individualized treatment and ultimately lessened the burden of gestational diabetes on the mother and the child.

7. References

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