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Navigating Gestational Diabetic Mellitus:Challenges And Management

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Abstract

One common pregnancy problem is gestational diabetes mellitus (GDM), which affects 16% of pregnant women worldwide. However, as early and accurate GDM prediction may lower the disease's risk, it is preferred. Creating a smart healthcare monitoring model to analyze data, forecast disease, and identify fetal monitoring is the main goal of this endeavor. Hence, this work presents an IoT based GDM prediction using multi-modality data. In first step, the ultrasound images are enhanced by Contrast Adaptive Limited Histogram (CLAHE). Once the enhancement is done, next step is feature extraction. The features are extracted using pre-trained Inception-V3 model based on CNN. The GDM data obtained from the Kaggle repository is also gathered and pre-processed. The dataset is balanced, standardised, and outliers are removed during the pre-processing stage. Adaptive Golden Eagle Optimisation (AGEO) is used to choose the critical features required for the GDM prediction.

Keywords : Gestational Diabetes Mellitus, Convolutional Neural Network, Deep Learning

I. INTRODUCTION

Gestational diabetes mellitus (GDM) is regarded as one of the common problems that arise during pregnancy. It is the erratic glucose level that is typically discovered between weeks 22 and 26 of pregnancy. A few of the complications include breathing issues, preterm birth, metabolic issues, and possible increases in the fetus's weight [1].

Although, the GDM go away after the delivery, there is a chance of developing Type-II diabetes. Various research works proved that the high risk complications are overcome when the medical treatment is given at the first or second trimesters [2]. The major problem is how to find women at high-risk of developing GDM in early Gestational time [3]. The early identification GDM and fetal monitoring is essential to avoid the above complications and it is major in problems like: (a) the analysis proved that the treatment of pre-diabetes response differs when the history of GDM is considered. (b) Individual prediction of risk and estimation of treatment analysis. (c), women can able to know about the risk of diabetes using the GDM history. Generally, Ultrasound (US) images are used for finding the fetal movement. Artificial intelligence (AI) is a machine which is used for performing the human intelligent model. The clinical data and the US images are applied on the AI model for predicting the GDM prediction and fetal movement [4]. Most of the GDM prediction research works utilized the conventional ML (machine learning) approaches which develops an implicit consideration for the analysis.

Motivation

Deep learning (DL)-based smart healthcare systems are becoming more and more common in real-world uses. The use of DL models to analyze clinical data for computer-aided diagnosis (CAD) has gained popularity in recent years. Previous studies looked into medical data in a medical field and offered useful knowledge.A crucial tool that may help with more proactive and preventive healthcare decisions is predictive analytics for health data.

The previously proposed method plays a significant region that is receiving focus in unsupervised learning and can be particularly important for medical imaging based on current developments in deep learning.

The key contributions of the work are given as follows:

- To present an automated based deep learning model for the prediction of the Gestational diabetes mellitus (GDM) and fetal monitoring.

- To extract the image features using the pre-trained CNN based Inception-V3 model from the ultrasound images.

Motivation and Problem Statement

Deep learning (DL)-based smart healthcare systems are becoming more and more common in real-world uses. The use of DL models to analyze clinical data for computer-aided diagnosis (CAD) has gained popularity in recent years. Previous studies looked into medical data in a medical field and offered useful knowledge.A crucial tool that may help with more proactive and preventive healthcare decisions is predictive analytics for health data.

However, the conventional model doesn't handle the unbalanced data and the conventional single models are also not able to handle the data. Furthermore, no research works are carried out on the basis of the clinical as well as the ultrasound images for monitoring the fetal. Hence, this work presents a multi-modal data (text+image for the GDM prediction and fetal monitoring which reduces higher risk at the pregnancy.

Objectives

- The following are the work's main contributions: To introduce a deep learning model that is automated and based on prediction for gestational diabetes mellitus (GDM) and fetal monitoring.
- To extract the ultrasound pictures' features using the pre-trained CNN-based Inception-V3 model.
- Adaptive Golden Eagle Optimization (AGEO) is used to pick text characteristics, which lowers the dimensionality of data from the Kaggle source.
- To combine the features of the image and text by employing multi-modal compact bi-linear pooling.

Proposed Methodology

Around 16% of pregnant women worldwide suffer from gestational diabetes mellitus (GDM), a common pregnancy complication. However, as it may lower the risk of the condition, an accurate and timely GDM prognosis is preferred. Additionally, there is a huge surge in the use of sensor devices.

The major aim of this work is to develop a smart healthcare monitoring model for analysing the data and predicting the disease and identifying the fetal monitoring. Hence, this work presents an IoT based GDM prediction using multi-modality data.

This work presents a hybrid deep learning (DL) model for the fetal monitoring of the diabetes affected women using the ultrasound images and the medical information. Initially, the ultrasound images are enhanced by the **Contrast Adaptive Limited Histogram (CLAHE).** Then, the features are extracted using the **pre-trained CNN based Inception-V3 model**. Similarly, the GDM data from Kaggle repository is collected and pre-processed. In the pre-processing stage, the dataset is **balanced, standardized and outliers removal processes** are carried out. Analysing the large amount of data is a challenging process which affects the time of execution and prediction process. Hence, the important features essential for the GDM prediction is selected using the metaheuristic algorithm **Adaptive Golden Eagle Optimization (AGEO).** Then, the features extracted from the ultrasound images and the Kaggle data are fused using the **multi-modal compact bi-linear pooling** and provided into the softmax layer. This layer will monitor the fetal movement and risk factor of the pregnant women.

This work presents a hybrid deep learning (DL) model for the fetal monitoring of the diabetes affected women using the ultrasound images and the medical information. Initially, the ultrasound images are enhanced by the Contrast Adaptive Limited Histogram (CLAHE). Then, the features are extracted using the pre-trained CNN based Inception-V3 model. Similarly, the GDM data from Kaggle repository is collected and pre-processed. In the pre-processing stage, the dataset is balanced, standardized and outliers removal processes are carried out. Analysing the large amount of data is a challenging process which affects the time of execution and prediction process. Hence, the important features essential for the GDM prediction is selected using the metaheuristic algorithm Adaptive Golden Eagle Optimization (AGEO). Then, the features extracted from the ultrasound images and the Kaggle data are fused using the multi-modal compact bi-linear pooling and provided into the softmax layer. This layer will monitor the fetal movement and risk factor of the pregnant women. The block diagram of proposed method is shown below in Figure 1.

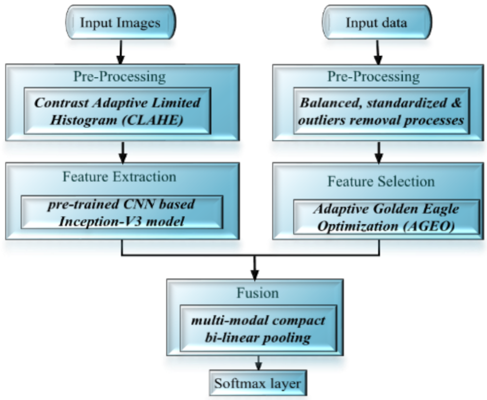


Fig.1. Block diagram of proposed methodology

Image Pre-Processing

The steps involved for monitoring GDM are pre-processing. The first stage removes noisy speckles from the input images before passing them to the following stage, which enhances the features using Contrast Limited Adaptive Histogram Equalization (CLAHE).For digital photos, particularly medical images, the CLAHE approach improves the poor contrast issue.

Specifically for medical imaging, CLAHE outperforms the Adaptive Histogram Equalization (AHE) and conventional Histogram Equalization (HE), making it superior.

By combining the CLAHE and Percentile techniques, we have improved the quality of those images. After the enhancement of the input images, next section is feature extraction. Figure 2 shows the block diagram of CLAHE.

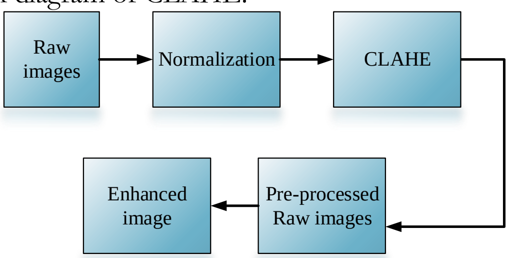


Fig.2. Block diagram of CLAHE

❖ Details of Back Propagation

Techniques like batch learning, momentum, and weight decay are utilized to speed up and stabilize training neural networks. Batch learning is used to increase learning efficiency and precision. In this process 128 input samples in a batch before changing the connection weights once for the entire batch, as opposed to updating them after each back propagation. Momentum weight update in addition to weight degradation is used to accelerate learning even more.

$$\Delta\omega_j(r+1)=\omega_j(r)-\eta\frac{\partial F}{\partial \omega_j}+\alpha\Delta\omega_j(r)-\lambda\eta\omega_j \quad (4)$$

The $\omega_j(r)-\eta\frac{\partial F}{\partial \omega_j}$ portion is the common name for back propagation, $\omega_j(r)$ represents the current weight vector, $\frac{\partial F}{\partial \omega_j}$ is a gradient of the error in respect to the value of the weight vector and η is the rate of learning. $\alpha \Delta \omega_j(r)$ Represent part of momentum, here α is rate of momentum. The current weight updates term facilitates learning during a faster rate. $-\lambda \eta \omega_j$ Represent decay part, λ represent delay rate of weight. Experimental testing are used to choose these learning parameters.

Problem Statement

Both the conventional approach and the conventional individual models are unable to manage unbalanced data. Additionally, no research projects are conducted to track the fetal development using clinical or ultrasound pictures. Due to the shortage of medical data and numerous problems with its accuracy, an essential area for research is how to incorporate expert knowledge with deep learning to direct it into the proper path. Data privacy concerns and the lack of easily accessible high-quality medical data frequently make it difficult to meet the need for large and labelled datasets. Deep learning model interpretability and explain ability to continue the crucial issues since they must be clear and understandable to medical experts.

Dataset Details:

Gestational diabetes dataset: https://www.kaggle.com/code/medahmedkrichen/gestational-diabetes/data

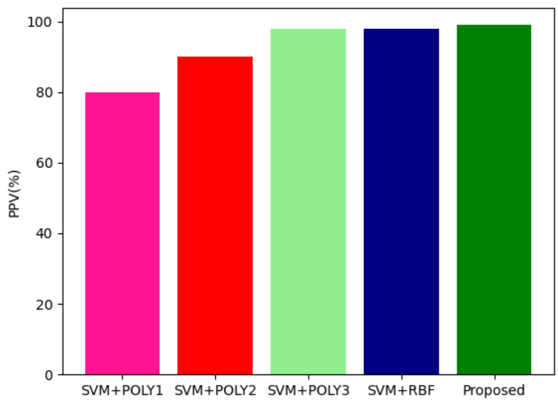
Real time Ultrasound images

Expected outcome: The major performance metrics will be computed and compared with the recent techniques.

❖ Implementation

A versatile neural computing software framework is needed for adapting to extremely various designs and include future concepts so as to experiment with alternative architectures and algorithms. In order to train many types of neural networks, including CNN, RBM, auto-encoder, and more, we created a customized neural network framework as opposed to utilizing the open-source CNN implementations that is currently available.

It takes a lot of computation to train the CNN system. On a top-tier Intel i7 processor, convolution and full connection neuron processing is both capable of 100 Gigaflop processes per second.



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PPV comparison of existing and proposed method

The above graph shows the specificity comparison of existing and proposed method. In this AlexNet method has the specificity rate of 95.97%. Next method is ResNet50, it shows the specificity rate of 79.08%. Third bar shows the specificity rate of GoogleNet method, in this the specificity range will be 75.01%. Next three bars shows the specificity rate of ConvNet-1, ConvNet-2, ConvNet-3 methods and the specificity rates are 61.12%, 68.88%, 81.53%. Next existing method is LPCS, in this method the specificity rate shows 97.28%. Finally, our proposed method reach the highest value of other all existing method, the specificity rate of proposed technique is 99.08%. So, the specificity comparison of existing method and proposed methods are briefly explained above. Proposed method reach the highest value than other techniques. Figure 11 shows the Positive predictive value (PPV) comparison of both existing and proposed method.

II. CONCLUSION

The main objective of this work has to create a smart healthcare monitoring framework for data analysis, disease prediction, and fetal monitoring. Therefore, this work proposes a multi-modality IoT-based GDM prediction. First, ultrasound images are enhanced using CLAHE. After image enhancement, feature extraction is done.

In future work, the technique could be combined using other efficient deep learning method for potentially increasing the probability of diagnosing disease.

III. REFERENCES

[1] Brand, J.S., West, J., Tuffnell, D., Bird, P.K., Wright, J., Tilling, K. and Lawlor, D.A., 2018. Gestational diabetes and ultrasound-assessed fetal growth in South Asian and White European women: findings from a prospective pregnancy cohort. BMC medicine, 16(1), pp.1-13.

[2] Scifres, C.M., Feghali, M., Dumont, T., Althouse, A.D., Speer, P., Caritis, S.N. and Catov, J.M., 2015. Large-for-gestational-age ultrasound diagnosis and risk for cesarean delivery in women with gestational diabetes mellitus. Obstetrics & Gynecology, 126(5), pp.978-986.

[3] Popova, P.V., Klyushina, A.A., Vasilyeva, L.B., Tkachuk, A.S., Vasukova, E.A., Anopova, A.D., Pustozerov, E.A., Gorelova, I.V., Kravchuk, E.N., Li, O. and Pervunina, T.M., 2021. Association of common genetic risk variants with gestational diabetes mellitus and their role in GDM prediction. Frontiers in endocrinology, 12, p.628582.

[4] Artzi, N.S., Shilo, S., Hadar, E., Rossman, H., Barbash-Hazan, S., Ben-Haroush, A., Balicer, R.D., Feldman, B., Wiznitzer, A. and Segal, E., 2020. Prediction of gestational diabetes based on nationwide electronic health records. Nature medicine, 26(1), pp.71-76.

[5] Zhang, X., Zhao, X., Huo, L., Yuan, N., Sun, J., Du, J., Nan, M. and Ji, L., 2020. Risk prediction model of gestational diabetes mellitus based on nomogram in a Chinese population cohort study. Scientific Reports, 10(1), pp.1-7.

[6] Amirian, A., Mahani, M.B. and Abdi, F., 2020. Role of interleukin-6 (IL-6) in predicting gestational diabetes mellitus. Obstetrics & Gynecology Science, 63(4), pp.407-416.

[7] El-Rashidy, N., ElSayed, N.E., El-Ghamry, A. and Talaat, F.M., 2022. Utilizing fog computing and explainable deep learning techniques for gestational diabetes prediction. Neural Computing and Applications, pp.1-20.

[8] Naseem, A., Habib, R., Naz, T., Atif, M., Arif, M. and Allaoua Chelloug, S., 2022. Novel Internet of Things Based Approach Towards Diabetes Prediction Using Deep Learning Models. Frontiers in Public Health, p.2848.

[9] Liu, Y., Wang, Y., Zhang, Y. and Cheng, R., 2021. Detection of Gestational Diabetes Mellitus and Influence on Perinatal Outcomes from B-Mode Ultrasound Images Using Deep Neural Network. Scientific Programming, 2021, pp.1-8.

[10] Davidson, S.J., Susan, J., Britten, F.L., Wolski, P., Sekar, R. and Callaway, L.K., 2021. Fetal ultrasound scans to guide management of gestational diabetes: Improved neonatal outcomes in routine clinical practice. Diabetes Research and Clinical Practice, 173, p.108696.