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Survey on Gestational Diabetes and Fetal Monitoring System using Deep Learning Classification Techniques

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Abstract

Gestational diabetes mellitus (GDM) can cause adverse consequences to both mothers and their newborns. However, pregnant women living in low- and middle-income areas or countries often fail to receive early clinical interventions at local medical facilities due to restricted availability of GDM diagnosis. The outstanding performance of artificial intelligence (AI) in disease diagnosis in previous studies demonstrates its promising applications in GDM diagnosis. Candidate predictors included maternal demographic characteristics and medical history (maternal factors) and laboratory values at early pregnancy. The models were derived from the first 70% of the data and then validated with the next 30%. Variables were trained in different deep learning models and traditional logistic regression models. Deep Learning classification algorithms like Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Long Short Term Memory (LSTM) etc., are used in the prediction of gestational diabetes mellitus. Different validation dataset is used in the prediction of GDM and fetal monitoring. Different scientific approaches based on deep learning in the field of GDM prediction research for collecting the evidence based descriptions related to deep learning classification techniques are described in this paper. The survey on the analysis of fetal monitoring system has been presented and review to describe the performance patterns and impact of research in the area of GDM prediction. The limitations and advantages of the paper are also discussed.

Keywords: Gestational diabetes mellitus (GDM), Deep learning, fetal monitoring system, pregnancy, SVM,CNN.

1. Introduction

Gestational diabetes mellitus (GDM) is glucose intolerance that occurs in pregnant women and is characterized by onset or detection during pregnancy [1]. The clinical effects of GD can range from asymptomatic to severe hyperglycemia. GDM is thought to arise as the result of insulin resistance due to pregnancy hormones, which is not adequately compensated for by the pancreatic β-cells through increased proliferation and insulin secretion. The entire pathogenesis of the disease remains unknown, although a genetic predisposition is likely due to familial clustering and the identification of several candidate genes associated with increased risk. Nongenetic factors, including maternal age, obesity, diet, and lifestyle, are also associated with GDM [2].

There is wide variability in reported prevalence estimates for GDM in India, varying from less than 4% to nearly 18%. Despite a government mandate to screen all pregnant women for GDM, to date there has been incomplete implementation and uptake of screening programs. Existing studies on GDM in India are limited to single-center studies, with most conducted in urban, hospital-based populations. National data are emerging on the overall prevalence of type 2 diabetes in the Indian population. The overall prevalence is approximately 7%, higher in urban vs rural areas, among older age groups, and among higher socioeconomic status (SES) groups. Concern exists over an anticipated increase in the prevalence of diabetes and a corresponding rise in GDM [3]. Furthermore, the social conditions and prevalence of risk factors, such as obesity, hypertension, and type 2 diabetes, are shown to vary substantially across India's states. In this study, we investigate the prevalence, socioeconomic, demographic, and health-related factors associated with GDM among pregnant women in India using a large-scale nationally representative sample, with elevated random blood glucose as a proxy for GDM [4].

Deep Learning (DL) is a kind of ML that has taken off in recent times due to a confluence of improved employment of artificial neural networks, big data, and processing power [5]. DL systems employ training data to train a neural network by appropriately weighting connections between the nodes in the network to capture even weak correlations in data. Deep Learning methods have been successful in various real-world applications by learning the most relevant, unbiased information from large datasets. The initial simulations and experiments of applying Long Short Term Memory (LSTM) [6] and Convolutional Neural Networks (CNN) [7] for classification. LSTM is generally more suitable for forecasting patterns rather than classifying them, and there were also vanishing gradient problems during back-propagation when learning on long CTG records. CNN worked effectively with prolonged data through the use of moving filters and max-pooling.

In this paper, the survey of various works related to deep learning classification techniques and gestational diabetes and fetal monitoring system was presented. The limitations and advantages of the paper are also discussed.

2. Related Works:

a) Deep Learning classification techniques

A deep learning model able to detect medically interpretable information in relevant images from a volume to classify diabetes-related retinal diseases was described in [8]. A new deep learning model, Optical Coherence Tomography (OCT-NET), which is a customized convolutional neural network for processing scans extracted from optical coherence tomography volumes. OCT-NET is applied to the classification of three conditions seen in SD-OCT volumes. This method is able to classify the retinal diseases with high accuracy. The advantage of this method is its ability to produce interpretable clinical information in the form of highlighting the regions of the image that most contribute to the classifier decision. This datasets are relatively small and this method lacks an evaluation over larger datasets.

An individual's age based on a 3D MRI brain image was predicted in [9].Two models considered were: a conventional deep neural network, and a hybrid deep learning model which additionally uses features informed by anatomical context. A significant errors in predicted age had been introduced by adding imperceptible noise to an image, can accomplish this even for large batches of images using a single perturbation, and that the hybrid model is much more robust to adversarial perturbations than the conventional deep neural network. An erroneous predictions may be difficult to detect.

A pipeline based on deep learning techniques is presented in [10] to predict diabetic people. It includes data augmentation using a variational autoencoder (VAE), feature augmentation using an sparse autoencoder (SAE) and a convolutional neural network for classification. 92.31% of accuracy was obtained when CNN classifier is trained jointly the SAE for featuring augmentation over a well balanced dataset. This means an increment of 3.17% of accuracy with respect the state-of-the-art. The results was not compared exactly.

A series of automated deep learning-based algorithms for DR screening have been presented in [11] and achieved high sensitivity and specificity (> 90%) . The state-of-the-art deep learning algorithms on collected images, including image classification, semantic segmentation and object detection. Lesion segmentation and detection in fundus images remain a challenge and better algorithms needed to be developed.

Deep learning based approach for the identification and localization of pneumonia in Chest X-rays (CXRs) images was described in [12]. Deep neural network which incorporates global and local features for pixel-wise segmentation. This approach achieves robustness through critical modifications of the training process and a post processing step which merges bounding boxes from multiple models. This identification model achieves better performances evaluated on chest radiograph dataset which depict potential pneumonia causes. Sometimes weaker results were achieved on the training set with respect to the test.

The convolution neural network (CNN) was used in [13] to train the classifier for performing classification. The CNN, constructed for classification, comprises a combination of squeeze and excitation and bottleneck layers, one for each class, and a convolution and pooling layer architecture for classification between the two classes. Experimental results showed that this algorithm provides improved results, when compared to traditional schemes. The model yielded an accuracy of 98.7 % and a precision of 97.2 % while evaluated on the DIARETDB1 dataset. Overfitting makes this model complicated.

A new architecture, FT-MTL-Net, an MTL model enabled by feature transfer was presented in [14]. Traditional transfer learning deals with the same or similar task from different data sources. FT-MTL-Net utilizes the different tasks from the same domain. Four detection models, and three segmentation models using a publicly available Full Filed Digital Mammogram dataset for breast cancer diagnosis. Experimental results showed that the FT-MTL-Net outperforms the competing models in classification and detection and has comparable results in segmentation. The computing burden with the added parameters exists in this method.

A novel deep learning framework for the detection and classification of breast cancer in breast cytology images using the concept of transfer learning was presented in [15]. Features from images are extracted using pre-trained CNN architectures, namely, GoogLeNet, Visual Geometry Group Network (VGGNet) and Residual Networks (ResNet), which are fed into a fully connected layer for classification of malignant and benign cells using average pooling classification. It had been observed that the framework gives excellent results regarding accuracy without training from scratch which improves classification efficiency. Classification accuracy is not sufficient and needs to be improved.

A deep learning-based automated detection and classification model for fundus DR images was presented in [16]. This method involves various processes namely preprocessing, segmentation and classification. Synergic Deep Learning (SDL) model was applied to classify the DR fundus images to various severity levels. The experimentation results indicated that the presented SDL model offers better classification over the existing models. Filtering techniques are needed for improve the quality of classification.

A comprehensive evaluation of the performance of deep learning object detection networks for Diabetic Foot Ulcer (DFU) detection was conducted in [17]. Deformable convolutions appear to work well in DFU detections and contribute to the improvement to the best performing method. The number of false positive results is significant, and the networks are not always able to effectively discriminate ulcers from other skin conditions. This approach could also impact network size and complexity, which could negatively impact inference speed. Table 1 represents the comparison of various deep learning techniques in medical imaging with its advantages and limitation.

Table 1: Comparison of various deep learning techniques in medical imaging with its advantages and limitation.

Ref. No.	Method	Results	Limitation
9	Anatomical Context Protects Deep Learning from Adversarial Perturbations in Medical Imaging	Hybrid model is much more robust to adversarial perturbations	An erroneous predictions may be difficult to detect
10	Diabetes detection using deep learning techniques with oversampling and feature augmentation	3.17% of accuracy increased as compared to state-of-the-art.	The results was not compared exactly.
13	Deep learning architecture based on segmented fundus image features for classification of diabetic retinopathy.	Accuracy of 98.7 % and a precision of 97.2 % was achieved	Overfitting makes this model complicated.
14	A feature transfer enabled multi-task deep learning model on medical imaging	This model outperforms well in classification and detection.	The computing burden with the added parameters exists in this method.
16	Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model.	Better classification was done.	Filtering techniques are needed to improve the classification quality
17	Deep learning in diabetic foot ulcers detection: A comprehensive evaluation	The number of false positive results is significant and results are efficient	This approach could also impact network size and complexity, which could negatively impact inference speed.

b) **Gestational diabetes and fetal monitoring system**

The modeling, performance evaluation, and comparison analysis of an ANN technique known as the radial basis function network (RBFNetwork) was presented in [18] to identify possible cases of gestational diabetes that can lead to multiple risks for both the pregnant women and the fetus. This method achieved promising results with a precision of 0.785, F-Measure of 0.786, ROC area of 0.839, and Kappa statistic of 0.5092. These indicators showed that this ANN-based approach was an excellent predictor for gestational diabetes mellitus. Accuracy of this method was needed to be improved by using other ANN approaches, such as simple logistic, multilayer perceptron, sequential minimal optimization, support vector machines.

A prediction model of embryonic development was presented in [19] by using machine learning algorithms based on historical case data, in this way doctors can make more accurate suggestions on the number of patient follow-ups, and provide decision support for doctors who are relatively inexperienced in clinical practice. six representative machine learning algorithms including Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Back Propagation Neural Network (BNN), XGBoost and Random Forest (RF) to build prediction models were applied. Early pregnancy Loss (EPL) after the appearance of embryonic cardiac activity undergoing IVF-ET. Finally, Random Forest model outperformed the others. This model was verified with only one dataset and not with multiple dataset.

A novel framework for intelligent analysis and automatic interpretation of digital cardiotocographic signals recorded from the Internet of Medical Things (IoMT)-based fetal monitors was developed in [20]. The framework incorporates methods and systems that evaluate the fetal conditions in the cavity of the uterus. The methods accurately identify various critical features of cardiotocographic signals, thus making the interpretation results more accurate. According to clinical tests in hospitals, this framework had comparable accuracy to obstetricians' interpretations. It thus provides a supplement to traditional analysis that could help obstetricians function more effectively. IT was used as an automatic monitoring approach for fetal movement identification when health resources are limited, such as when no separate fetal movement probe is available.

Machine learning was used in [21] to determine whether there is a correlation between maternal thyroid profile in 40 first and second trimester of pregnancy and GDM. Twenty-nine variables were analyzed by ML using PCA for pattern recognition. Qualitative variables were transformed into categorical variables and all data was pre-processed by auto-scale. These results also showed that ML applied to clinical chemistry could be a powerful tool for diagnosis. Even though these results are preliminary and the number of patients is low.

The design and application of a classification module to automatically assign the appropriate meal and 'moment of measurement' to incomplete glycaemia data was presented in [22]. Different machine learning techniques were studied in order to design the best classification algorithm in terms of accuracy. The selected classifier was implemented with a C4.5 decision tree with 7 input features selected with a wrapper evaluator and the genetic search algorithm, which achieved 95.45% of accuracy with the training set on cross-validation. The automatic classification of glycaemia measurements minimizes the patient's intervention, allows structuring measurements in relationship to meals and made automatic data interpretation by expert systems more reliable. If the expert system detects altered glycaemia values but it is not able to determine whether they are caused by the breakfast or the lunch, it will not be able to recommend the reduction of carbohydrates in the appropriate intake or the administration of insulin to metabolize them.

A novel deep learning-based multi-step framework for brain extraction from 3D fetal MR images was developed in [23]. In the first step, a global localization network had been applied to estimate probability maps for brain candidates. In the second step, a local refinement network is implemented in the brain candidate area to obtain fine-grained probability maps. Experimental results demonstrate that this method had superior performance compared with existing deep learning based methods. This method is only validated on the subjects from one site. Due to the multi-site issue learning-based models often perform poorly on testing subjects acquired with different imaging parameters from the training subjects.

Deep learning techniques for non-invasive foetal electrocardiogram signal synthesis using artificial intelligent techniques was portrayed in [24]. Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back Propagation Neural Network (BPNN) had been utilized and tested for the proposal. The outcomes and performance were compared with reference to the synthesized high quality foetal electrocardiogram signal. This method uses very complicated procedure to achieve good accuracy.

The postpartum circulating miRNAs can predict the development of type 2 diabetes in women with previous GDM was determined in [25]. Utilising a discovery approach, 754 miRNAs were measured in plasma from type 2 diabetes non-progressors (n = 11) and type 2 diabetes progressors (n = 10) using TaqMan-based real-time PCR on an OpenArray platform. Machine learning algorithms involving penalised logistic regression followed by bootstrapping were implemented. This is the first demonstration of miRNA-based type 2 diabetes prediction in women with previous GDM. Improved prediction facilitate early lifestyle/drug intervention for type 2 diabetes prevention. A limitation is the number of progressors being smaller than desired in this study cohort.

Fetal ultrasound images of normal, pregestational diabetes mellitus (preGDM) and GDM mothers were used in [26] to develop a computer aided diagnostic (CAD) tool. A new method called local preserving class separation (LPCS) framework was presented to preserve the geometrical configuration of normal and preGDM/GDM subjects. The generated shearlet based texture features under LPCS framework showed promising results compared with deep learning algorithms. This method achieved a maximum accuracy of 98.15% using a support vector machine (SVM) classifier. Hence, this paradigm was helpful to physicians in detecting fetal myocardial hypertrophy in preGDM/GDM mothers. The limitation is that this method only analyzed 433 digital images belonging to two classes.

A multi-task fully convolutional neural network (FCN) architecture was presented in [27] to address the problem of 3D fetal brain localization, structural segmentation, and alignment to a referential coordinate system. This information is used to estimate an affine transformation to align a volumetric image to the skull-based coordinate system. Co-alignment of 140 fetal ultrasound volumes was achieved with high brain overlap and low eye localization error, regardless of gestational age or head size. The automatically co-aligned volumes showed good structural correspondence between fetal anatomies. Some errors in predicting the overall head orientation was attributed to the fetal head failing to occupy at least 50% of the image space, as per the protocol recommendations.

A convolutional neural network for automatic segmentation and measurement of fetal biometric parameters, including parietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL) from ultrasound images that relies on the attention gates incorporated into the multi-feature pyramid Unet (MFP-Unet) network was introduced in [28]. This approach, referred to as Attention MFP-Unet, learns to extract/detect salient regions automatically to be treated as the object of interest via the attention gates. Quantitative evaluation demonstrated the superior performance of the Attention MFP-Unet as compared to state-of-the-art approaches commonly employed for automatic measurement of fetal biometric parameters. The main limitations of the model are deficiency of the training images and lack of publically available fetal ultrasound images.

A fully-automatic framework to analyze operator clinical workflow solely from full-length routine second-trimester fetal ultrasound scan videos was presented in [29]. An original deep learning method was developed to temporally segment the ultrasound video into semantically meaningful segments. The resulting semantic annotation was then used to depict operator clinical workflow. Machine learning was applied to the knowledge representation to characterize operator skills and assess operator variability. This method need to be tested on a larger dataset containing more operators in each skill group and more scans per operator to be able to draw stronger conclusions.

A machine-learning method was described in [30] to assess automatically that trans ventricular ultrasound images of the fetal brain have been correctly acquired and meet the required clinical standard. A deep learning solution was presented, which breaks the problem down into three stages: (i) accurate localization of the fetal brain, (ii) detection of regions that contain structures of interest and (iii) learning the acoustic patterns in the regions that enable plane verification. The methodology developed on a large real-world clinical data set of 2-D mid-gestation fetal images. The automatic verification method approaches human expert assessment was shown. Suitable for Large dataset and tested with that dataset but it is not suitable for smaller dataset. Table 2 represents the comparison of various deep learning techniques in Gestational diabetes and fetal monitoring system with its advantages and limitation.

Table 2: Comparison of various deep learning techniques in Gestational diabetes and fetal monitoring system with its advantages and limitation.

Ref. No.	**Method**	**Results**	**Limitation**
19	Machine learning algorithms to predict early pregnancy loss after in vitro fertilization-embryo transfer with fetal heart rate as a strong predictor	Random Forest model outperformed the others.	Verified with only one dataset and not with multiple dataset.
21	Maternal thyroid profile in first and second trimester of pregnancy is correlated with gestational diabetes mellitus through machine learning	Powerful tool for diagnosis.	The number of patients taken for analysis is low.
23	Automatic brain extraction from 3D fetal MR image with deep learning-based multi-step framework	Superior performance is achieved	Poor testing subjects are acquired even from various imaging parameters from the training subjects.
24	Deep learning strategies for fetal electrocardiogram signal synthesis	Synthesized high quality fetal electrocardiogram signal.	Complicated procedure is used to achieve good

			accuracy.
25	Postpartum circulating microRNA enhances prediction of future type 2 diabetes in women with previous gestational diabetes	Improved prediction is facilitated early lifestyle/drug intervention for type 2 diabetes prevention.	A limitation is the number of progressors being smaller than desired in this study cohort
26	Local Preserving Class Separation Framework to Identify Gestational Diabetes Mellitus Mother Using Ultrasound Fetal Cardiac Image	Efficient in preGDM/GDM mothers.	Analyzed 433 digital images belonging to two classes.
28	Automatic fetal biometry prediction using a novel deep convolutional network architecture	Superior performance is achieved	Deficiency of the training images and lack of publically available fetal ultrasound images
29	Knowledge representation and learning of operator clinical workflow from full-length routine fetal ultrasound scan videos	Characterization operator skills and assess operator variability was done.	Equipped with larger dataset, so that operators required are high

3. Conclusion

Different scientific approaches based on deep learning in the field of GDM prediction research for collecting the evidence based descriptions related to deep learning classification techniques have been described in this paper. The survey on the analysis of fetal monitoring system has been presented and review to describe the performance patterns and impact of research in the area of GDM prediction. The limitations and advantages of the paper are also discussed. The problems encountered in most of the existing methods, datasets used were relatively small, an erroneous prediction were occurred and it is very difficult to detect GDM and fetal movements. There is also computation burden occurred for large datasets as it is added with more number of parameters. In some state- of- art methods, Filtering techniques are needed for improve the quality of classification even though the deep learning techniques are applied. Fetal movement identification is also difficult in some cases when health resources are limited. To overcome these limitations, an efficient IoT based deep learning classification techniques for GDM and fetal monitoring are used in the further research.

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