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Local Preserving Class Separation Framework to Identify Gestational Diabetes Mellitus Mother Using Ultrasound Fetal Cardiac Image

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ABSTRACT In the presence of gestational diabetes mellitus (GDM), the fetus is exposed to a hyperinsulinemia environment. This environment can cause a wide range of metabolic and fetal cardiac structural alterations. Fetal myocardial hypertrophy predominantly affecting the interventricular septum possesses a morphology of disarray similar to hypertrophic cardiomyopathy, and may be present in some GDM neonates after birth. Myocardial thickness may increase in GDM fetuses independent of glycemic control status and fetal weight. Fetal echocardiography performed on fetuses with GDM helps in assessing cardiac structure and function, and to diagnose myocardial hypertrophy. There are few studies in the literature which have established evidence for morphologic variation associated with cardiac hypertrophy among fetuses of GDM mothers. In this study, fetal ultrasound images of normal, pregestational diabetes mellitus (preGDM) and GDM mothers were used to develop a computer aided diagnostic (CAD) tool. We proposed a new method called local preserving class separation (LPCS) framework 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. The proposed method achieved a maximum accuracy of 98.15% using a support vector machine (SVM) classifier. Hence, this paradigm can be helpful to physicians in detecting fetal myocardial hypertrophy in preGDM/GDM mothers.

INDEX TERMS Fetal myocardial hypertrophy, gestational diabetes mellitus, local preserving class separation, computer-aided diagnosis, ultrasound images.

I. INTRODUCTION

Diabetes in pregnancy is one of the common risk factors for adverse perinatal outcomes, with a prevalence of 7% to 11% in India and up to 17% in South India [1], [2]. Neonates born to diabetic mothers — either gestational diabetes mellitus (GDM) or pregestational diabetes mellitus

(preGDM), that is, with diabetes only during or pre-existing before pregnancy, respectively— are at risk of cardiovascular disease due to structural cardiac defects or impaired myocardial function. Fetal circulation is fundamentally different from neonatal circulation. There are structural and functional adaptations that take place in response to a hypoxemic intrauterine environment [3], [4]. Fetal cardiac changes that are demonstrated on imaging, are known to have influence on neonatal outcome [5]. In GDM, this developmental abnor-

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mality ranges widely from structural heart disease to subclinical myocardial dysfunction [6]–[8]. The hyperinsulinemic state interferes with fetal metabolism, resulting in increased expression and affinity of insulin receptors, which leads to proliferation and hypertrophy of cardiac myocytes. Cardiac hypertrophy in these fetuses exhibits myocardial derangement similar to hypertrophic cardiomyopathy [9]. This disarray in myofiber alignment alters the diastolic function of the heart. GDM fetuses sometimes exhibit cardiac diastolic dysfunction even in the absence of cardiac hypertrophy [10]. GDM manifests comprehensive adverse effects ranging from subclinical cardiac involvement to neonatal complications requiring medical attention. Subtle cardiac dysfunction has been confirmed by speckle tracking echocardiography. Most recently, use of four-dimensional (4D) ultrasonography along with two-dimensional (2D) fetal cardiac imaging showed promising results in the detection of cardiac malfunction early in pregnancy [11]–[13]. Therefore, screening fetal cardiac structure and function among GDM and preGDM mothers could be helpful to identify subtle pathology early in gestation [14]. Maintaining adequate glycemic control in these groups may help prevent fetal complications related to GDM. Computer-Aided Detection/Diagnosis (CAD) uses a rule-based support system for patient diagnosis. At present, it is utilized in numerous applications in day-to-day clinical practice. For instance, it is useful in detecting breast malignancies, skeletal abnormalities, and pathology in brain and vascular tissues. The need for CAD in our study is evident because of the poor prognosis of the disease if left untreated. GDM or preGDM may lead to fetal death, which can be averted if diagnosed early and strict glucose control measures are implemented. The CAD in this study is based on ultrasound (US) imaging. Many recent studies have proposed accurate CAD models using US images [15]–[23]. Physicians can typically distinguish or identify the disease by manual interpretation of the images, but the process is intensive, induces fatigue, and is prone to bias and human error. Fetal myocardial hypertrophy (FMH) ranges from subtle to overt myocardial hypertrophy, and the clinical course is heterogeneous. Few works have been published in the literature on this topic. There have been a few works recently that examined the thickness of the interventricular septum (IVS), which separates the left and right ventricles, in FMH. Carolina *et al.* [24] evaluated the prevalence of FMH in the fetuses of pregnant women with GDM, and they found that 54% of 63 fetuses tested positive for FMH on fetal echocardiography. Mohammed *et al.* [25] employed five-dimensional (5D) fetal echocardiography for the diagnosis of prenatal fetal hypertrophic cardiomyopathy on three separate groups: healthy members, controlled diabetic mothers, and uncontrolled diabetic mothers. They obtained a maximum mean IVS thickness of 0.57 ± 0.08 cm for a group of 37 uncontrolled diabetic mothers. They also suggested that the infants of diabetic mothers could reverse FMH, provided these neonates are given special care and constant monitoring. A similar study is reported in [26]. The fetal state is evaluated

using fetal heart rate (FHR) with the help of continuous wavelet transform and convolutional neural network (CNN) [27]. They have achieved an accuracy of 98.34%. In [28], the authors have used the recurrence plot and CNN to achieve an accuracy of 98.69% using FHR signals. We believe that the CAD model presented herein is the first to be developed for the detection of FMH in preGDM/GDM mothers. The major contributions of the paper are:

- The shearlet based texture features are generated to characterize the normal and preGDM/GDM US images.
- The discriminative capability of the locality sensitive discriminant analysis (LSDA) is enhanced under a local preserving class separation framework.
- To the best of our knowledge, this is the first work to identify the fetal cardiac structure of a gestational diabetes mellitus mother automatically using US images.

The remainder of the paper is structured as follows. The description of dataset and details of the proposed methodology are delineated in Section II. The experimental results and the comparative study are presented in Section III. The results are analyzed and discussed in Section IV. The paper ends with a future scope in section IV and conclusion in section V.

II. MATERIALS AND METHODS

A. DATA ACQUISITION

A case control study was performed in a tertiary referral hospital from March 2017 to March 2019. In this study, pregnant women with preGDM and GDM having a gestational age between 32 and 37 weeks were included. Non-diabetic healthy pregnant women at similar gestational age served as controls. Women with preeclampsia, pre-existing hypertension treated with antihypertensive drugs, renal disease, liver disease, hematologic diseases, maternal cardiac disease, evidence of fetal congenital anomaly of any organ including heart, intra-uterine growth retardation, chromosomal abnormalities, and twin pregnancy were excluded from the study. Institutional Ethics Committee approval was obtained. Informed written consent was obtained from all participants. PreGDM mothers had known diabetes before the pregnancy. GDM was diagnosed using the International Association of Diabetes in Pregnancy Study Group criteria for oral glucose tolerance test (blood glucose cutoffs of 93/183/152 mg% at baseline/1 hour/2 hours following 75 gm oral glucose) between gestational age 24–28 weeks. All participants underwent fetal echocardiographic examination. A trained obstetrician imaged the cardiac chambers which were stored at end diastolic frame of 4-chamber view. Likewise, a trained sonographer measured the parameters. In each subject, a standard lateral 4-chamber view was obtained. In total, we enrolled 74 normal subjects (at least two images from each subject, total: 221 images) and 71 preGDM/GDM subjects (at least two images from each subject, total: 212 images) in this study. Figure 1 shows sample normal and abnormal US subjects.

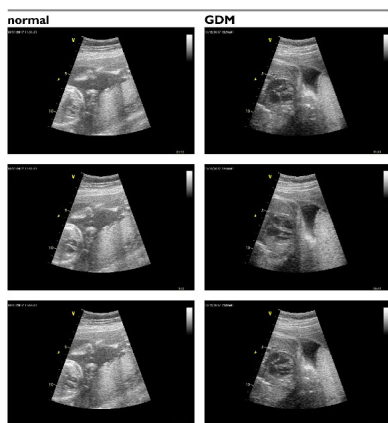


FIGURE 1. Ultrasound images of fetal hearts from normal and diabetic mother.

to remove the labels, color map indication, etc. Further, the resultant image is rescaled to a predefined size i.e., 256×256 pixels for generality purposes. In the next step, the shearlet transform is used to generate the shearlet coefficients. Shearlets are very efficient tools for directional representation compared to wavelets [30]. They are used in many applications for better representation of the images [31], [32]. They consist of functions with parabolic scaling, shearing operators and translation operators that can be used to change resolution, orientation and position, respectively. Sometimes, a more precise shearlet system is referred to as cone-adapted, as it is adapting a cone-like structure in the frequency domain. To have flexible shearlets, a parameter is introduced in the scaling matrix for measuring anisotropy [33]. The generating functions are associated with the conic and low frequency regions [34]. On the other hand, for data restoration and feature extraction techniques, shearlets with optimal sparse representation perform better. In this work, a scale of 2 is used to obtain twenty coefficients.

Generally, textures convey significant information of an image that pertains to the structural arrangement and relationship between neighboring pixels [35]. For pattern recognition, various texture features can be generated using a gray-level co-occurrence matrix (GLCM). It is a function of nearest pixels' distance with angular relationship. In this study, GLCM is calculated for angles 0, 45, 90, and 135 degrees. For every GLCM, the features information correlation measures 1 and 2, energy, correlation, contrast, homogeneity, difference entropy and difference variance, sum variance, sum entropy and sum average as defined in [35] and cluster shade, maximum probability, autocorrelation, entropy, and dissimilarity as defined in [36] are calculated. Finally, the average value of all the features that are computed from each GLCM is computed to describe the US image. Usually, coarse texture and fine texture have long and short gray level runs, respectively [37]. For a given image, textures were extracted from the run-length matrix (RLM). The features formulated in [38], [39] were extracted and the combination of gray level and run length were used to obtain various statistical measures [40]. As a result, 11 features pertaining to RLM were extracted. Furthermore, variance, kurtosis, and skewness were also computed for every shearlet coefficient. Hence, thirty features were calculated for each shearlet coefficient. A total of 600 shearlet based texture features are generated for each US image. The complete process of feature extraction is shown in Figure 3.

2) LOCAL PRESERVING CLASS SEPARABILITY

Generally, the local structure of the data points becomes more important than its global structure when training samples are insufficient [41], [42]. Linear discriminant analysis (LDA) is widely used in many applications to maximize the separation between data points from various classes [43]. In practice, subspace learning is performed by mapping whereby data points with different labels are isolated from each other while data points with the same label points are aggregated close

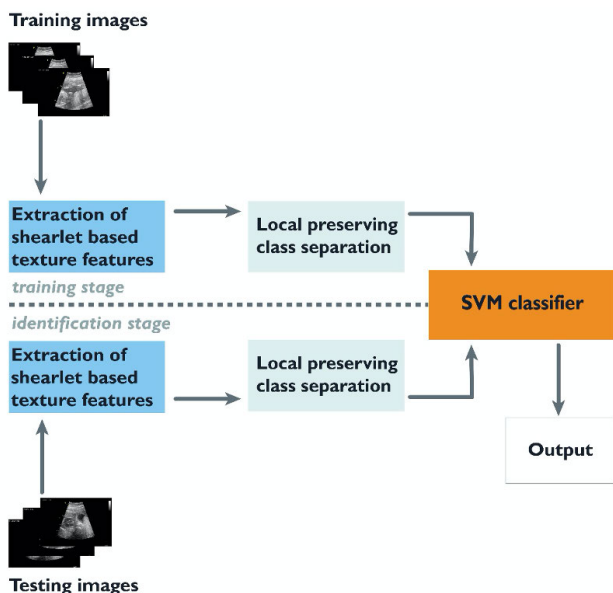


FIGURE 2. Architecture of proposed model.

B. PROPOSED METHOD

Figure 2 highlights the active modules of the proposed approach. It consists of three modules namely: i) feature extraction, ii) subspace learning, and iii) classification. In the first stage shearlet based texture features are extracted to characterize US images. In the second stage the data were reduced by using a local preserving class separation method. Herein, local manifold structure of each class and discrimination among the classes are embedded efficiently, while representing the data in a lower dimensional space. Further in the last stage, the support vector machine (SVM) was used to classify the ranked features with different kernels. The detailed description of each stage is explained in the subsequent section.

1) SHEARLET BASED TEXTURE FEATURES

Initially, every image is preprocessed, where the mask is generated using a morphological close operation to extract the region of interest [29]. The application of a mask helps

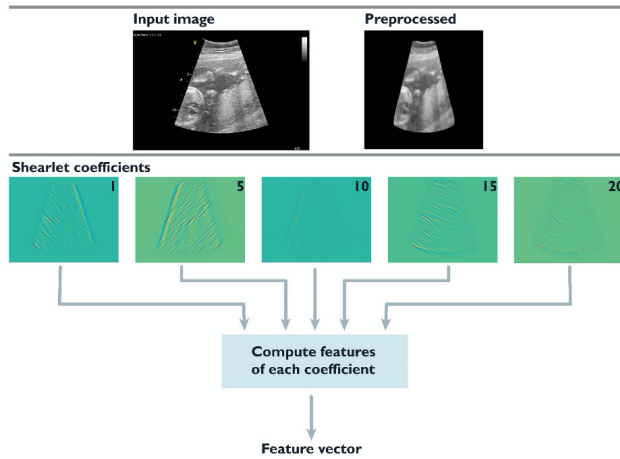


FIGURE 3. Generation of feature vector using shearlet coefficients.

to each other. When data points exhibit non-linearity, then preserving the local structure of the data points is the primary requirement for efficient training. Hence in this article, a local preserving class separability (LPCS) algorithm was introduced to enhance the discrimination power of LSDA method. The proposed LPCS consists of two steps, which are described as follows,

Initially, a weight matrix is computed to describe the local structure of the data points. Consider data points x_1, x_2, \dots, x_r in \mathbb{R}^q , where r is the number of data points. The directed edge is placed between the nodes if data points are k -nearest neighbors, i.e., if there is an edge between nodes i and j , then it can be denoted as $i \sim j$. The weight matrix w_{ij} has the value of the edge weight if there is existence of an edge between i and j , otherwise it is zero [41]. Further, the projection using neighborhood preserving is performed to preserve the required local distribution of the data points. The obtained new space \mathbb{R}^n , where $n \ll q$, is used for further class separation.

In the second step, mapping is performed using the between-class and within-class graphs (g'_d and g'_s , respectively). Consider a map on new space as $y' = (y'_1, y'_2, \dots, y'_r)^T$, and the following objective functions are used for better mapping. [43]:

$$\min \sum_{i'j'} (y'_i - y'_j)^2 w'_{s,ij} \quad (1)$$

$$\max \sum_{i'j'} (y'_i - y'_j)^2 w'_{d,ij} \quad (2)$$

where $w'_{s,ij}$ is defined as 1 if neighbors share the same label, $w'_{d,ij}$ is defined as 1 if neighbors have different labels on new space \mathbb{R}^n . The above equations are solved by using $y' = Z^T x'$, where Z is the projection matrix. Hence, the dimension reduction technique using the LPCS method completely preserves both the local geometrical structure as well as discrimination of the data. Finally, LPCS is used to reduce the dimension of the shearlet based texture features efficiently.

3) CLASSIFICATION

Further, generated features with greater differences between the means and standard deviations (SD) were selected, and subjected to classification in order to determine the accuracy. Typically, extracted features contain some insignificant and excess information, which may debase the arrangement process. To make an effective arrangement model, a Student's t -test based highlight choice calculation was utilized [44] and features were ranked based on p -values. The ranked features were subjected to classifiers with different kernels. In the present study, we used the SVM classifier [45]–[47]. In many cases, linear functions cannot separate the data. Mapping input data into a different space is a solution. Here, kernel functions were employed as the dot product had been used on the training data. Therefore, the decision function using kernel functions could be included with SVM, and is denoted by $K(\cdot)$. For a given $K(\cdot)$, test sample h is given by:

$$f(h) = \text{sign} \left(\sum_{i=1}^N \lambda_i l_i K(v_i, h) + b \right) \quad (3)$$

where N is the number of support vectors (SVs), λ_i is Lagrange multipliers, l_i is the labels, v_i are the SVs, and b indicates the bias term. In our study, we used two basic kernel functions: polynomial (with 1, 2, and 3 order) and radial basis function (RBF). For RBF kernel scaling factor is varied from 1 to 5 to achieve a maximum result. To assess the system performance, classification accuracy, sensitivity, specificity, and positive predictive values (PPV) were calculated. A *ten-fold* cross validation strategy was used to validate the technique. In *ten-fold* cross validation, the dataset is first split into *ten* equal parts with *nine* parts being used for training to test on the remaining *one* part; and the process is repeated ten times, which means that each part participates in testing once.

III. RESULT

The complete algorithm was implemented using a MATLAB environment on an Intel core i5 system with 4GB RAM. The generated shearlet features for every US image were reduced to thirty LPCS features. The LPCS features are ranked in descending order using t -value as shown in Table 1. Then these ranked LPCS features were classified using the SVM classifier with a one-against-all strategy. Table 2 shows the performance of the SVM classifier with different kernels. It is observed that the proposed system achieved 98.15% accuracy, 97.22% PPV, 99.05% sensitivity, and 97.28% specificity using twenty-eight features. The performance obtained for individual features is shown in Figure 4. It is noted that SVM+POLY3 achieved 16.4%, 7.39%, and 1.85% higher accuracy compared to POLY1, POLY2, and RBF kernels, respectively. To assess the performance of the proposed system, a comparative study was carried out, which is described in the subsequent section.

TABLE 1. Statistical Details (Mean, SD, p-value, and t-value) of LPCS Features.

Features	Normal		preGDM/GDM		p-Value	t-Value
	Mean	SD	Mean	SD		
LPCS 10	-2.6456	0.0818	-2.6876	0.0728	3.15E-08	5.635757
LPCS 6	-2.5853	0.1041	-2.6278	0.0870	5.68E-06	4.595326
LPCS 7	8.2466	0.0852	8.2082	0.0934	1.01E-05	4.467531
LPCS 3	13.0484	0.0976	13.0919	0.1208	4.42E-05	4.126719
LPCS 1	-1.4851	0.6124	-1.2454	0.6363	7.65E-05	3.993743
LPCS 5	6.0943	0.1153	6.0530	0.1035	0.000105	3.915837
LPCS 4	1.9324	0.1126	1.9702	0.0916	0.000151	3.822911
LPCS 2	10.7941	0.2165	10.7294	0.1987	0.001317	3.233401
LPCS 8	5.3723	0.0845	5.3480	0.0795	0.002211	3.078843
LPCS 9	4.3397	0.0853	4.3170	0.0702	0.00274	3.012875

TABLE 2. Performance of Proposed System.

#Fea	tp	tn	fp	fn	accuracy(%)	PPV(%)	sensitivity(%)	specificity(%)
SVM+POLY1								
15	173	181	40	39	81.75	81.22	81.60	81.90
SVM+POLY2								
30	197	196	25	15	90.76	88.73	92.92	88.68
SVM+POLY3								
28	210	215	6	2	98.15	97.22	99.05	97.28
SVM+RBF								
15	204	213	8	8	96.30	96.22	96.22	96.38

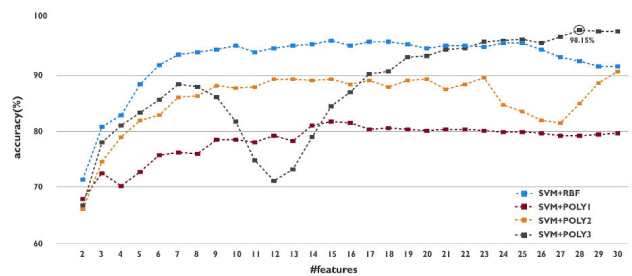


FIGURE 4. Performance of different classifiers using individual features one at a time. #features, number of features.

A. COMPARATIVE STUDY

The efficiency of the proposed LPCS was verified by comparing various data reduction techniques. In the present study, principal component analysis (PCA) [48], independent component analysis (ICA) [49], neighborhood preserving embedding (NPE) [41], and LSDA [43] were used. Figure 5 shows the performance in terms of accuracy of the various data reduction techniques with different numbers of features used. It is observed that the peak performance of the proposed LPCS method achieved improvements of 38.8%, 41.34%, and 15.01% compared with the peak performances of PCA, ICA, and NPE techniques, respectively. The proposed LPCS increased the accuracy of LSDA by approximately 2%. It is also noted that sensitivity of LSDA increased by 4.72%, which is an important requirement for medical image analysis.

Nowadays, deep learning algorithms are increasingly applied to many applications, such as face recognition, traffic sign recognition system, medical image analysis, etc. using large datasets. Herein, we assessed how the proposed technique compared against various deep learning techniques. Six different deep network structures were

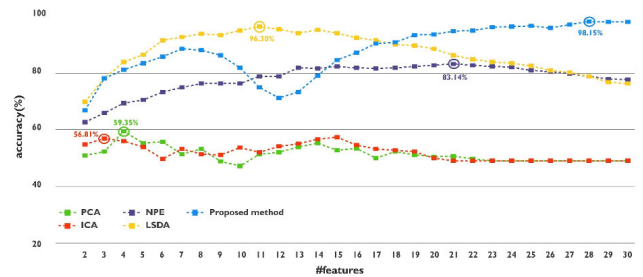


FIGURE 5. Performance of various data reduction techniques.

TABLE 3. Structure of Various Used ConvNet.

ConvNet-1	ConvNet-2	ConvNet-3
Convolution1 (8 3x3 convolutions)	Convolution1(8 3x3 convolutions)	Convolution1(8 3x3 convolutions)
ReLU1	ReLU1	ReLU1
Max Pooling1 (3x3 max pooling with stride [2 2])	Max Pooling1 (3x3 max pooling with stride [2 2])	Max Pooling1 (3x3 max pooling with stride [2 2])
Convolution2(16 3x3 convolutions)	Convolution2 (16 3x3 convolutions)	Convolution2(16 3x3 convolutions)
ReLU2	ReLU2	ReLU2
Max Pooling2 (3x3 max pooling with stride [2 2])	Max Pooling2 (3x3 max pooling with stride [2 2])	Max Pooling2 (3x3 max pooling with stride [2 2])
Convolution3(32 3x3 convolutions)	Convolution3 (32 3x3 convolutions)	Convolution3(32 3x3 convolutions)
ReLU3	ReLU3	ReLU3
Max Pooling3 (3x3 max pooling with stride [2 2])	Max Pooling3 (3x3 max pooling with stride [2 2])	Max Pooling3 (3x3 max pooling with stride [2 2])
Convolution4(64 3x3 convolutions)	Convolution4(64 3x3 convolutions)	Convolution4(64 3x3 convolutions)
ReLU4	ReLU4	ReLU4
Max Pooling4 (3x3 max pooling with stride [2 2])	Max Pooling4 (3x3 max pooling with stride [2 2])	Max Pooling4 (3x3 max pooling with stride [2 2])

considered for feature extraction: AlexNet [50] (please refer to <https://in.mathworks.com/help/deeplearning/ref/alexnet.html>), ResNet50 [51] (please refer to <https://in.mathworks.com/help/deeplearning/ref/resnet50.html>), GoogleNet [52] (please refer to <https://in.mathworks.com/help/deeplearning/ref/googlenet.html>), and three convolutional neural network (ConvNet) models (i.e., ConvNet-1, ConvNet-2, and ConvNet-3)(please refer to <https://in.mathworks.com/help/deeplearning/ug/create-simple-deep-learning-network-for-classification.html>). In the present study AlexNet, ResNet50, and GoogleNet is used with a depth of 8, 50, and 22 respectively (please refer to <https://www.mathworks.com/help/deeplearning/ug/pretrained-convolutional-neural-networks.html>). Herein we have used pretrained networks for classification. Since the data set is comparatively small it is difficult to fine tune the parameters. Hence a feature extraction is done by using the layer activations of the pretrained network as features. The structure of used ConvNet-1, ConvNet-2, and ConvNet-3 is shown in Table 3. For classification, the SVM classifier was used, with the scale and box constraint equal to 1. Initially, US images were used and all images

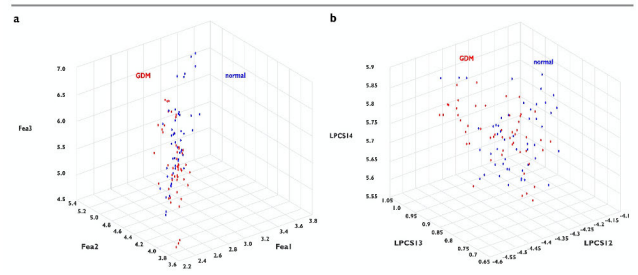
TABLE 4. Comparison With State-of-the-Art Deep Learning Techniques.

Method	accuracy(%)	sensitivity(%)	specificity(%)
AlexNet	95.99	96.12	95.97
ResNet50	78.83	79.37	79.08
GoogleNet	75.79	77.39	75.01
ConvNet -1	60.46	62.11	61.12
ConvNet -2	70.46	74.71	68.88
ConvNet -3	81.39	82.34	81.53
Proposed	98.15	99.05	97.28

were preprocessed to remove artefacts and extract the regions of interest. Further, they were rescaled to predefined sizes: 64×64 for ConvNet and 224×224 for other networks. During classification, data was divided into ten equal parts, and 90% and 10% were used for training and testing, respectively, for 10 times until all parts had been tested. The networks were trained with a stochastic gradient descent with the momentum trainer using learning rates of 0.1, 0.01, and 0.001 with epochs of 10, 20, 30, 40, and 50, utilized by keeping two iterations per epoch with data shuffled per epoch. It is observed that the network achieved a maximum result for a learning rate of 0.01 and epoch of 30. It is also noted that all ConvNet models have achieved maximum results for image size of 64×64 when compared to 32×32 and 128×128 . Ten passes of each network were obtained, and accuracy, sensitivity and specificity were calculated. From Table 4, it can be seen that among the 6 Networks AlexNet was relatively more consistent and accurate. On the other end, ConvNet-1 was unreliable and inconsistent. It is noted that ResNet50 and GoogleNet were quite consistent with similar output ranges. It is observed from Table 4 that our proposed model showed promising results compared with deep learning techniques.

IV. DISCUSSION

Myocardial hypertrophy in the fetus and its associated complications require further study. There are different causes of FMH, including inheritable genetic diseases. Here, we have focused on acquired FMH associated with diabetes in pregnancy. Myocardial hypertrophy is identified commonly in fetuses of mothers with diabetes, and is characterized by thickening of the IVS or more subtle abnormalities. In a diabetic mother, high levels of insulin causes hyperplasia and hypertrophy of the fetal heart, resulting in FMH. We have developed a CAD model that can differentiate normal fetuses from affected fetuses. A few other methods exist for this particular capability in the literature. A prenatal IVS thickness greater than 4.5 mm has been reported to be an indication that the fetus has FMH [53]. In the current study, the mean values of myocardial thickness measured at IVS, left ventricular wall, and right ventricle among preGDM/GDM cases were higher than that of non-diabetic controls. The mean values in preGDM/GDM with adequate glycemic control were also higher than those in non-diabetic controls (data not shown). We did not report the prevalence of FMH in our study subjects as there is no standard threshold for defining FMH in South Indian, where the study had been carried out.

**FIGURE 6. Plot of feature distribution a) original feature space and b) LPCS feature space.**

We applied shearlet transform, enhanced edges and curve-like structures in the images, to improve the quality of the 2D US images. It minimized redundant features and enhanced only significant information in the images. Further, texture variations in these coefficients were captured using various texture features. To differentiate the structure of normal versus preGDM/GDM images, we developed the LPCS method. The resultant feature distribution in a lower dimensional space is shown in Figure 6. It characterizes local structure and amplifies discrimination among classes, which boosts its superiority compared with other data reduction techniques as shown in Figure 5.

Figure 6 shows the strength of the proposed method in discriminating the two classes, which enabled the classifier to generate the hyperplane easily. Although the normal and preGDM/GDM classes exhibited similar structures, the proposed LPCS separated the features in an efficient way. To our knowledge, this is the first work carried out to develop a CAD tool to categorize fetal cardiac structure using US in GDM mothers. The advantages of the proposed method are:

- The proposed features can efficiently characterize the heart structure.
- The LPCS method is generalizable and can be applied to the images of various modalities.
- The performance evaluated using ten-fold cross-validation is robust.
- It is computationally efficient and can be deployed in rural hospitals for screening.

A. FUTURE SCOPE

This is the first CAD model that has been developed for the detection of fetal abnormalities associated with preGDM/GDM. In the future, the method can be combined with ConvNet, which may yield a higher probability for identifying disease. One limitation of our work is that we have only analyzed 433 digital images belonging to two classes. We are planning to include more images to further test the algorithm. In addition, a future direction for the CAD system will be to develop an Internet of Things (IoT) based model that can analyze the input images from a remote place, and send the results of analysis to both doctors and patients. This type of advanced screening tool can assist doctors in their routine screening and in follow-up of diabetic mothers. Figure 7 shows the future IoT based CAD model, where

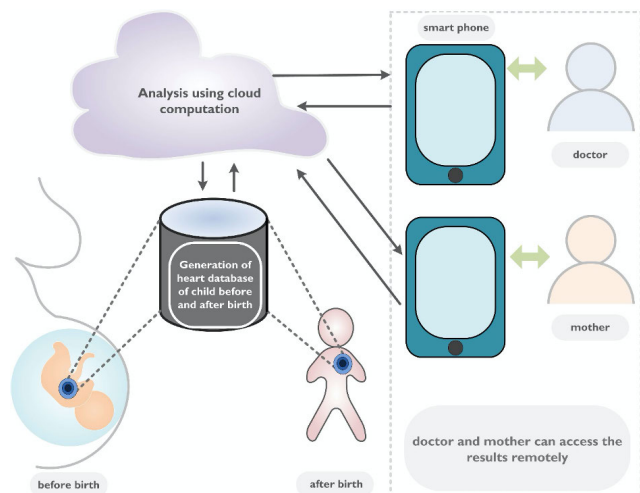


FIGURE 7. IoT based CAD tool for the detection of FMH.

cloud based image analysis is proposed. The antenatal results need to be scrutinized to ensure that fetuses with FMH are identified immediately. The test can also be performed after birth for neonatal monitoring.

V. CONCLUSION

We studied fetal US images obtained from 74 normal subjects and 71 diabetic mothers. The shearlet based texture features showed remarkable performance under the LPCS framework using only twenty-eight features. The results were promising and should lead to more studies on the automatic detection of FMH with a greater number of subjects, including studies involving ante- as well as post-natal US examinations. This will help clinicians better understand the longitudinal disease progression in FMH.

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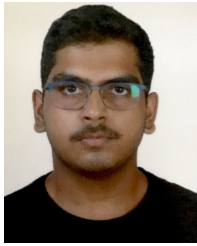
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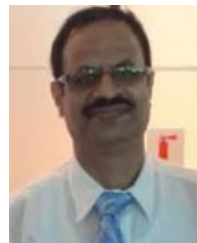
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