CHAPTER 7

VOLUME ESTIMATION AND CLASSIFICATION OF PLACENTA

7.1 NEED FOR VOLUME ESTIMATION

Placenta is a curved structure. This makes it difficult to measure the size of the placenta and to extract the essential features. If the placental volume has to be measured, an expensive machine and specialized training in 3D ultrasound imaging is necessary. Moreover, the duration of ultrasound exposure is more in the case of 3D ultrasound imaging, the frequency of which poses risk to the fetus. The standard common obstetric diagnostic mode is 2D scanning. But volume measurement of placenta is usually uncommon during the routine pregnancy screening. The limitation in the ultrasound scanning prevents monitoring the growth of the placenta. Placental volume assessment is uncommon in routine obstetric practice, a lack that prevents obstetricians from identifying their patients with extremely small or large placentas. This is a population who are at risk of sudden intrauterine fetal demise.

7.2 CONVEX CONCAVE SHELL MODEL

Generally, human placentas are round or oval, but few other shapes are also common. Anomalies of the placenta shape or multi-lobated placenta may develop from abnormal fetal genes (expressed in the placenta). Maternal diabetes is a condition that can be associated with large placentas, although the differential diagnosis largely includes fetal hydrops, congenital syphilis,
and villous edema or Beckwith-Wiedemann syndrome. Large placentas, however, should raise the suspicion for a maternal diabetic state.

Fetal growth depends upon the proper supply of nutrients from the mother to the fetus. Placental thickness and volume have been used to predict chromosomal anomalies and other complications of pregnancy. Currently, sonographic assessment of placental volume is time-consuming and requires expensive technology. The best approach so far has been three-dimensional ultrasound measurements but this technique requires specialized training.

A new method to determine the volume of the two dimensional ultrasound placentas using a mathematical model is proposed. The aim of the work is to correlate the height, width and thickness of the ultrasound placenta in measuring the placental volume. The size and shape of the placenta plays a very important role in classifying this into normal and abnormal.

The convex hull of a set of points $S$ in $n$ dimensions is the intersection of all convex sets containing $S$. For points $P_1, P_2, ..., P_N$ the convex hull $C$ is then given by the expression

$$C = \left\{ \sum_{j=1}^{N} \lambda_j P_j : \lambda_j \geq 0 \text{ for all } j \text{ and } \sum_{j=1}^{N} \lambda_j = 1 \right\}$$

(7.1)

The convex hull is then typically represented by a sequence of the vertices of the line segments forming the boundary of the polygon, ordered along that boundary as in Figure 7.1.
For planar objects, i.e., lying in the plane, the convex hull may be easily visualized by imagining an elastic band stretched open to encompass the given object; when released, it will assume the shape of the required convex hull.

To show that the convex hull of a set $X$ in a real vector space $V$ exists, notice that $X$ is contained in at least one convex set (the whole space $V$, for example), and any intersection of convex sets containing $X$ is also a convex set containing $X$. It is then clear that the convex hull is the intersection of all convex sets containing $X$. This can be used as an alternative definition of the convex hull.

The convex-hull operator $\text{Conv}()$ has the characteristic properties of a hull operator.

- Extensive $S \subseteq \text{Conv} (S)$
- Nondecreasing $S \subseteq T \Rightarrow \text{Conv} (S) \subseteq \text{Conv} (T)$ and
- Idempotent $\text{Conv} (\text{Conv}(S)) = \text{Conv} (S)$
Thus, the convex-hull operator is a proper "hull" operator.

The convex hull of \( X \) can be characterized as the set of all of the convex combinations of finite subsets of points from \( X \): that is, the set of points of the form

\[
\sum_{i=1}^{n} t_i x_i
\]  

(7.2)

where \( n \) is an arbitrary natural number, the numbers \( t_i \) are non-negative and sum to 1, and the points \( x_i \) are in \( X \). It is simple to check that this set satisfies either of the two definitions above. So the convex hull \( H_{\text{convex}}(X) \) of set \( X \) is:

\[
H_{\text{convex}}(X) = \left\{ \sum_{i=1}^{k} \alpha_i x_i \mid x_i \in X, \alpha_i \in \mathbb{R}, \alpha_i \geq 0, \sum_{i=1}^{k} \alpha_i = 1, k = 1,2,\ldots \right\}
\]  

(7.3)

7.2.1 Parameters for the estimation of volume

The statistical parameters for the estimation of volume are derived using the above method. The shape of the placenta in general is a round or oval. Using this as reference, the major axis length \( l \) and minor axis length \( b \) of the ultrasound placenta of a segmented image is obtained using ‘regionprops’ in Matlab 7.0. The thickness \( h \) of the placenta was obtained from the point of chord insertion. This was obtained using the measure tool in Matlab 7.0. The mathematical representation of the segmented placenta is shown in Figure 7.2. The feasibility for classifying the ultrasound images of placenta with complicating diabetes based on placenta thickness using statistical textural features was analyzed.
7.2.2 Volume Estimation using Convex Concave Shell Model

Placental volume is calculated using the linear measurements like placental thickness, height and width obtained from segmentation. The ultrasound placenta is represented using the concave-convex shell formula. Based on these measurements the placenta can be classified as normal or abnormal placenta. The estimation of placental volume can identify the fetal risk in conditions of gestational diabetes mellitus. This would help to diagnose the complications at the earliest which would minimize the fetal loss, birth defects and placenta abruption. The statistical parameters obtained from section 7.2.1 are used in the volume estimation. The volume of the placenta is then calculated using the concave-convex shell formula as given in equation 7.4. These values are recorded in the Table 7.1

The concave-convex shell formula

\[
V = \left( \frac{\pi h}{6} \right) \left[ 4b(l - h) + l(l - 4h) + 4h^2 \right]
\]  \hspace{1cm} (7.4)

Where,

h=Thickness, b=Minor Axis Length, l=Major Axis Length

Figure 7.2 Measurement of Major Axis Length and Minor Axis Length to calculate Area and Perimeter
The high values of major axis length and minor axis length strongly indicate placenta complicated by gestational diabetes mellitus.

**Figure 7.3 Concave-Convex Shell Representation of Ultrasound Placenta**

The Figure 7.3 represents the mathematical model of volume estimation from the ultrasound images of placenta. The volume estimated by measuring the length (black marker) of the placenta, height of the placenta (green marker) as seen in ultrasound and the thickness (red marker) measured from point of chord insertion.

**Table 7.1 Volume Estimation from Statistical Parameters**

<table>
<thead>
<tr>
<th>Img Id</th>
<th>Major Axis Length (l)</th>
<th>Minor Axis Length (b)</th>
<th>Height (h)</th>
<th>Volume (V)</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Img1</td>
<td>7.482</td>
<td>3.79</td>
<td>2.31</td>
<td>104.689004</td>
<td>1</td>
</tr>
<tr>
<td>Img2</td>
<td><strong>13.72</strong></td>
<td><strong>4.63</strong></td>
<td><strong>3.6</strong></td>
<td><strong>433.1933952</strong></td>
<td>2</td>
</tr>
<tr>
<td>Img3</td>
<td>5.76</td>
<td>4.13</td>
<td>0.98</td>
<td>47.90461872</td>
<td>0</td>
</tr>
<tr>
<td>Img4</td>
<td>7.9</td>
<td>3.71</td>
<td>1.54</td>
<td>94.78968781</td>
<td>1</td>
</tr>
<tr>
<td>Img5</td>
<td>6.95</td>
<td>3.51</td>
<td>1.9</td>
<td>80.3664945</td>
<td>1</td>
</tr>
<tr>
<td>Img6</td>
<td>7.482</td>
<td>3.79</td>
<td>2.31</td>
<td>104.689004</td>
<td>1</td>
</tr>
<tr>
<td>Img7</td>
<td>14.78</td>
<td>4.01</td>
<td>4.78</td>
<td>469.4087275</td>
<td>2</td>
</tr>
<tr>
<td>Img8</td>
<td>5.23</td>
<td>2.1</td>
<td>1.98</td>
<td>29.95954698</td>
<td>0</td>
</tr>
</tbody>
</table>
7.3 BASIC PRINCIPLES OF NEURAL NETWORK

The Neural Networks consist of many small units, the formal neurons. They are interconnected and work together. Each neuron has several inputs and one output only. In Figure 7.4, a biological neuron and an artificial neuron are shown. The neuron has inputs $x_i$, each one weighted by a weight factor $w_i$. All of the neural inputs from the same neighbor neuron is modeled by just one weighted input. Typically, the activation $z$ is modeled by a weighted sum of the $n$ inputs. The output activity $y$ is a function $S$ of the activation. For a radial basis function

$$z = \sum_{i=1}^{n} w_i x_i$$

$$S_i(z) = e^{-z^2} \text{ with } z^2 = \frac{(c_j - x)^2}{2\sigma^2}$$

![Figure 7.4 A biological neuron and an artificial one](image)

7.3.1 Neural Network Architecture

A neural network is a general mathematical computing paradigm that models the operations of biological neural systems. A key benefit of neural networks is that a model of the system or subject can be built just from the data. Supervised learning is a process of training a neural network with examples of the task to learn i.e. learning with a teacher. Unsupervised
learning is a process when the network is able to discovery statistical regularities in its input space and automatically develops different modes of behavior to represent different classes of inputs. The advantage of the neural network is high accuracy of classification.

7.4 CLASSIFICATION OF PLACENTA FEATURES USING RADIAL BASIS FUNCTION

A Radial Basis Function (RBF) neural network has an input layer, a hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the centre of the neuron. The main difference is that Probabilistic Neural Network (PNN) or General Regression Neural Network (GRNN) networks have one neuron for each point in the training file, whereas RBF networks have a variable number of neurons that is usually much less than the number of training points. For problems with small to medium size training sets, PNN/GRNN networks are usually more accurate than RBF networks, but PNN/GRNN networks are impractical for large training sets.

RBF networks have three layers:

1. **Input layer** – There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used where N is the number of categories. The input neurons (or processing before the input layer) standardize the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer.

2. **Hidden layer** – This layer has a variable number of neurons (the optimal number is determined by the training process). Each neuron
consists of a radial basis function centered on a point with as many dimensions as the predictor variables. The spread (radius) of the RBF function may be different for each dimension. The centers and spreads are determined by the training process. When presented with the \( x \) vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron’s center point and then applies the RBF kernel function to this distance using the spread values. The resulting value is passed to the summation layer.

3. Summation layer – The value emerging from a neuron in the hidden layer is multiplied by a weight associated with the neuron (\( W_1, W_2... W_n \) in this Figure 7.5) and passed to the summation which adds up the weighted values and presents this sum as the output of the network. Not shown in this figure is a bias value of 1.0 that is multiplied by a weight \( W_0 \) and fed into the summation layer. For classification problems, there is one output (and a separate set of weights and summation unit) for each target category. The value output for a category is the probability that the case being evaluated has that category.
The following parameters are determined by the training process:

1. The number of neurons in the hidden layer.
2. The coordinates of the center of each hidden-layer RBF function.
3. The radius (spread) of each RBF function in each dimension.
4. The weights applied to the RBF function outputs as they are passed to the summation layer.
The framework of the classification process is given in the Figure 7.6.

**Figure 7.6 Framework of Classification Process**

**Placenta Classification using Radial Basis Function**

**Input:** Haralick Features, Area, Perimeter and Volume

**Output:**
- Class 1: Normal
- Class 0: Abnormal Placenta
- Class 2: Abnormal Placenta complicated by GDM

**Network Used:** Radial Basis

**Steps:**

1. Input Haralick Features, Area and Perimeter of the entire synthesized image, estimated volume, to Neural Network.
2. Supply the target class 0, 1 and 2.

3. Train the network using the above as inputs.

4. Test the network using a test data.

5. Network outputs 0 for abnormal placenta, 2 for abnormal placenta complicated by Gestational diabetes mellitus and 1 for normal placenta.

7.5 CONFUSION MATRIX FOR MULTICLASS PROBLEM

Confusion Matrix lists the correct classification against the predicted classification for each class. The rows correspond to the known class of the data. The columns correspond to the predictions made by the model. The value of each of element in the matrix is the number of predictions made with the class corresponding to the column for samples with the correct value as represented by the row. The number of correct predictions for each class falls along the diagonal of the matrix and off diagonal elements show the errors made.

**Accuracy:** The overall correctness of the model is calculated as the sum of correct classification divided by the total number of classification.

**Sensitivity / Recall:** It is a measure of the ability of a prediction model to select instances of a certain class from a data set. It corresponds to the true positive rate.

**Specificity/Precision:** It is a measure of the accuracy provided that a specific class has been predicted. It corresponds to the true negative rate.
Three different number of classes involved in the classification of placenta image, where 1 is normal and 0 refers to class of abnormal placenta which is a non GDM case and 2 refers to class of abnormal placenta which is a GDM case.

Sensitivity of class 0 is referred to as \( Sensitivity_0 \)

\[
Sensitivity_0 = \frac{t_n_0}{t_n_0 + e_{01} + e_{02}}
\]

Specificity of class 0 is referred to as \( Specificity_0 \)

\[
Specificity_0 = \frac{t_n_0}{t_n_0 + e_{10} + e_{20}}
\]

F-measure \( (F_0) \) can be used as a single measure of performance of the test. It is the harmonic mean of precision and recall.

\[
F_0 = \frac{2 \cdot precision_0 \cdot recall_0}{precision_0 + recall_0}
\]

The confusion matrix for multiclass 0, 1, and 2 obtained for Radial Basis Function is given in the following Table 7.2 (sample data)

**Table 7.2 Confusion Matrix – Multiclass 0, 1, 2 – Radial Basis Function**

<table>
<thead>
<tr>
<th>Class Type</th>
<th>Class 0</th>
<th>Class 1</th>
<th>Class 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Class 1</td>
<td>0</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Class 2</td>
<td>0</td>
<td>0</td>
<td>13</td>
</tr>
</tbody>
</table>

The Precision, Recall, F-score and Accuracy obtained for sample data using Radial Basis Function is given in the following Table 7.3 (sample data).
Table 7.3  Precision Recall F-Score and Accuracy for Radial Basis Function

<table>
<thead>
<tr>
<th>Class Type</th>
<th>Recall</th>
<th>Precision</th>
<th>F-Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Class 1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Class 2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

The confusion matrix for multiclass 0, 1, and 2 obtained for Elman Back Propagation is given in the following Table 7.4

Table 7.4  Confusion Matrix –Multiclass 0,1,2 –Elman Back Propagation

<table>
<thead>
<tr>
<th></th>
<th>Class 0</th>
<th>Class 1</th>
<th>Class 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Class 1</td>
<td>4</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>Class 2</td>
<td>0</td>
<td>0</td>
<td>13</td>
</tr>
</tbody>
</table>

The Precision, Recall, F-score and Accuracy obtained for Elman Back Propagation is given in the following Table 7.5

Table 7.5  Precision Recall F-Score and Accuracy for Elman Back Propagation

<table>
<thead>
<tr>
<th></th>
<th>Recall</th>
<th>Precision</th>
<th>F-Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>1</td>
<td>0.84</td>
<td>0.91</td>
<td>0.92</td>
</tr>
<tr>
<td>Class 1</td>
<td>0.66</td>
<td>1</td>
<td>0.79</td>
<td>0.91</td>
</tr>
<tr>
<td>Class 2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
The confusion matrix for multiclass 0, 1, and 2 obtained for Feed Forward Back Propagation is given in the following Table 7.6

### Table 7.6 Confusion Matrix – Multiclass 0, 1, 2 – Feed Forward Back Propagation

<table>
<thead>
<tr>
<th>Class</th>
<th>Class 0</th>
<th>Class 1</th>
<th>Class 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Class 1</td>
<td>7</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Class 2</td>
<td>0</td>
<td>0</td>
<td>13</td>
</tr>
</tbody>
</table>

The Precision, Recall, F-score and Accuracy obtained for Feed Forward Back Propagation is given in the following Table 7.7

### Table 7.7 Precision Recall F-Score and Accuracy for Feed Forward Back Propagation

<table>
<thead>
<tr>
<th>Class</th>
<th>Recall</th>
<th>Precision</th>
<th>F-Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 0</td>
<td>1</td>
<td>0.72</td>
<td>0.83</td>
<td>0.34</td>
</tr>
<tr>
<td>Class 1</td>
<td>0.16</td>
<td>1</td>
<td>0.20</td>
<td>0.79</td>
</tr>
<tr>
<td>Class 2</td>
<td>1</td>
<td>0.91</td>
<td>0.95</td>
<td>0.93</td>
</tr>
</tbody>
</table>

### 7.6 RESULTS

It is clear from the above tables that the neural network plays an important role in the classification process. Selection of a classifier is a vital task because all classifiers may not be suitable for all applications. As per the Table 7.8, the performance of Radial Basis is better compared to Back
Propagation, Feed Forward and Perceptron Neural Network. This research suggests that the Radial Basis Classifier can be employed in the classification of ultrasound normal placenta and placenta with GDM nature.

**Table 7.8 Performance analysis of the Classifier**

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radial Bias Network</td>
<td>98.9%</td>
</tr>
<tr>
<td>Back Propagation</td>
<td>93%</td>
</tr>
<tr>
<td>Feed Forward</td>
<td>96%</td>
</tr>
<tr>
<td>Perceptron</td>
<td>93%</td>
</tr>
</tbody>
</table>

7.7 CONCLUSION

Placental volume is calculated using the linear measurements of placental thickness, height and width using the concave-convex shell formula. The clinical references are compared against the statistical measurements obtained using Matlab 7.0. Based on these comparisons the statistical measurements of the ultrasound placenta were classified as normal or abnormal placenta. The high values of major axis length and minor axis length strongly indicate the placenta complicated by gestational diabetes mellitus. The features obtained from Haralick features extraction phase and segmentation is given as inputs to the neural network. These inputs are trained and tested using Back Propagation, Feed Forward, Perceptron and Radial Bias classifier algorithms. The performance analysis of the classifiers showed 98.9% accuracy with Radial Bias classifier when compared to other classifiers. It is thus found that the Radial Bias Classifier is best suited for the classification of ultrasound placenta images.