DEEP LEARNING PLACENTA ABNORMALITIES WITH CUSTOMIZED ARCHITECTURE USING DEEPLEARNING4J

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Abstract

The conditions at the origin place of physical birth namely placenta is normally analyzed and determined by physicians as well as by the support of Image Processing techniques during pregnancy. Such support is measured by the performance metrics like Accuracy, ROC, Precision, Recall, and F-Measure generated by the models based on Machine Learning. In this study we apply the customized approach implemented in Weka tool, especially the package DeepLearning4j..They are found to be comparable with the usage of standard architectures like LeNet, VGGnet, ResNet, and Alexnet. Quality of the proposed architecture is tested and refined for optimization using DeepLearning4j, iterated over both the Loss functions set at input layer as well as the errors measured at the output layer. It has been found the experimental results using 'MCXENT' function, denoting 'Multi-class Cross Entropy' among selected seven different loss functions generates more accuracy and less error. And the best performance is achieved with the maximum accuracy of 95.7%. These results support and present a new confidence for yet another machine learning approach using interactive development tool for gynecologists.

Keywords: DeepLearning4j, AlexNet, Placenta abnormalities, Multi-class Cross Entrophy, SoftMax, VGG, Loss Function, F-Measure, Precision, ROC

1. Introduction

The application of Deep learning gained momentum after the work [1,2]. The design and construction of neural networks connected in stacked layers with appropriate activation functions and setting the parameters determine the performance for classifying the data samples generated in any application. The rarity of data availability on sensitivity and specificity in this type of current investigation is reported by many authors [3-13]. The clinical significance very much depends on the evaluation of the input image such as placenta and cord, in turn that implies the process of evaluating the viability of the fetus, and ultimately the quality of infant delivered. Most placental abnormalities come to light just before or during delivery with the advent of ultrasound. Moreover, most of the serious placental abnormalities leading to serious morbidities with potential risk for haemorrhage.

1.1. *Related Works*

At present, well-known convolutional neural networks include LeNet [5], VGG [6,33], DarkNet-19 [7], and the deep residual networks ResNet-34 [8] and DarkNet-53 [4]. The model structure of DarkNet-19 is similar to that of VGG [6,33]. DarkNet-19 has 19 convolutional layers and 5 maximum pooling layers. DarkNet-53 combines the elements of DarkNet-19 and ResNet [8]. For massive data, DarkNet-53 is much more effective than DarkNet19 [9]. At the same time, DarkNet-53 achieves the highest floating point calculation speed per second in the network structure. This means that its network structure can make full use of the GPU [4]. Nevertheless, the deeper the network, the more difficult it is to converge. Many researchers have changed the Activation function [10] for preventing the gradient from disappearing. However, the problem still exists [11,12]. The disappearance or explosion of the gradient may be due to the high nonlinearity of the deep network. DarkNet53, ResNet-101, and ResNet-152 use residual learning methods to solve the problem of accuracy that increases first and then saturates. However, this will also lead to network redundancy [13].

Following this section for introduction, the contents are organized into five sections as follows: Section 2 contains the materials and methods needed to superficially understand the Placenta complications and methods of diagnosis. It also contains details of the process involving medical image data collection. Section 3 describes the capabilities of the weka tool, Deep learning4j, for designing the desired architectural variations. section 4 explaining the proposed architecture in terms of standard convolution of neural networks, section 5 describing the results obtained from experimental setup within the proposed framework with covering interpretations and followed by conclusion finally.

2. Material and Methods

The section is inserted for a quick scanning of materials and methods required for this research study and it is divided into two, first being materials on placenta complications and findings whereas the second being performance metrics for controlling the errors in the experiments to be carried out for this study.

2.1 Placenta complications diagnosis using ultrasound

Based on the literature from 2000 to 2021, we found, ultrasound is useful in diagnosing most of the placenta inefficiencies. Pre-eclampsia (PE) is a complication that causes high blood pressure in pregnant women who have not experienced the condition before and leads to excessive protein in their urine [14]. Recently experts agree that that analysing the uterine artery at the second tri-semester with a Doppler ultrasound is a useful screening strategy to identify PE [15] Placenta abruption (PA) is a complete or partial separation of the placenta from the uterine wall before the delivery. It is potentially a fatal complication of pregnancy, and it is a significant reason for bleeding in third-trimester. Appearance of retroplacental haemorrhage on the ultrasound can be an indicator for PA when there is a pre-gestational haemorrhage [16] When placenta implants unusually low in the uterus, next to or covering the cervix defined as Placenta Previa (PP). PP is a commonly underestimated condition with a considerable number of fetus morbidity and mortality [14]. According to [17], the role of trans-abdominal ultrasound is highly useful in diagnosing the severity of placenta Previa [18]. Vasa Previa is a complication when blood vessels from the placenta or umbilical cord that either cross or run close to internal cervical os. A mid-trimester ultrasound scan may reveal a suspicion on vasa Previa, and it confirmed in the third trimester. Identification of vasa Previa on ultrasound includes: placental cord insertion, transvaginal scan, apply colour Doppler over the cervix, and three-dimensional (3D) ultrasound [19,20,21]. Placenta accrete is a condition where the placenta or a part of the placenta attaches to the myometrium of the uterine wall, and it becomes inseparable from the uterine wall. It is graded as placenta accrete when the placenta attaches too deep into the uterine wall. Placenta increta when placenta attached even deeper into the uterine wall and to the uterine muscle. Placenta percreta when placenta penetrates to other organs such as bladder through the entire uterine wall.

Recent research points to the usage of ultrasound as sensitive and specific enough for the diagnosis of placenta accrete [22]. The grayscale ultrasound findings usually based on the number of lacunae, loss of retro placental clear space, bladder wall irregularity, and loss of visualization of myometrium and for colour Doppler, the presence or absence of sub placenta level, vessels bridging to the uterine, gaps in myometrial blood flow, or turbulent lacunae are analysed [23]. Placenta calcification is a medical name for the changes that happen to the placenta during pregnancy. The placenta matures and calcifies as the pregnancy nears the full term. In more than 50% of cases, the placenta has some level of calcifications. While 20% show severe Grade-3 calcification around 33 weeks [24]. The placenta is usually going through four grades from 0 to 3, where 0 is the most immature and 3 is the most mature. Placental calcification at early preterm is associated with severe complications such as fetus distress, fetus growth restriction, and fetus anomaly[25]. Currently, the placenta grading is performed mainly on subjective observation by the doctor, which is unpredictable as it depends on the experience of the clinicians [26]. Conventionally Grannum grading is used to assess placental calcification during ultrasound scanning [27]. Grannum et al. (1979) placenta classification based on changes occurring in the chorionic plate, placental substance, and basal layer of the placenta using ultrasound images. For Grade 0: A uniform echogenicity and smooth chorionic plate can be the identification during the first and early second trimester. For Grade 1: Some subtle indentations of the chorionic plate and small diffuse calcifications randomly dispersed in the placenta from 18 to 29 weeks. For Grade 2: Appears larger indentations along with the chorionic plate and larger dot-dash along with the basal plate from 30 weeks to delivery. For Grade 3: Chorionic plate indentations that extend to basal layer from 39 weeks to postdate [28]. The Grannum et al. (1979) approach is a subjective interpretation of ultrasound images. Texture analysis, feature extraction, and high intensity are the general approaches to analyse placenta calcification from ultrasound images. Geetha hari priya et al. [32] apply similar classification algorithm for studying the IVF data set. The tree in fig 1 tries to cover the most of the complications during the diagnosis period during pregnancy.

2.1. *Data collection*

As we have highlighted earlier the rarity of image data in the current theme of studies, the authors could collect a total of 1130 anonymous ultrasound images from 89 pregnant women during second and third trimesters prenatal visits were obtained for this research. To prepare the training set the images were verified and annotated by authorized experts. This data collection is given approval by the ethical committee as seen in [30]. The distribution of placenta image classes happens to be in the ration 1:3.6. The effect of imbalance in the class distribution is refined later by subsampling layers in the proposed architecture.

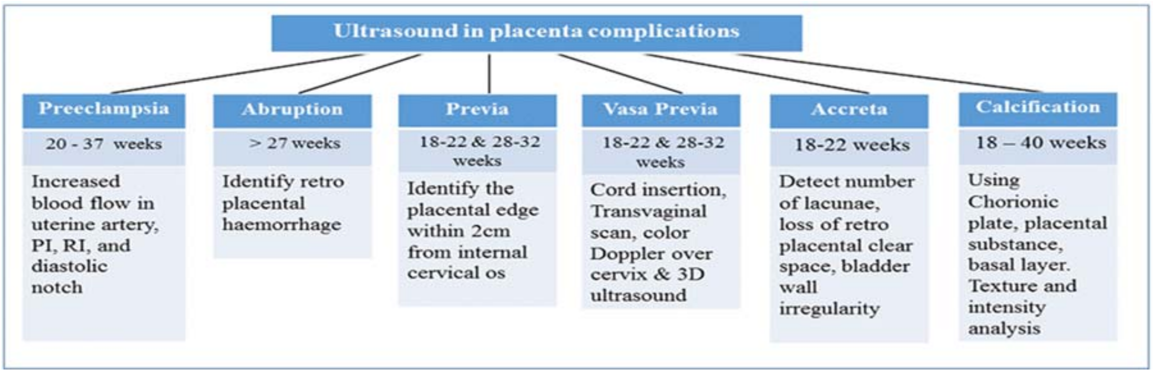


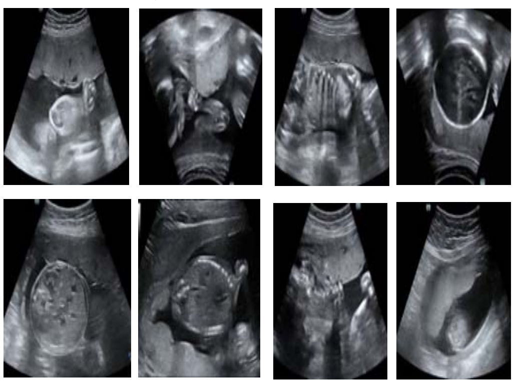
Fig 1: Placenta complications diagnosis period during pregnancy

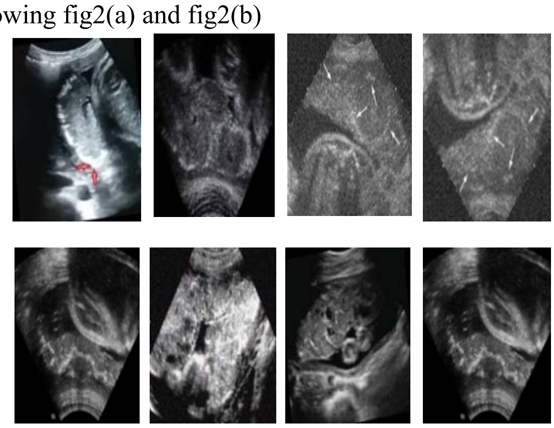
S.No	Class	Count
1.	Abnormal	245
2.	Normal	885

Table 1: Class distribution in the training set for placenta image set

2.2. *Dataset Description*

Sample set of normal and abnormal (as indicated by the medical expect at the center of studies in the hospital) ultra sound images are stacked and shown in the following fig2(a) and fig2(b)





Fig(2a): Normal placenta images

Fig(2b): Abnormal placenta images

2.3. *Loss functions for Performance measure*

This section enumerates the list of various loss functions as well as the corresponding names for implemented functions as followsLossL1 is the function using L1 norms, LossKLD is the function using Kullback Leibler Divergence loss, LossHinge is the function using the Hinge Loss, LossMSE is the function using Mean Squared Error Loss, LossMSLE is the function using Mean Squared Logarithmic Error Loss, LossSquaredHinge using

Squared Hinge Loss, LossMCXENT using multiclass entropy loss.[29]. The single row and column Table 2 below shows the code segment revealing the various construct methods in Java for these type of loss functions.

```
publicstaticfinalTag[] TAGS_SELECTION_OPTIMIZATION = {
newTag(OptimizationAlgorithm.CONJUGATE_GRADIENT.ordinal(), "Conjugate gradient"),
newTag(OptimizationAlgorithm.GRADIENT_DESCENT.ordinal(), "Gradient descent"),
newTag(OptimizationAlgorithm.HESSIAN_FREE.ordinal(), "Hessian free"),
new Tag(OptimizationAlgorithm.ITERATION_GRADIENT_DESCENT.ordinal(), "Iteration gradient descent"),
new Tag(OptimizationAlgorithm.LBFGS.ordinal(), "LBFGS") };
publicstaticfinalTag[] TAGS_ACTIVATION = { new Tag(ActivationFunction.SIGMOID.ordinal(), "Sigmoid"),
new Tag(ActivationFunction.LINEAR.ordinal(), "Linear"),
new Tag(ActivationFunction.TANH.ordinal(), "Tanh"), new Tag(ActivationFunction.EXP.ordinal(), "Exp"),
new Tag(ActivationFunction.SOFTMAX.ordinal(), "Softmax"),
new Tag(ActivationFunction.HARDTANH.ordinal(), "HardTanh"),
new Tag(ActivationFunction.RECTIFIEDLINEAR.ordinal(), "RectifiedLinear"),
new Tag(ActivationFunction.ROUNDLINEAR.ordinal(), "RoundLinear"),
new Tag(ActivationFunction.MAXOUT.ordinal(), "Maxout") };
publicstaticfinalTag[] TAGS_LOSSFUNCTION = { new Tag(LossFunctions.LossFunction.MSE.ordinal(),
"MSE"),
newTag(LossFunctions.LossFunction.EXPLL.ordinal(), "Exp log likelihood"),
newTag(LossFunctions.LossFunction.XENT.ordinal(), "Cross entropy"),
newTag(LossFunctions.LossFunction.MCXENT.ordinal(), "Multi-class cross entroy"),
new Tag(LossFunctions.LossFunction.RMSE_XENT.ordinal(), "RMSE cross entropy"),
new Tag(LossFunctions.LossFunction.SQUARED_LOSS.ordinal(), "Squared loss"),
new Tag(LossFunctions.LossFunction.RECONSTRUCTION_CROSSENTROPY.ordinal(),
"Reconstruction cross entropy"),
New Tag(LossFunctions.LossFunction.NEGATIVELOGLIKELIHOOD.ordinal(), "Negative log likelihood"), };
```

Table 2: Code for loss functions implementation

The Performance metric which plays a major role is based on principle of information gain and it is extracted using the following equations (1) and (2):

$$\text{Binary\_ cross \_entropy} = -(p(x).\log q(x) + (1- p(x).\log (1-q(x)))$$

where p(x) is the probability of getting target 0 and q(x) is that of getting target 1. Hence Multi class binary cross entropy (implemented in weka as MCXENT) gives the following for the total number of distinct ‘m’ classes

$$\text{Total Loss} = \sum_{l=1}^{m} (Binary\ cross - Entropy)_{\mathrm{i}}$$

2.4. *Details for parameter settings*

The parameter tuning is an art and usually the trained set of standard values is selected for the design of a deep learner. While constructing the deep neural network layers it has been selected sub set of parameters suitable for proposed classifications and it is shown in the following table 3 as follows:

Experimental Tool Parameters	Setting
Input Image	256*256
Conv	3*3
Epoch	10
Filters	3
Number Of Rows and Columns in Kernel	2*2
Padding	1,1
Stride	2,2
Dropout-Probability	0.2
MAXPOOL	3*3
Batch Size	16
Classifier in FCNN	Softmax

Table 3: parameter for the customized architecture

3. DeepLearning4j components

Weka Deeplearning4j is the tool implemented in the java platform and which is getting familiarity among the image processing research community very fast. The package manager in the conventional weka tool enables the users to plug in the Deep learning modules seamlessly.
The java APIs are supplied for constructing the layers and parameters like activation functions and other parameters in the types of layers as given below:

- Convolution Layer: This is for designing the selected convolution, making useful for images and text embeddings
- Subsampling Layer: This is for subsampling the groups of neurons of the parent layer by variety of strategies (average, maximum, etc.)
- Batch Normalization: This is for generating normalized activations values on the common batch using normalization strategy to reduce the divergent results
- Dense Layer: This is for extracting all the nodes fully connected configuration from the current to the next set of layers.
- Output Layer: This is for generating the results / outputs either for classification / or regression.

The WekaDeeplearning4j [31] extension of Weka is very convenient for academic research purpose and packages supplied with it supports the following components: fully connected feedforward types, convolutional layers, and recurrent connectivity. Data file loader facilities for standard relational data, as well as image, text, and sequence data, are supplied. It is also possible to train a neural network and use it as a feature extractor to provide suitable input data for another learning algorithm implemented in Weka, such as a support vector machine. Because the neural network predictors in the package are standard Weka "classifier" objects, they can be used and deployed in the same way. The following interface shown from the tool for the snapshot of setting up the parameters for the function of designing the layers of the selected architecture.

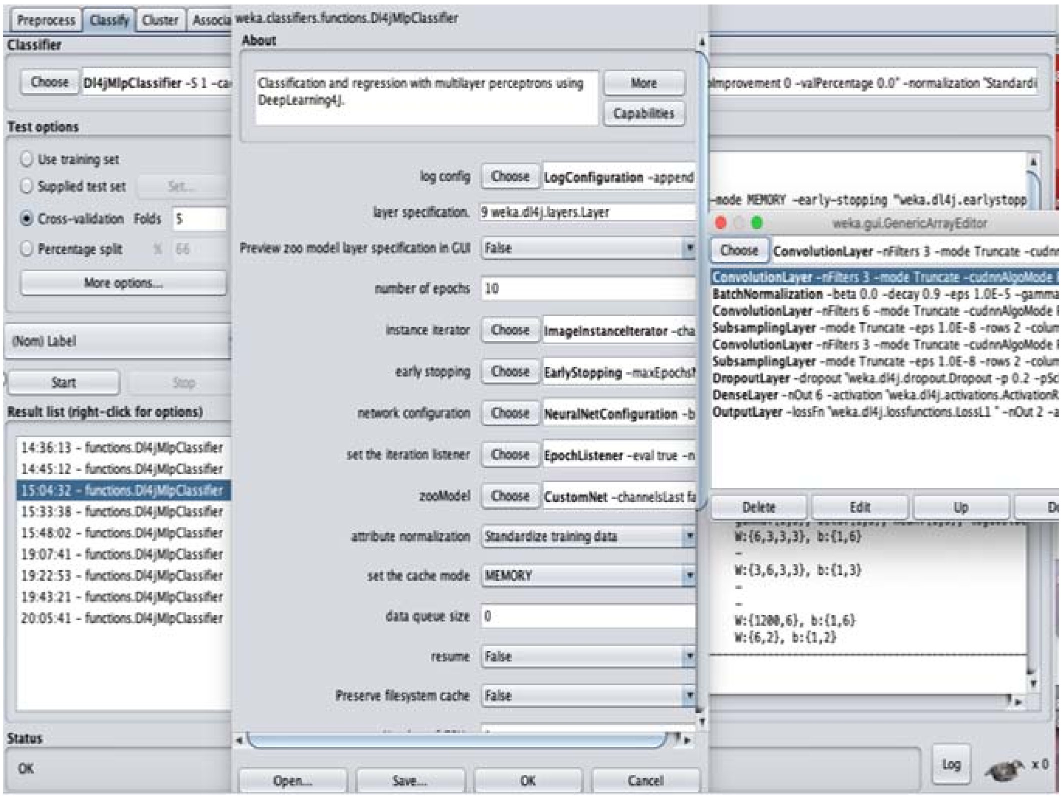


Fig 3:WEKA User Interface layer specification

4. Proposed Architecture

The standard architectures like Alex Net, VGG Net, Res Net, etc. are compared and chosen customized layers for our context as explained below:

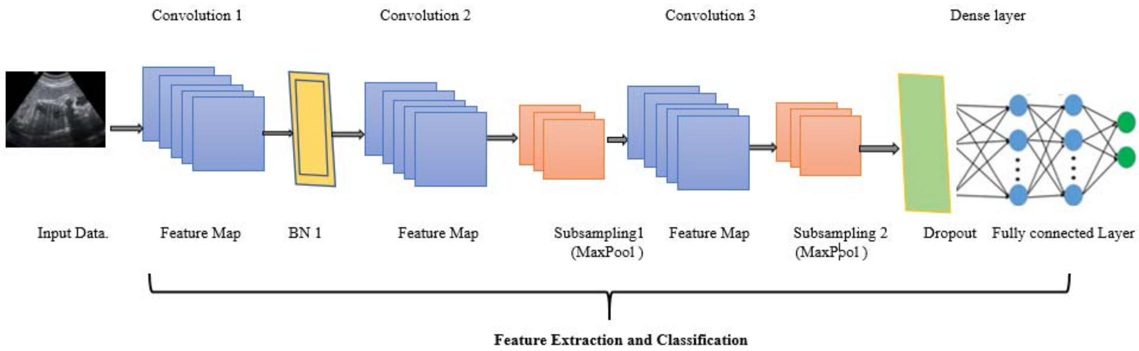


Fig 4: Proposed Architecture by customization

In the proposed Architecture Batch Normalization and Dropout layers are selected one each, whereas the subsampling layers applied twice with max pooling for further convolutions with appropriate kernels for extracting the features leading ultimately by a dense layer for much waited classification. The sequence of layers in our customized architecture is depicted in the following table:

Types of Architecture Version	Layers details
Customized	Convolutional Layer, Convolutional Layer, Batch Normalization, Subsampling Layer, Dropout layer, Convolutional Layer, Subsampling Layer, Dense Layer, Output Layer

Table 4: Layer Details

5. Result and Discussion:

The proposed architecture is constructed with the parameters set as given in the Table 3. The iterations are carried out over the loss functions of seven types out of sixteen available in Deeplearning4j. The subset of loss functions is extracted by the nature of domain and error types accordingly.Minimum error is sought using various loss functions. We opt seven such functions implemented in Weka. Deep learning 4j

Loss Function	Accuracy	Weighted Avg. Precision	Weighted Avg. Recall	Weighted Avg. F_Measure	Weighted Avg. ROC
LossL1	87.7	92.8	92.8	92.5	94.3
LossKLD	90.1	89.8	90.1	89.9	93.5
LossHinge	92.8	87.2	87.7	86.8	88.7
LossMSE	93.8	95.8	95.7	95.7	97.9
LossMSLE	94.2	94.4	94.2	94.3	96.9
LossSquaredHinge	94.2	93.7	93.8	93.8	95.9
LossMCXENT	95.7	94.3	94.2	94.3	97.1

Table 5: Various metrics for performance controlled by Loss functions

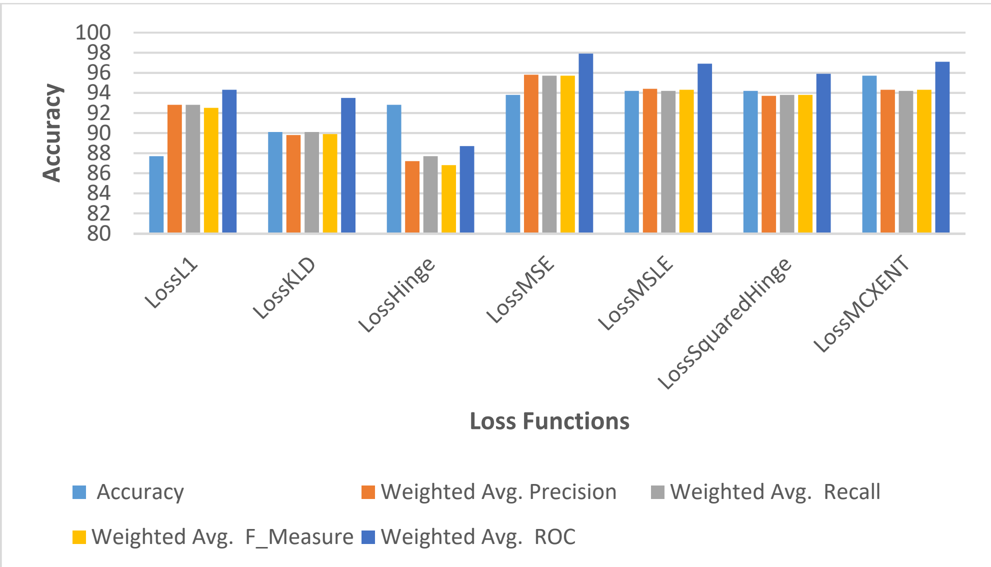


Fig 5: Various metrics for performance controlled by Loss functions

Overall the performance of the customized architecture yields maximum results in the final row by the 'LossMCXENT' function (Multi Class Cross Entropy) namely accuracy of 95.7%.

Loss Functions	Mean absolute error	Root mean squared error	Relative absolute error	Root relative squared error
LossHinge	0.072	0.260	0.059	0.175
LossKLD	0.165	0.308	0.135	0.207
LossL1	0.144	0.332	0.118	0.224
LossMCXENT	0.055	0.195	0.045	0.131
LossMSLE	0.071	0.226	0.058	0.152
LossMSE	0.080	0.234	0.065	0.158
LossSquaredHinge	0.069	0.221	0.057	0.149

Table 6: Loss functions of various errors to monitor the architectural performance

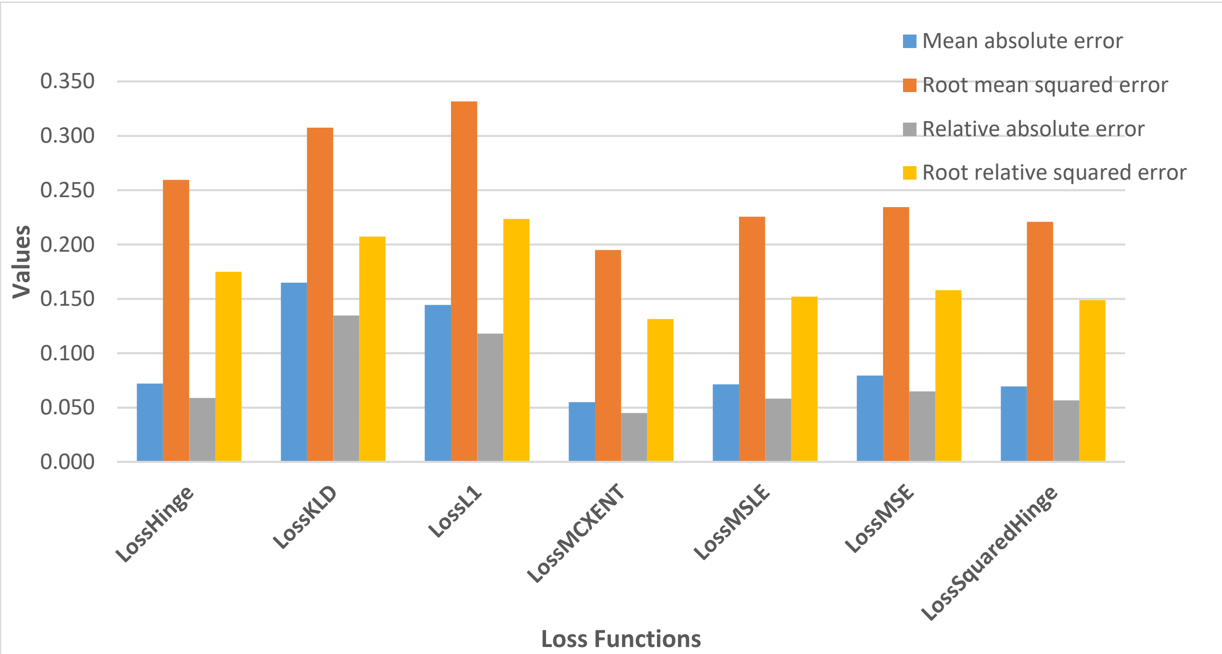


Fig 6: Loss functions of various errors to monitor the architectural performance

Here we find once again the ‘MCXENT’ gives relatively less error comparing overall performance as shown in the Fig 6 and table 6 numerical values.

6. Conclusion

This experiment enables the novel path paved for exploring with better accuracy for placenta abnormalities using interactive tools like Weka DeepLearning4j. Since the learning curve for this tool is shorter than any other conventional approach by either automatic programming or manual programming, this segment of studies happens to be the first attempt of its kind. Quality of the results is tested for its optimal value searched over the implemented set of loss functions defined for various types of error measures. The final result show ‘MCXENT’ function among sixteen different loss functions generates more accuracy and less error. The accuracy rate is achieved as 95.7%. Future plans on this study may be for broaden the spectrum of placenta complications namely the patterns in calcifications evolving during trimesters of the candidate. Moreover, extending the architectural studies with different types of inputs namely the ontology knowledge graphs and annotations will be of worth research.

Conflicts of Interest

The authors declare no conflict of interest.

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