D-NET BASED FETAL BRAIN ANOMALY CLASSIFICATION FROM MRI IMAGES

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ABSTRACT

Early detection of brain abnormalities reduces the risk of defects in the child birth and premature baby. A survey reveals that of the 1000 pregnant mothers, three of them were found to have had foetuses with brain defects. Magnetic Resonance Imaging (MRI) is a generalised medical imaging technique highly used for scanning the fetal brain. Primary detection and classification of abnormalities is essential. The proposed work ensures the detection of abnormalities with the help of MRI images in accordance to wide variety of fetal gestational age (GA) by cost-efficient and highly optimal solution. The proposed algorithm is comprised of four major phases which includes MRI segmentation, data enhancement, feature extraction and Image classification. Adaptive threshold, noise reduction, Convolution Neural Network are used to obtain the desired result. The proposed method uses segmentation of the MRI images to obtain only the part of image of the brain. A series of training is done using the segmented images, based on a D-NET (Dilated Convolution Neural Network). The dilated CNN is based on multiple layers, activation functions and the neurons at each layer which are determined by manual analysis to achieve the best accuracy. The proposed method dilated CNN exhibits a maximum accuracy of 92% when trained with 70% of training set images and tested against 30% of the test image dataset. Thus our proposed system is efficient in classifying fetal brain with abnormalities by the application of various fetal GA of different age groups. The results are found to be satisfying and promising.

Keywords: D-NET, segmentation, classification, fetal GA, MRI

1) INTRODUCTION

Anencephaly is a congenital defect that affects the development of the brain and the skull bones that surround it. Without a forebrain, infants are frequently blind, deaf, unconscious, and unable to feel. Anencephaly is seen pre-dominantly in females than males. An absence of bony covering over the back of the head, as well as missing bones surrounding the front and sides of the head, are some of the symptoms that indicate the presence of anencephaly. Diagnostic tests performed during pregnancy can help detect anencephaly for the babies. According to several studies, anencephaly is 100 percent fatal in the first year of life. Others claimed that the foetal death rate was 100 percent within the first few days to weeks. Anencephaly does not have a cure or a standard treatment. The prognosis is poor since many anencephalic fetuses do not survive delivery, and those that do die from cardio-respiratory arrest within a few hours or days of delivery[20]. Latest advanced machine learning algorithms have helped crave the need for early detection of anencephaly. There is a clear trend for a more comprehensive neurosonogram in the second or even first trimester of pregnancy. Certain brain abnormalities are only apparent late in childbirth[19] . The development of region and region-based convolutional neural networks R-CNNs has led to the replacement of fast R-CNN by edge technologies in image detection. The existing system is not highly scalable and thus provides less accuracy. The existing prediction restricts to the application of different kinds of algorithms as it is time consuming.The proposed method aims to satisfactorily predict anomalies in the fetal brain in order to ensure sufficient time for diagnosis. Therefore it is aimed to classify images of MRI from different age groups. The training data is made much available, thus the accuracy is very much improved. This proposed method aims to provide a computationally non intensive method for the easy detection of brain anomalies.

1.1 RELATED WORKS:

The machine learning algorithms have already found its place in the fetal brain anomaly detection. The detection and classification of the Fetal Brain abnormality[111] using the machine learning classifier Support Vector Machine (SVM) has been developed with a reduced dataset[8]. The main disadvantage of the author's work was that the dataset used in the algorithm was much smaller. [12] The author suggested a time series based approach using accelerometer data using eigen values and eigen vectors and movements of the fetus with an estimated accuracy of 95 percent wherein the major con of the study is that the abnormalities in fetal movements to know the development of the fetus is not predicted[13] follows old traditional measurements to measure the abnormalities in the FHR signal using dictionary learning algorithms. [14] used Doppler myocardial performance indices for the estimation of the performance of fetal myocardial development during the phase of maturation. But the performance value obtained from the analysis is low as it follows old methodologies. [15] used Kalman Filter and least mean square algorithm to effectively characterize and segregate the abnormality classes thus detect the deceitful mitral stenosis present in fetus. [16] used contour models to monitor the development of fetal using ultrasound image by using minimized energy to diagnose a specific feature in the medical image but the method involved is complex. Through the Eigen analysis based subspace separation methodology, it provided [17] an adaptive signal processing strategy based on Wiener filter to eliminate maternal chest signal and various noisy signals. The main disadvantage was that just a preliminary investigation on foetal cardiac signal abnormalities detection is conducted. [21] study revealed that ICA based algorithm was not robust to the signals which were contaminated by EMG. [22] suggested an old traditional measurement methods even though it was effective and practical. In order to study relevant regions inside the placenta, a three-dimensional structure-aware surface slicing methodology[23] was developed. [25] proposed a new strategy, in which fetal anomalies were identified in the foremost trimester in the phase of pregnancy using ultrasound and the fetal data wass processed using feature extraction, median filter, adaptive K mean clustering, and ANFIS classification.

2) MATERIALS AND METHODS

On several Computer Vision tasks, deep convolutional neural networks have performed exceptionally well. However, to prevent overfitting, these networks are heavily dependent on big data. The various methods of how data is collected and organized is discussed in here.

2.1) DATA ACQUISITION

A public medical imaging dataset accessible online[25] is the dataset used in this article. It was obtained at Harvard medical school by a medical team. The dataset originally comprised of 104 images which indicated abnormal fetal scans and 105 images which denotes normal MRI scans. A basic CNN model is built using the original dataset. Several data augmentation methods have been performed and thus the number of images has been accounted to 624 and 630 images in the normal and abnormal phases respectively. There are 1254 MRI scans for fetuses in the augmented dataset, with the GA ranging from 16-39 weeks.

2.1.1) DATA AUGMENTATION

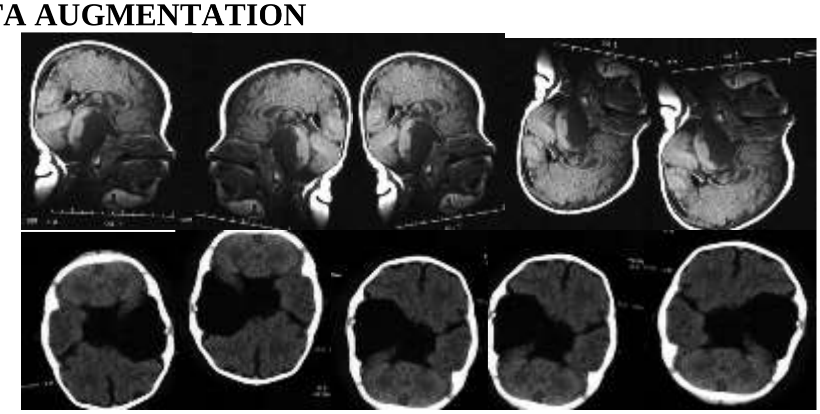

Fig 1 Horizontal and vertical flips of sample images

Over-fitting refers to the phenomenon when a network learns a very high-variance function, such as modeling the training data perfectly. Most anatomical structures are symmetrical-take, for example, the brain and kidneys. The flip augmentation is determined by a Boolean horizontal or vertical flip statement in the ImageDataGenerator class function Object() { [native code] }. Using randomized flipping, in which the image information is replicated horizontally or vertically, medical images containing symmetrical features are best suited for augmentation. The application of GANs-based augmentation techniques was also highly successful.

2.2) PROPOSED METHOD

The proposed method aims to satisfactorily predict anomalies in the fetal brain in order to ensure sufficient time for diagnosis. The proposed work comprises of four phases viz segmentation phase, the intensification or enhancement, the extraction of features, and the classification phase. In the initial phase of segmentation, from the fetal body, the region of interest (ROI) is segmented from the rest of fetal body. After that, the minor ROI, which contains the anomaly, is segmented from the entire brain picture. The ROI is indeed enhanced to improve the contrast. Finally the mask is applied on the original image and a data set is established. The dataset is then utilized to train the Dilated Convolution Neural Network. The proposed system is feasible as it takes fixed size input and generates fixed size outputs. The dataset is consistent and minimal pre-processing is sufficient as feed forward ANN is deployed.

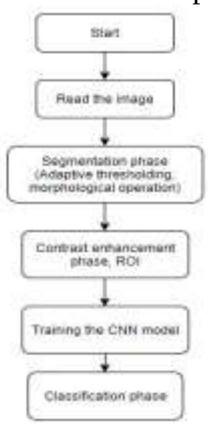

Fig 2 Flowchart of the proposed framework

2.2.1 SECTIONALIZATON / SEGMENTATION PHASE – PHASE 1

The fetal brain is first removed from the cerebrospinal fluid (CSF) and amniotic fluid surrounding the fetal head. For this stage, the adaptive local threshold technique is utilised to determine the best intensity threshold T. The image is then sent through an adaptive threshold function, which creates an initial histogram of pixel intensity values. The adaptive threshold algorithm will iterate through each intensity and continuously find the maximum variation and finally we set the threshold to be the one which differentiates most of the intensity values. After the threshold has been found, the image is converted into binary, the pixel intensities larger than threshold are converted into white and those below it are 27 converted into black. Then the largest contour, continuous set of pixels is found using depth first search mechanism and finally the largest contour alone is retained. The inner region of the obtained contour is also set to white and a suitable mask is obtained. This mask is now applied to the original image which separates the image of the brain from all the surrounding image data.

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Fig 3 Segmentation phases of MRI brain scan

2.2.2 ENHANCEMENT OF CONTRAST – PHASE 2

Using a mixture of local and global stretching contrast enhancement approaches, the minor ROI image is enhanced in this stage. This procedure is used to improve the quality, contrast, and brightness of the embryonic brain region. This phase is also included to improve the accuracy of the classifications performed later in the suggested method. The classes obtained include Normal fetal brain segmented minor ROI after contrast enhancement, and aberrant foetal brain segmented minor ROI after contrast enhancement. This will allow the Neural Network model to easily extract the suitable features from the image and we can increase the accuracy of the model. Using a suitable search algorithm, the contrast level which will give the maximum variation between the two peaks of the histogram are determined.

A suitable search algorithm is used to determine this contrast level. This stage of the process also includes several other image enhancement processes including denoising, in which high frequency and low amount pixels are separated from the ROI segmented image. The brightness must be preserved and we must ensure that the brightness remains consistent across all the training and test images so that the Neural Network will not take into consideration the brightness information as one of the features, which may reduce accuracy of the classification. This phase is implemented as an adapter that will take an image and convert it into a fixed size with best contrast, consistent brightness and less noise before feeding it to the neural network. The images to be predicted will also be passed through this stage before prediction. The main intent to use a densely connected deep layered convolution neural network is to reduce the vanishing gradient problem, improve feature propagation, and better feature reuse which increases the precision of classification. The proposed model aims to use dilated convolution network to further improve the resolution and performance.

2.2.3 TRAINING THE MODEL

MODEL 1:

The model chosen is a densely connected deep layered Convolution Neural Network. The first layer consists of 4 neurons with Sigmoid activation followed by two layers of Relu activation. All the training images are initially available in a labeled folder. The images are read one by one and all passed through the previous two stages, and the corresponding output is stored in a 'Preprocessed' folder but maintaining the same labels. The two classes, 'Normal' and 'Abnormal', identified by 0 and 1 respectively. The images are read and stored in a vector. The vector is properly shuffled before training. 70% of the images from the original dataset are used as training set and the rest of the images are used to test the accuracy of the model. The vector elements are stochastically fed as input to the CNN which will update the weights and biases. The CNN consists of a set of filters which will convert the image to a mathematical format which is suitable for classification. If the image contains anomaly, it is classified as Class 1, else it is classified as Class 0. Initially a random set of weights and biases is set up, which will constantly improve throughout the training process. An epoch value is set which is the number of iterations the images are fed. Gradient descent is used as the loss function and the goal is to minimize the loss function to be at most the given threshold. The Keras framework which is an extension of

TensorFlow is used to construct the CNN. A suitably low error margin is permitted and training takes place till the model has an error margin lower or equal to the threshold. The model is saved as a binary file for future use. For the prediction purposes, the model saved to the disk can be imported and there is no need to perform training again, thus saving CPU power. Also, training can also take place in bursts, to further conserve CPU usage.

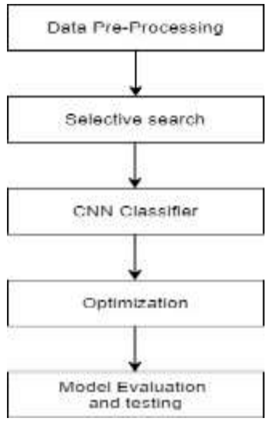

Fig 4 Process flow of classification methodology

MODEL 2:

The model chosen is a deep layered Convolution Neural Network with enhanced layers than model 1. The first layer consists of 4 neurons with Sigmoid activation followed by two layers of Relu activation and then a dense and fully connected layers are added. All the training images are initially available in a labeled folder. The images are read one by one and all passed through the previous two stages, and the corresponding output is stored in a 'Preprocessed' folder but maintaining the same labels. We have two classes, 'Normal' and 'Abnormal', identified by 0 and 1 respectively. The images are read and stored in a vector. The vector is properly shuffled before training. 70% of the images from the augmented dataset are used as training set and the rest of the images are used to test the accuracy of the model (1254 images in total). The vector elements are stochastically fed as input to the CNN which will update the weights and biases. The CNN consists of a set of filters which will convert the image to a mathematical format which is suitable for classification. If the image contains anomaly, it is classified as Class 1, else it is classified as Class 0. Initially a random set of weights and biases is set up, which will constantly improve throughout the training process. A epoch value is set which is the number of iterations the images are fed. The model is trained for 150 epochs. Gradient descent is used as the loss function and the goal is to minimize the loss function to be at most the given threshold. The Keras framework which is an extension of TensorFlow is used to construct the CNN. A suitably low error margin is permitted and training takes place till the model has a error margin lower or equal to the threshold.

MODEL 3 (D-NET)

Similar to the previous methods, several image pre-processing techniques were used to the enhance the quality of images. Then segmented pre-processed images were fed into the classification network. A deep convolutional dilated CNN network with a dilation rate of(2,2) was applied at the last three layers and trained with the input using the dataset obtained after the pre-processing described earlier. The results and accuracy were found to remain consistent with the other models. Dilated convolution is a way to increase the receptive view (global view) of the network by exponential and linear accretion parameters. One general use of dilated CNN is the segmentation of the image where each pixel is labeled by its corresponding class. The state-of-art way of implementing dilated CNN is to apply convolution and then add de-convolution layers to the up sample. It does, however, introduce many more learning parameters. Instead, dilated convolution is used to keep output resolutions high and avoid the need for upsampling. Dilated CNN is used in our suggested study because it allows for the detection of tiny details by processing inputs at greater resolutions. It could be utilized to get a shorter run time by reducing the number of parameters.

2.2.3.1 REASON TO USE DILATED CNN

Our main intent to make use of dilated convolutions is dense prediction. In any vision application, the need to integrate information from different spatial scales such as segmentation based on semantics with one label for one pixel, achieve super resolution, key point detection, and maintain properties such as pixel-level accuracy. Instead of using a multi-scale convolutional neural network, dilated convolutions helps to achieve the highly scalable and increased efficacy without actually elevating the count of training parameters.

2.2.3.2 Dilated CNN model:

Taking into consideration the purely convolutional network, which is said to be made of multiple layers composed of k×k convolutions, with no pooling. The size of each unit's receptive field—the pixel block that can affect its activation—is easily seen to be l*(k1)+k, where l is the layer index. As a result, the effective receptive field of units can only develop in a linear fashion as layers are added. The following is the definition of the dilated convolution between signal f and kernel k with dilution factor l:

$$(k *_l f)_t = \sum_{\tau=-\infty}^{\infty} k_\tau \cdot f_{t-l\tau}$$

Where f => denotes the signal f, k=> denotes the kernel, l=> dilation factor

For a basic convolution, this equation would be defined as $f_{t-\tau}$. In the convolution with dilation, the kernel comes in contact with the signal upon a single input. This formula can be extended to 2D convolution. Although the count of parameters increases linearly with layer depth, the effective receptive field of the units increases exponentially. The receptive field expands faster than the count of parameters, which can only be accomplished by putting new limitations on the parameters throughout the receptive field.

2.2.3.3 TRADITIONAL CNN VS DILATED CNN

A pooling operation can give the convolution kernel a bigger receptive field in standard CNN, although it's not a required aspect of the algorithm. Excessive pooling operations usually result in a significant degree of data loss. Dilated convolution may widen the receptive field without pooling, allowing each convolution output to encompass a broader range of information, and it's been used on difficulties like speech as well as text that require a longer chain of information dependencies. The ultimate goal of dilated convolution is that to affix a fixed element zero that doesn't adjust between original convolution kernels during the learning process, which attains the goal of dilating the convolution kernel's receptive field without increasing the number of kernel parameters. The dilated convolution operation is an efficient modified variant of the conventional convolution. The dilation factor can be denoted as K_d. Thus for a l * k convolution kernel, the size of K_d can be expressed as,

$$K_d = K + (K-1)(d-1)$$

2.2.3.4 WORKFLOW OF DILATED CNN

Our proposed model makes use of the model 1's CNN layers where the layers are converted to dilated layers by adding a dilation rate of 2. We intend to build our model using an exponentially increasing dilation rate within each block and stack multiple blocks to create a full network in the future works.

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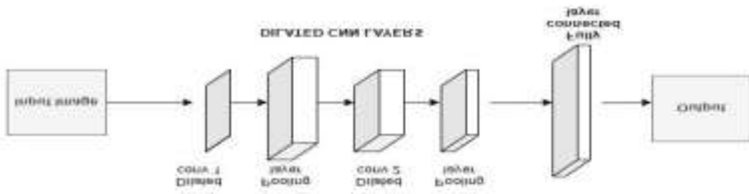


Fig 5 Architecture of dilated CNN

The time taken for training the dilated CNN model is comparitively reduced by an average of 10 per cent. As number of iterations in the training phase increase, the accuracy obtained by training the dilated model and the traditional CNN model increase, and it is found that the accuracy of the CNN model added with dilation is higher than that of the traditional CNN model.

2.2.4 MODEL EVALUATION

The trained model saved in the training/ directory must be evaluated as the final step. The model is evaluated by finding the accuracy metrics by comparing with the test labels and its window coordinates with the ground truth label of the test images which is in detection dataset. The images to be tested are also read into a vector after applying all the aforementioned preprocessing stages. The vector is shuffled and the vector is split into a vector containing only the data and another vector containing only the class name. This vector is called the 'expected values'. Only the data vector is fed as input to the model which is imported from the state saved to the disk and the output is obtained for each image. This gives the 'actual values'. The expected values vector is compared to the actual values. This gives a training accuracy. If the accuracy obtained is not sufficient, the training process may be repeated using different set of properties including, different type of activation function, different threshold, until the required accuracy is obtained.

A graph is plotted showing how the loss function varies with the time, to show that the model increases its accuracy when more data is fed to it. A confusion matrix denotes a table which is generally applied to demonstrate the performance of the classifier model on the test data for which truth values are defined. The confusion matrix is a comparison against the actual and predicted values. The confusion matrix gives the number of true positive values, true negative values, false positive and false negative values. The F1 score can be calculated from the confusion matrix obtained. Multiple metrics which includes classification precision, accuracy, and sensitivity, are used to assess the efficiency of the proposed process. The average precision, accuracy, sensitivity for the classification are determined according to the formulae given.

Accuracy metric is determined by performing division between the count of instances in a dataset which are properly identified and the grand total of the count of instances.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Where TP is defined as true positive values, TN denotes True Negative values, FP denotes False Positive value, and FN denotes False Negative values.

Precision (P) denotes the count of positive instances predicted precisely among the total count of positive values predicted.

$$\text{Precision} = \text{True Postive values} / \text{True Positive values} + \text{False Positive values}$$

Recall , could also be defined as sensitivity denotes the count of instances of positive class that categorized properly among the count of instances of positive classes present in the total data.

$$\text{Recall} = TP / TP + FN$$

2.2.5 HYPERPARAMETER SEARCH

After finding the accuracy of model, the hyper-parameter search is the optional method if the model generalization is satiable or poor. The hyper parameters are the metrics that can tune like a knob to increase the model performance on validation datasets. There are two types of searches available one is hyper-parameter grid search and another one is random search. The grid search method is good tuning process but not suitable for deep neural networks such as CNN, RNN etc the random search sometimes may fail but gives the optimum parameters for the particular model. Random Search uses a random selection process to replace the exhaustive enumeration of all possible combinations. This can be applied directly to the discrete situation described above, but it also applies to continuous and mixed spaces. When only a few hyper-parameters affect the machine learning algorithm's final performance, the hyper parameter search can outperform the grid search method. The optimization problem is said to have a low intrinsic dimensionality in this case. Random Search is also embarrassingly parallel, and it allows prior knowledge to be included by specifying the distribution to sample from.

2.2.5.1 RANDOM SEARCH ALGORITHM

Let f: $\mathbb{R}$ n $\rightarrow$ $\mathbb{R}$ defined as the cost function f(n) which is set to be minimized. $\mathbb{R}$ (n) allocates a candidate solution in the space of search defined. The random search algorithm could be defined accordingly:

Step 1: Instantiate the variable x with any random position in space of search.
Step 2. Redefine a sample position y from the hyper-sphere of any given radius corresponding to the current position x using any hyper-sphere sampling technique.
Step 3. If the cost function f(y) < cost function(x) , Set y to x and navigate to new position.
Step 4. Perform step (2,3) until the termination criterion is met .

3) RESULTS AND DISCUSSION

The table 1 shows the different models undertaken into the study and how the proposed model outperforms the other models are described.

Parameters	MODEL 1 (Traditional CNN on Predefined Dataset)	MODEL 2 (Modified CNN on Augmented Dataset)	MODEL 3 (D-NET on Augmented Dataset)
Score	0.88	0.892	0.918
Accuracy	87%	89%	92%
Average precision value	0.885	0.894	0.921
Average time	2.15	2.51	2.45

Table 1 Model performance based on essential parameters

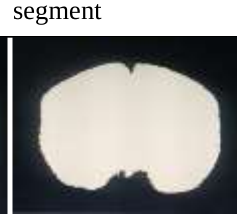
Original image (fetal mri)	Adaptive thresholding	Determining the central momentum	Mask of the segment	Segmented image
				

Table 2 Different phases of fetal brain segmentation and ROI classification

The results evidently reveal that the suggested method holds a maximum accuracy of 92% where in the dilated layers perform significantly better than the traditional CNN layers. This reveals that our proposed solution has achieved the efficient classification of brain abnormalities present in fetus based on various gestational ages of fetuses. This proposed method aims to provide a computationally non intensive method for the easy detection of brain anomalies. The proposed solution is found to provide better results and ultimate accuracy compared with other algorithms. The CNN layers can be made dense further to obtain better improved accuracy and the dilation rate could be increased further. After finding the accuracy of the model, the hyper parameter search would be performed if the model generalization is not convincing. Several machine learning classifiers such as DQDA (Diagonal Quadratic Discriminates Analysis), KNN (K – Nearest neighbors), Random forest algorithms, naïve bayes and Radial Basis Function (RBF) neural network classifiers can be embarked for further enhancements and improve the accuracy. Deep-learning algorithms can be trained in regular axial planes for segmentation and classification of normal and irregular fetal brain ultrasound images. This research lays the groundwork for further studies on the differential diagnosis of intracranial fetal anomalies.

The proposed method consists of four phases; segmentation, enhancement, feature extraction followed by classification. The initial phase of segmentation involves the separation or segmenting the brain part from the MRI image. The image is first converted to grayscale by simply taking the average of the three color channels and applying the average to all the color channels and the image is sent to adaptive threshold function. The adaptive threshold is based on the edges of objects and the contrast difference between any two sections of the image. The adaptive threshold initially generates a histogram of the pixel intensity values and iterated through each intensity and continuously finds the maximum variation which is finally set as the threshold value. After the threshold has been found, the image is converted into binary, the pixel intensities larger than threshold are converted into white and those below it are converted into black. Then the largest contour, continuous set of pixels is found using depth first search mechanism and finally the largest contour is retained.

In the contrast enhancement phase, a combination of local and global stretching contrast enhancement methods are used to improve the minor ROI image. The purpose of this step is to improve the quality, contrast, and brightness of the foetal brain region as well as the accuracy of the model proposed. This will allow the Neural Network model to easily extract the suitable features from the image. A suitable search algorithm is used to determine this contrast level. The brightness must be preserved and it is ensured that the brightness remains consistent across all the training and test images so that the Neural Network will not take into consideration the brightness information as one of the features, which may reduce accuracy of the classification. This phase is implemented as an adapter that will take an image and convert it into a fixed size with best contrast, consistent brightness and less noise before feeding it to the neural network. The images to be predicted will also be passed through this stage before prediction. The model is saved as a binary file for future use. For the prediction purposes, the model saved to the disk can be imported which lowers CPU usage.

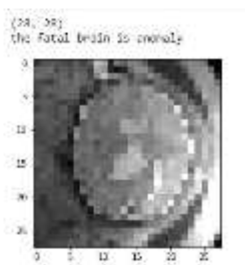


Fig 6: Sample test image – predicted class : anomaly exists

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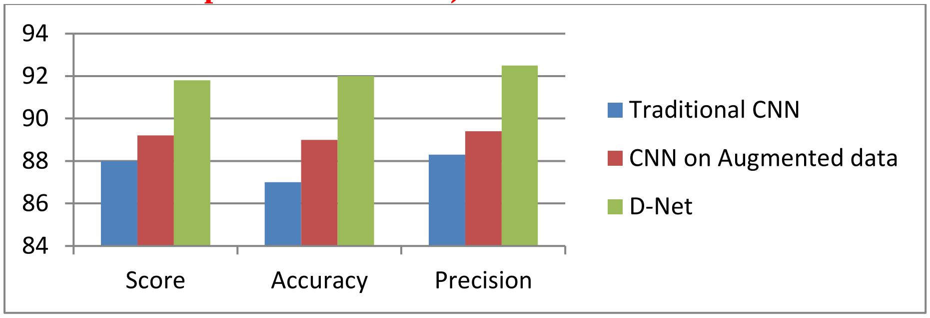

Fig 7 Visualization of model performance based on F1Score, accuracy and precision

4) CONCLUSION

Segmentation and classification of the fetal brain anomaly is increasingly gaining interest with the acquisition of better quality images and the increased focus on fetal and neonatal development. The proposal presented a methodology for brain tissue segmentation in fetal MRI into two major classes using convolutional neural networks. The proposed method learns to cope with intensity in homogeneity artifacts by augmenting the training data with synthesized intensity in homogeneity artifacts. The concept of sensitivity analysis is deployed to isolate regions critical for CNN performance, and it is discovered that the most sensitive regions were regions that are high in metabolic activity in early human brain development. In this proposed system we can implement morphological operations, guided active contour method and dilated CNN based classification. The dilation rate of the CNN classifier could be improved further to achieve even better accuracy. Future work explores extracting diagnostic features in the segmented brain regions of the MRI image and integrates these methods in the developed CAD system for autism. In order to enhance the diagnostic accuracy, future work will investigate integrating other diagnostic features that will be extracted from other brain structures

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