

# Deep Learning Algorithm for Classification of Cerebral Palsy from Functional Magnetic Resonance Imaging (fMRI)

## Classification of Cerebral Palsy from Functional Magnetic Resonance Imaging

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**Abstract**—Cerebral palsy is a disorder of neurology that may be caused by prenatal, perinatal or postnatal reasons that result in the failure of motor functioning in children besides mental well-being. Referring to the location of brain injury and the effect of it on the muscle tone, cerebral palsy is classified into subgroups namely spastic, non-spastic etc. Each type of palsy varies in symptoms and hence the therapy planning and rehabilitation are decided depending on the factors involved in each type. This urges the requirement of a suitable technique to classify the type of Palsy at the earlier stages to effectively plan therapy. Functional MRI of the neonatal brain helps in imaging and classification of cerebral palsy. The deep neural network is a subset of machine learning that is widely used in image classification applications. This technique is applied to the functional magnetic resonance brain images of infants to classify the type of cerebral palsy using a deep convolutional network of modified AlexNet architecture that helps the physician further in a planned rehabilitation to facilitate the lifestyle of the affected children.

**Keywords**—Cerebral palsy; deep neural network; functional magnetic resonance image

### I. INTRODUCTION

Cerebral palsy is a disorder in neurology caused due to non-progressive brain injury or any malformation due to underdevelopment of the brain in preterm infants. This primitively affects motor actions and muscle coordination. The World Health Organization (WHO) reports that 10% of the total population is estimated to be affected, by any of the types of cerebral palsy and 3.8% of Indian population is a victim of this neurological disorder [1]. Diagnosis of cerebral palsy is highly challenging in infants. The fMR image of a cerebral palsy affected infant is shown in Fig. 1. When there is any delay in the motor or cognitive responses during the growing phase of the child, cerebral palsy may be diagnosed. But diagnosis after the elapsing of the critical period will not be effective in rehabilitation. Early diagnosis of cerebral palsy at the infant level will help the physicians to plan for oculomotor rehabilitation, which suitably helps in the Neuroplasticity and eventually improves the lifestyle of the cerebral palsy affected child [2].

The scientific verity of the intellectual organ, namely brain can be demonstrated by neuroimaging techniques like Functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET) scans. The functional magnetic resonance imaging helps in recording the brain activity with respect to the changes occur because of the variation in the blood flow.

fMRI is also widely used to study on the reorganization of the neural connectivity after early brain injuries and also viewed as a most vital tool in investigating neuroplasticity. Recent research have proved that even though fMRI is widely used in adults, there are few challenges observed when used in children especially in infants with lack of head stability during scanning and excessive anatomical variations in whole brain mapping etc. This increases the complexity in analyzing the fMRI and also classifying accordingly [3].

The existing methods of classification of cerebral palsy widely use the cerebral magnetic resonance imaging techniques that are majorly dependent on the grades of severity in periventricular (PVL) anomalies. MRI based classification mainly focus on the irregular ventricular dilation, widening of the inter hemispheric fissure, long lasting hemorrhage. Some researchers have also attempted to classify cerebral palsy with respect to the motor abnormalities namely diplegia, dyskinesia, spastic etc. The results were promising and the classification accuracy was good when the experimentation carried is between ages 2 to 6. It is also observed that very limited approaches are available to classify palsy before the age of two. The study has also complemented that diagnosing and classification of cerebral palsy at earlier stages is challenging owing to the factors like gross motor functions cannot be analyzed for the infants under this age group [4].

This paper [5] aims at diagnosing cerebral palsy at the earlier stages of infant, preferably six to twelve weeks old by comparing the fMRI of these infants and their oculomotor responses. Further, to classify the type of cerebral palsy namely spastic, dyskinetic, ataxic and mixed cerebral palsy using deep neural network [6]. The obtained fMRI images are subjected to removal of noise using fuzzy adaptive filter and then the type of cerebral palsy is classified by the three layer deep neural

network trained with tensor flow. After the training phase the testing of the obtained images resulted in the classification of the type of Palsy with increased accuracy.

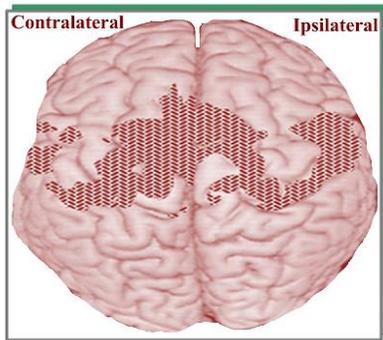


Fig. 1. FMR Image of Cerebral Palsy Affected Infant.

Section II of the paper discusses on the literature review and the research challenges existing in the classification of palsy. Section III describes the methodology of the proposed method and the results obtained are discussed in Section IV.

## II. LITERATURE REVIEW

First, Research on Cerebral Palsy has started in the early 1940's when Arnold E. Joyal indicated that Cerebral Palsy is one of the major reasons for the slow and poor growth in children. The factors that affect the cognitive functioning of children with a mean age of nine and affected with cerebral palsy were discussed by Paul E. Polani in 1958. Patricia Myers in 1965 reported the language disabilities in cerebral palsy affected children. M. V. Durkin et al in 1976 analyzed the history of the mentally retarded subjects to identify the pathogenesis of cerebral palsy. This work was also funded by USPHS Grants and the Wisconsin Department of Health's Grant to CWC - Central Wisconsin Colony and Training School in support of the Genetic Counseling Unit and CWC Diagnostic. Ruth Koheil et al in 1987 studied the effect of EMG auditory feedback training of the orbicularis oris using a biofeedback trainer and there was a considerable increase in the motor actions by the patients after the training.

In 1993, D. F. Parker et al. Measured the level of interrelation between the motor actions and the physiological fitness of the cerebral palsy affected children. Robert Palisano et al. in 2008 insisted on the necessity of a standardized system for gross motor function classification in children affected by cerebral palsy. Donna S. Hurley published a research registry on cerebral palsy in 2011 to fill the gap between the clinical research and the patients and to promote fruitful research in this area. Sophia Gosling, in 2016 reviewed the recent developments in the pediatric neuropsychological rehabilitation of cerebral palsy affected children. Kristine Stadskleiv in 2018 reviewed the neurophysiology profiles of the cerebral palsy affected children. Deepa Jeevanantham et al. in 2018 attempted the subgrouping of cerebral palsy affected children in developing two different body function index for them that aids in exploring the difference between the gross motor functions.

Anupam Gupta et al. in 2008 assessed the effectiveness of single stage multilevel soft tissue surgery for the CP affected

patients for their active locomotion. Ruchi Kothari et al. in 2010 investigated the connection between findings of BAEP and VEP abnormality with different clinical factors in children having spastic cerebral palsy. Vykuntaraju K Gowda et al. studied the clinical patterns, co-morbidities and predisposing factors of cerebral palsy affected children in 2015. The study was concluded that out of 100 affected children, 12% of hypotonic, 81% of spastic, 2% of mixed CP, and 5% of dystonic cases. The mean presentation age was 2 years, 2 months, and it is in the ratio of 1:2 for male to female. S Surender et al in 2016 focused on the cerebral palsy impact on HRQOL of children and their families, relationship with the dysfunction of gross motor [7, 8].

The rehabilitation council of Indian Academy of CP has acknowledged that there is positive growth in the medical interventions provided to CP affected patients. However, more scientific research and studies based on systematic documentation and validated reference materials in India may help the rehabilitation of the rural population.

But it is evident from the literature that the classification of the type of cerebral palsy from the fMRI analysis is challenging owing to the factors like the understanding of the functional connectivity of brain and requires much more investigations on the anatomical details regarding the classification on the type of Palsy [9, 10]. These real time challenges requires a robust method to analyse the fMRI obtained from the infants irrespective of the nonlinear and complex changes in the neurons and classify accurately to aid in the therapy planning that results in better rehabilitation planning at the earlier stages.

## III. METHODOLOGY

This research attempts to diagnose cerebral palsy at the earlier stages, particularly in the age group of six to sixteen months and also to classify the types of cerebral palsy [11] that helps in planning for better rehabilitation by overcoming the existing challenges in correlating the gross motor responses and the fMRI analysis. The overall flow of the proposed method is shown in the below Fig. 2.

### A. Overview

Functional Magnetic Resonance Imaging is used in measuring brain activity with respect to the blood flow measurement. This non-invasive imaging technique is capable of even detecting a small change associated with neuron activities. This imaging is based on the Blood Oxygen Level Dependency (BOLD) of the brain cells and widely used in medical diagnosis owing to the high spatial resolution in the activated brain regions, their visibility with respect to the neighboring cells. Repeated stimuli also help in eliminating the imaging noise much better than in normal MR images besides the fact that, fMR image quality is increased by using spin echo pulse in accordance with the magnetic field strength. The fMR images of the cerebral palsy affected children are acquired. The BOLD signal is highly complex and non-linear because of the transient changes in the neurons and vascular structures. The images are preprocessed for the removal of random and other noises acquired because of image acquisition and the subjects themselves, being a neonatal group.

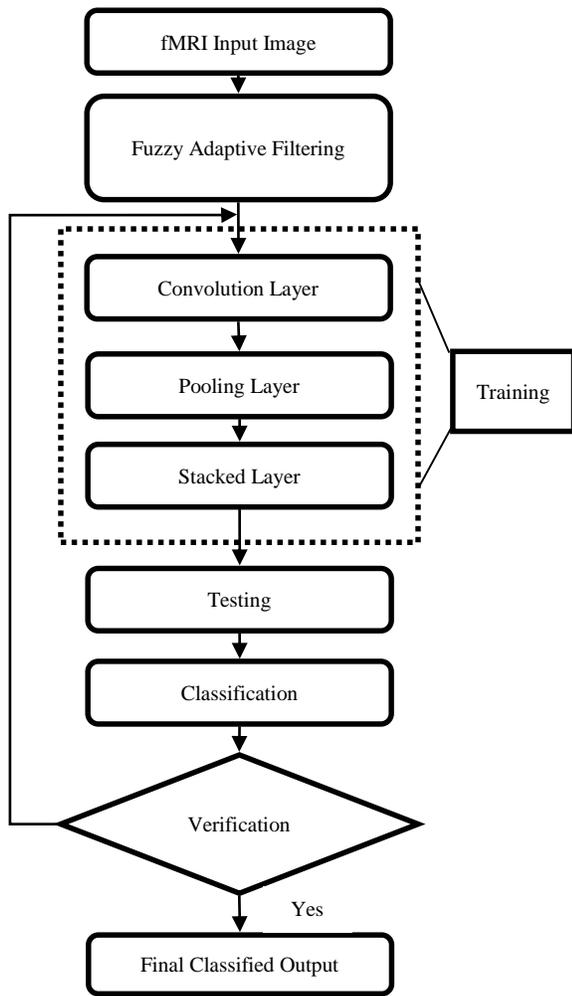


Fig. 2. Overall Flow of the Proposed Method.

Also, the amplitude of the thermal noise increases with respect to the strength of the magnetic field. Fuzzy adaptive median filters are used in eliminating the noise from these test images [12]. Fuzzy adaptive filters reduce the additive, salt and pepper or impulse noise, but preserve the image details compared to the adaptive median filters.

B. Fuzzy Adaptive Filtering

Fuzzy adaptive filtering is a modified version of median filters that improve the visibility of an image by intensifying the smoothing effect besides removing the noise factors when compared to other traditional filtering techniques. This method involves the identification and comparison of each pixel in the input image and replacing the noise affected pixel with the median value according to the intensity of the local noise with increased flexibility. The intensity differences are measured using a sliding window function and the mean square error is calculated as follows,

$$MSE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \{ \hat{f}(m,n) - f(m,n) \}^2 \quad (1)$$

The noise-free image is now fed into the training phase of the deep learning networks framed of convolution, pooled and

stacked layers and the architecture of the proposed method is shown in Fig. 3.

C. Deep Learning

Computer Aided diagnosis plays a vital role in medical imaging since 1990 for the detection of micro calcifications, lung nodules, pulmonary embolism and mitotic cells. In the recent years Computer aided diagnosis uses the extended version as the convolution neural networks (CNN) in the classification of pancreas, brain tumor and other medical applications. The major advantage of CNN is the ability to transfer the data interpreted in the pre trained layers to the next level. This transfer learning ability of CNN can be used for two different applications in medical imaging. The first application uses the pre trained CNN to generate the features required for training phase. On the other hand the pre trained CNN can be used in image classification by replacing the fully connected pre trained CNN layers by the logistic layer and the training is done only for the newly added layers. LeNet, AlexNet and GoogLeNet are the three major CNN that is implemented widely in image analysis specifically in medical image classification. AlexNet was introduced in 2012 by Alex Krizhevsky et al with a unique feature of introducing non linearity into the network through ReLU during the training phase that increases the speed when compared with the saturating nonlinear function including hyperbolic and sigmoid functions. This paper uses the modified AlexNet architecture where the different stages of information processing in multiple hierarchical structures are implemented to improve the accuracy of classification. Another important advantage of using AlexNet is that it is used in overcoming the over fitting problem [21].

This paper uses a modified AlexNet with five convolution layers followed by pooling layer. The convolution layers aid in detecting the local features throughout the input image. The local structures are detected by connecting each node to a subset of spatially connected neurons. The similar image pattern is searched in each input image channel by enabling three connection weights shared between the nodes in the convolution layer called as kernels. The number of kernels depends on the number of parameters to be detected from the input layer. The hierarchical set of image features is attained by adding pooling layers in subsequent to the convolution layers. The max pooling layer helps in the reduced size by selecting the features in overlapping and non-overlapping neighborhood and eliminating the maximum responses. This also results in improved translation invariance. This is followed by the regression or softmax layer that generates the expected output. The BPN algorithm is used in training the CNN that effectively minimizes the cost function.

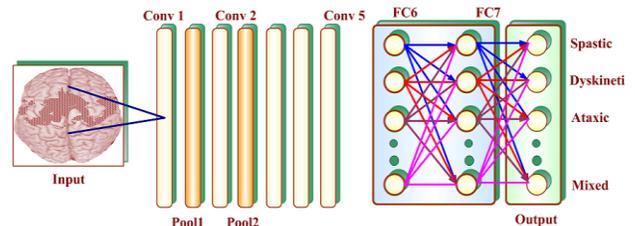


Fig. 3. Architecture of the Proposed Method.

The proposed method consists of five convolution layers followed by two fully connected layers. The kernel size, of the first convolution layer is 12 so that each unit of the feature map is mapped to 12 X 12 neighborhoods and this layer is to normalize the local response by convolving after every 4 pixels. This layer leads to 96 feature maps, followed by the pooling layer with a kernel size, of 6 and stride rate of 2. This layer is again followed by the convolution layer 2 with a kernel size, of 6 and stride rate of 2. Thus the pooled feature maps in each layer are convolved subsequently in the convolution layer and fed into the two fully connected layers for the rectified linear operation. This modified AlexNet results with 4096 feature maps for each image as tabulated in Table I.

TABLE I. SPECIFICATIONS OF PROPOSED CNN

Parameters	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
Number of Filters	96	96	384	256	256
Kernel Size	12 X 12	6 X 6	6 X 6	3 X 3	3X 3
Stride	4	2	2	2	2
Learning Rate	0.02				
Weight Decay	0.0016				
Training Epochs	40-60				
No. of units in fully connected Layer					4096

Deep learning is a discipline of machine learning that is recently used in object recognition among a large volume of data. This is implemented effectively by rising the number of artificial neural network layers and each layer is designed to extract an exact feature that enhances the image classification[13, 14]. After preprocessing, the images are split into subclasses for calculating the gradient of the images in each data set, thereby reducing the voluminous data and parallel processing occurs to reduce the computational time. [15, 16].

Convolution neural networks (CNN) are widely used deep feed forward networks for image classification. CNN is more or less similar to feed forward neural networks, but the only difference between them is the connection pattern of the adjacent layers. CNN involves the connection of all nodes between the adjacent layers, whereas feed forward networks few nodes may be eliminated because of the complexity riveted in including too many parameters like over fitting, slow speed etc. This major challenge in feed forward networks is overcome by the CNN that includes kernel layers: convolution and pooling layers. The former layer uses only a portion of the previous layer as input in the size of preferably 3 X 3 or 5 X 5. But it deeply analyzes the limited input to gain maximum abstraction of the required features. The latter layer involves reducing the matrix size from the previous layers and hence minimizes the number of parameters in the entire network [17],[18]. This results in increased speed of computation and also avoids over fitting problems as in the case of feed forward networks.

1) *Convolution layer:* The features that are identified to represent the input images are extracted in this convolution layer which consists of neurons oriented to form the feature maps. These feature maps are interconnected with the neighboring neurons in the preceding layer through predetermined weights [19], [14]. These are known weights are used in framing the new featured maps by convolving with the input, which results in a non-linear activation function. Even though the weights of all the neurons in a feature map tend to be equal, the feature extraction is effective in extracting different features at each level because different feature maps have variable weights. The  $n^{\text{th}}$  feature map output is denoted by  $Y_n$ . This is computed as follows,

$$Y_n = f(W_n * x) \tag{2}$$

Where  $x$  is the input and  $W_n$  is the convolution window for the  $n^{\text{th}}$  feature map,  $f(.)$  denotes the non-linear activation function that is featured to extract the non-linear features in the given input image.

2) *Pooling layer:* This layer reduces the spatial resolution of each feature map besides increasing the spatial invariance that occurs due to the distortion input. The average value of all the input neurons can be propagated to the next layer with an average pooling function when a relatively small window of the neighborhood image is considered. But the maximum value of the input is propagated to the next layer through the maximum pooling aggregate function by selecting the largest element of the receptive field as follows,

$$Y_{nij} = \max_{(p,q) \in I_{ij}} X_{npq} \tag{3}$$

Where the feature map output of  $n^{\text{th}}$  element is denoted by  $Y_{nij}$  and  $x_{npq}$  is the element in  $(p,q)$  in the pooling region with a receptive field around the location  $(i,j)$ .

3) *Stacked layers:* When more features are required to be extracted for the classification of images, then the number of pooling layers along with convolution is stacked over one another. Softmax operator is used as it is widely used for classification problem using the Back Propagation Training (BPT) algorithm. The output from the final stack is a vector function  $f(x)$  that mainly depends on the confidence in classifying the input  $x$  in a given class of feature maps and it is obtained by the summation of the class scores of each layer. The class scores will not be an integer and it is a floating point value that is generally unbounded but the final output of the softmax output is a multidimensional vector and it is bounded that ranges from 0 to 1. This function has an exclusive property of breaking down the maximum value to get a maximum part of the distribution and other elements are assigned to a part of the distribution. This property makes this method more suitable in interpreting images in classification problems.

#### IV. RESULTS AND DISCUSSION

The fMRI of infants are collected from the open neuro, neuroimaging data, starplus fMRI data, CRCNS and oasis brain database and analyzed by synthesizing the images. The drift component, seasonal component, noise is removed by subjecting the images to fuzzy adaptive mean filtering.

##### A. Testing and Training

The data set obtained from the online sources is used in the training phase. Even though specific classification is not required in machine learning, since this research aims at the classification of medical images, the dataset is categorized specifically [20-24]. They are categorized based on the type of palsy and age of the infants. The sample images of infants with various types of palsy are shown in Fig. 4.

##### B. Pre-training

The experiments were carried out using tensorflow, an open source framework available for building and training multilayer neural networks. Here, the weights of the convolution layer were trained on the dataset available on the website and screen shot is shown in Fig. 5. Tensorflow is used to build the coding for the deep learning algorithm.

Four hundred fMRI images were trained and one hundred and fifty images were tested. The output nodes of the CNN are converted into class probabilities by the softmax function. The error between the predicted class and the actual output class is the loss function. The major challenge in training CNN for medical images is the limitations in the availability of the labelled data set. Very few datasets of fMRI is available for research, namely, neuroimaging data, starplus fMRI data, CRCNS data, etc.

But the final output layers were trained with real-time fMRI images obtained from the cerebral palsy society and indicated in Table II.

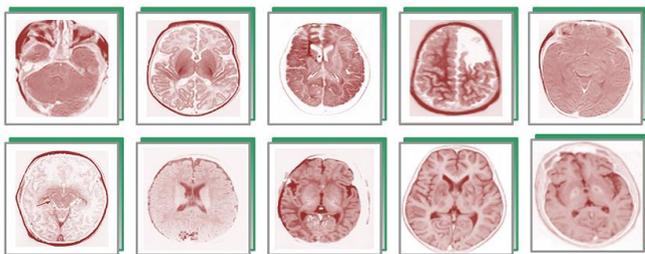


Fig. 4. fMRI Sample Dataset.

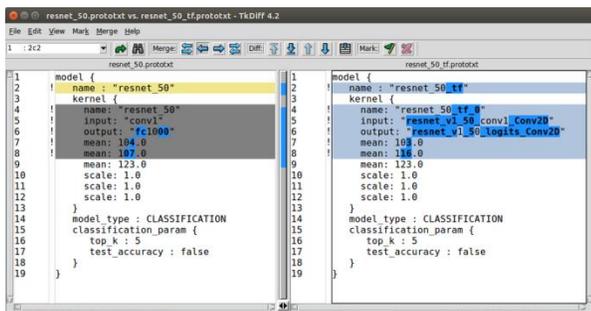


Fig. 5. Screen Shot of Tensorflow.

TABLE II. TESTING AND TRAINING DATASET

Image Category	Training	Test	Total
Spastic	89	44	133
Dyskinetic	54	25	79
Ataxic	26	17	43
Mixed	48	34	82
TOTAL	217	120	337

The training of the framed network was repeated for the available dataset until the loss function is minimized by adjusting the assumed weights[23] ,[25]. The training progress is continuously measured by mapping the training loss with the iterations. The number of images in each iteration is assumed to be twenty. The accuracy of each data set is also examined and plotted beside the loss function as indicated in Fig. 6.

This challenge is overcome by the concept of transfer learning. Here the weights used in training a smaller dataset is derived from any large dataset with an assumption that the required image features are shared among the two data sets.

##### C. Comparative Result Analysis

The research experiment included training and testing phase with each set running 150 epochs. The accuracy tends to increase in each training set and losses were lowered consequently. Classification of fMRI is absolutely different from training MR images with increased complexity due to three dimensional time series nature. The training session is focused with high accuracy level and eliminating the false data with the best chosen hyper parameters. Thus the CNN with three layer model and twice the length size have converged with highest accuracy of 66.8%

The performance of this algorithm can be analyzed by the confusion matrix shown in Table III. The image data set is categorized into five image groups comprising of twenty images in a group. The confusion matrix is useful in identifying the number of images classified properly as the type of cerebral palsy.

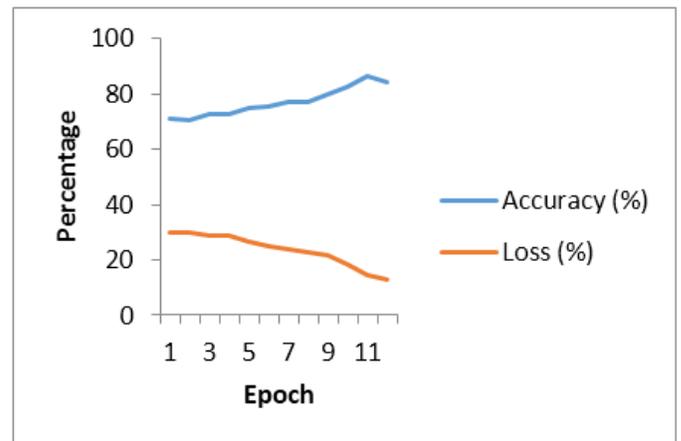


Fig. 6. Training and Validation Results.

TABLE III. CONFUSION MATRIX

Details	1	2	3
TP	12	16	11
FP	2	1	2
TN	3	2	3
FN	3	2	4
Accuracy	0.75	0.86	0.7

TP- True Positive, FP- False Positive, TN- true Negative, FN- False Negative

A true positive value ( $t_p$ ) is the total images which is affected with CP and correctly identified as an affected image by the algorithm. A true negative (TN) is the quantity of affected images which is not recognized by the algorithm. Similarly, false negative ( $f_n$ ) is the number of images which is not affected by the CP and identified by the algorithm correctly. False positive (fp) is the quantity of CP affected fMRI identified as not affected with CP by the algorithm. The performance of the algorithm for fMR images is measured using various parameters like precision, recall and accuracy. The precision value is calculated based on the ratio of the true positive (tp) to the addition of the true positive (tp) and false positive (fp) rates. Recall value is estimated based on the ratio of the true positive (tp) value to the addition of the true positive (tp) with the rates of false negative (fn). Accuracy is defined as the ratio of the addition of tn and tp to the addition of tn, tp, fn and fp.

$$Precision = t_p / (t_p + f_p) \quad (4)$$

$$Recall = t_p / (t_p + f_n) \quad (5)$$

$$Accuracy = (t_p + t_n) / (t_p + t_n + f_p + f_n) \quad (6)$$

The trained tensorflow network resulted in a final accuracy of 66.8% of the collected test data set. When the same test data set is classified by the radiologists the accuracy level was 62.4%.

The analysis of the fMRI of the cerebral palsy [25]affected infant is done using the deep learning algorithm and a sample is depicted in Fig. 7.

The experimental results were compared with GoogleNet, AlexNet and LeNet. The performance parameters like runtime, training loss, test accuracy and validation accuracy is recorded in Table IV.

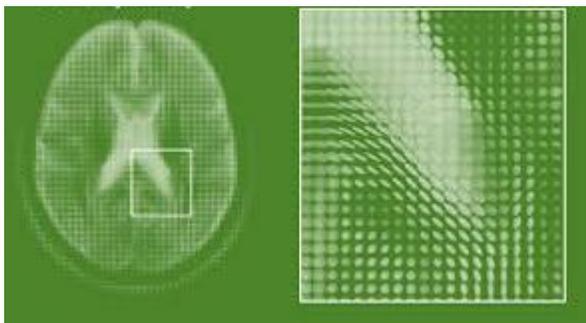


Fig. 7. Analysis of fMRI.

TABLE IV. COMPARATIVE ANALYSIS OF PERFORMANCE PARAMETERS WITH OTHER TECHNIQUES

Method	Runtime (sec)	Training Loss	Validation Accuracy %	Test Accuracy %
GoogleNet	1655	1.6	65	63
AlexNet	33466	1.4	74	70
LeNet	52470	1.51	53	55
Modified AlexNet (Proposed)	16728	0.82	80.4	78.6

It is evident from the experimental results that the classification algorithm for medical imaging analysis cannot be similar to the architecture used in natural image classification. Better accuracy in the classification of cerebral palsy is achieved by the modified AlexNet in terms of the number of convolution layers, normalization function for the local response, kernel size and stride rate.

## V. CONCLUSION

In this paper, we recommended a novel architecture of CNN based on AlexNet that incorporates five layers of convolution and layers of pooling stacked together for higher level of accuracy in the classification of the fMRI brain images of the cerebral palsy infants. The experimental results have vividly shown that deep learning network proposed in this paper presents with a higher level of precision and accuracy compared to other existing methods besides overcoming the high level of complexity due to the challenges in acquiring the fMRI of infants. However, the medical image data set was very limited due to privacy and other security reasons that increased the hunger of deep learning architecture. Even though the samples were limited the features considered were numerous that aided inappropriate classification of the cerebral palsy. This research shall be further extended in developing a network to classify the types further by considering the fMRI along with the oculomotor responses to improve the accuracy level still better.

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