Infant Brain MRI Abnormalities Detection Using Deep Learning

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Abstract
Magnetic Resonance Imaging (MRI) is considered as a critical tool for the medical investigation of brain. The defect of congenital brain has distinct set of symptoms and impairments which are difficult to identify and classify with the MRI images. Studies has revealed that the rate of women with the infants of abnormal brain in increasing at a high rate. Early identification of the symptoms can help in precise diagnosis of the brain defect and helps to carry out with the effective treatment plan. The literature survey has shown the segmentation of adult brain and not infants of month's year old. In this proposed system, steps of processes are proposed for infant brain classification which uses deep learning technique. The significant contribution of this proposed system is to diagnosis the defective brain at the early stage on the infant's brain development. The proposed system has four phase of pre- processing (filtering noise), enhancement, Feature extraction, CNN based segmentation and classification using the trained network. The constructed algorithm does the gray level conversion of the test image selected. In pre-processing stage, removal of noise takes place and it is followed by the image enhancement using Histogram equalization filter and IM filtering. Gray Level Co-Occurrence Matrix (GLCM) function extracts the feature from the filtered image output. Convolution Neural Network (CNN) does the classification, detection and the segmentation of the image using the trained datasets. The Deep learning based classification and segmentation can improve the prediction accuracy and reduce generalization errors. The all the test image results is updated in a web page with the time stamp using an IoT module for the accurate patience's survey reporting and other further future analysis. Our future work aims at transfer learning method in which the algorithm concentrates on automatically solving different problems from the knowledge gained while solving the previous set of problems and also improving the output efficiency using more disenable data sets.

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I. INTRODUCTION

Automated segmentation of fine detailing of an image shows a pivotal motion in the recent image processing techniques. Image processing is widely used in medical investigations, monitoring of the delicate internal organs and it's working like knowing several series of neuropathological

variations. Approximately 3 in 1000 pregnant women give birth to infants with different types of brain abnormalities. Out of which tumors are the regarded as the common brain abnormality that affects infants which develop due to the abnormal cell growth. The brain tumors in infants are termed as pediatric brain tumor. Primarily brain tumor begins when normal cells acquire errors in its DNA strands. These process errors are called as mutation. The mutation of the cells causes the cells to multiple at high rates. This will in turn continue to live even when healthy cells would die. Thus this accumulation results is a mass of abnormal cells, which is termed as tumor or cancer. There exists two types of pediatric brain tumor, where some are non cancerous cell growth (Benign) and while some are cancerous cell growth (Malignant).These can affect the functions of the nervous system depending of the location where the tumor evolves in the brain and also its growth rate. Treatment for brain tumor in infants is typically quite different from the treatment for adults. The proper treatment and the chances of recovery depends on the type of tumor, its location inside the brain, whether it has spread or not. The early and accurate determination and examination of the tumor cells type can facilitate in deciding the appropriate treatment in dealing with the abnormality to cure the cancer effectively.

Machine learning(ML) is an emerging popular filed in computer Science Engineering which has wide spread applications in many other major field like medical, electronics, industrial and automotive applications for automatic image processing pattern recognition and AI. Deep learning algorithms are inspired by the function and traits of the brain and so termed as Artificial Neural Networks. These algorithms are deployed for medical imaging and classifications to help physicians with clinical diagnosis. The brain structures and tissues have very minute variations which are difficult to trace out and our proposed system prevents human interventions based diagnostic errors.

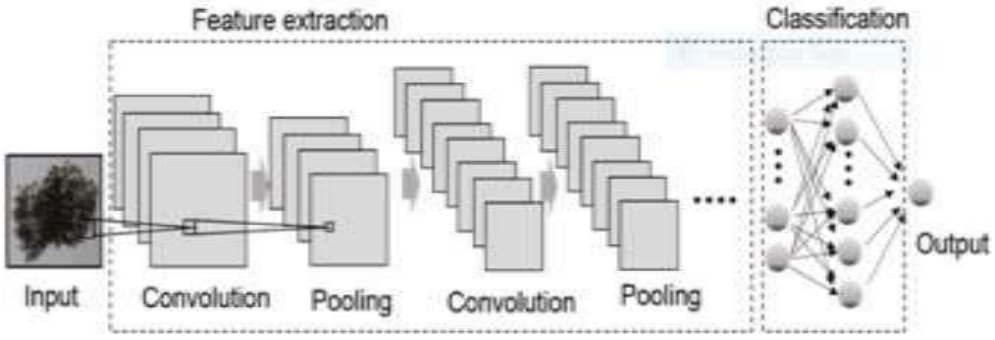
II. RELATED WORK

Many researchers have done their work using computer vision & image processing to detect malicious tumor in different organ of human body. In most cases, the development of an automatic learning model called deep learning has enabled the development of medical image analysis approaches that can exhibit remarkable accuracy rates. Manual identification of tumor presence inside the brain using MRI is highly challenging and needs more effort during examination. Manual diagnosis can lead to many human based diagnostic errors. Most of the existing works has its own challenges in handling the intensity in homogeneity and noise in the data. The analysis of the level of co-relation in the existing works has permitted to limit the features to only significant component which greatly affects the accuracy of the output. Most of the works does manual or semi automatic segmentation and identification of pathological tissues of brain using composite feature vectors comprising of wavelets and statistical parameters. The most classification stage is carried out by using Support Vector Machine and fuzzy c-means algorithms. Execution of these algorithm is complex, time consuming and requires high level of computation speed.

III. THEORITICAL BACKGROUND

Deep Learning algorithms are prompted by the structure and functional traits of the human brain called Artificial Neural Networks (ANNs). Artificial neutral network is a budding

technology which got its traces from the distributed chemical signal sending communication nodes in biological systems and information processing. Though the computer based ANNs were influenced by the brain activities, it its own differences from working of the biological brains. Deep Learning uses multiple layers called as nodes, which progressively extract the prominent higher level features from the raw input data given. Deep learning algorithms are framed in such a way that they exploit the unknown structure of the input distribution which in turn aids to provide us with good representations with the higher-level learned features extracted in terms of lower-level features provided.



IV. LITERATURE SURVEY

A. Generative Model for Image Segmentation Based on Label Fusion

Mert R. Sabuncu, B. T. Thomas Yeo, Koen Van Leemput, Bruce Fischl, and Polina Golland proposed label fusion algorithms can be compared in both practical and theoretical ways in the theoretical way the white matter cerebral cortex and the subcortical structure are separated manually and in the practical way the free surfer whole brain segmentation tool is used so in this way they are analyzed in both theoretical and practical ways.

B. Automatic Detection of Abnormal Brain Tissue in MR Image

Shuqian Luo and Jie Cai proposed an auto associative memory based technique which can automatically detect the abnormality of a tissue in MR images in this the MR image will be compared with the auto correlation of normal image vectors and in this way it can detect any abnormality. This method is a feasible technique for detecting abnormality in the MR image

C. Implementation Absolute Brain 1H-MRS Quantification Method

Matthieu Bagory, Francoise Durand-Dubief, Danielle Ibarrola, Jean-Christophe Comte, Francois Cotton, Christian Confavreux, and Dominique Sappey-Marinier proposed that the MRS will be used for measuring the cerebral metabolite so that it can help in characterizing the brain disease diagnosis. metabolite concentration qualification will be based on metabolite ratio referring to creatinine. If the metabolite concentration was assumed to be constant it may vary in pathological process. So, absolute concentration methodology is used.

D. Brain Tissues Extraction Based on Improved Brain Extraction Tool Algorithm

Jiaqing Qiu, Wenqiang Cheng proposed a paper a paper with a framework of BET which is an useful tool for segmenting brain tissue from MRI. The deformable model is used which fits to the brain surface by a set of model forces. The method is fast and it has more precision in segmentation. The accuracy was low in this method due to the problems in the BET algorithm.

V. PROPOSED ARCHITECTURE

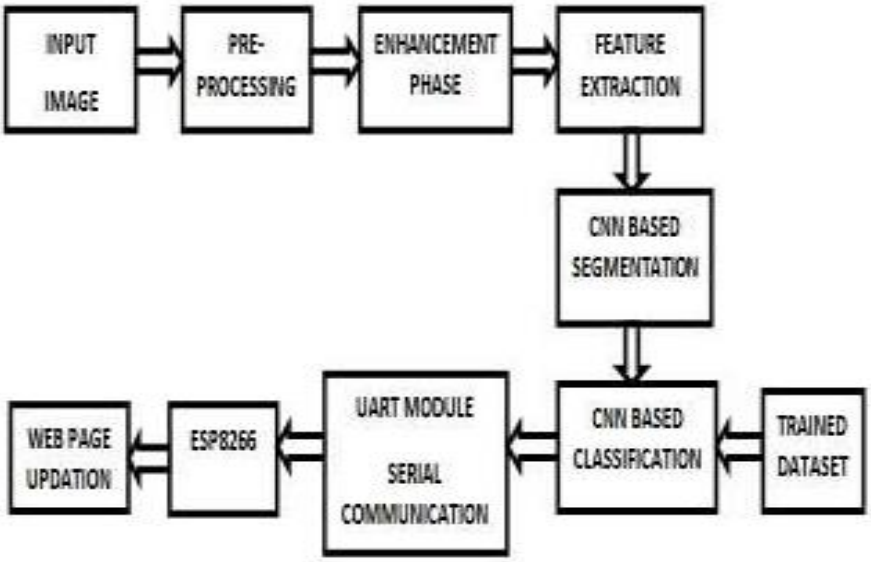


Fig. 1. Proposed system in Block diagram..

VI. PROPOSED SYSTEM

In general manual examination of the defects in the human brain is challenging and time consuming.

In this system an efficient technique has been presented for the categorization of the infant brain abnormalities. The section presents the technique that uses in developing an algorithm that uses Deep Learning Convolution Neutral Network (CNN) model to classify the tumor in infant brain as Normal, Benign or Malignant. The proposed system mainly consists of 6 major phases – Pre-processing, enhancement, Feature Extraction, Segmentation, classification and instant web page updation using IoT technology through UART serial communication and WiFi module. The main advantageous part of this system is that the image segmentation and Classification is done based on CNN, so that the segmentation does not require human intervention and expertise. The segments of the image are feeded as the inputs to the CNN network in the segmentation stage, which them labels out the pixels. The system is totally automatic and the processing time is very less but accurate. It throws out the output within a couple of minutes once the test image is selected. The system is user friendly and updates the result in a separate webpage along with the accurate time stamp which can be highly beneficial in remote monitoring and analysis of the tumor in different stages.

VII. WORKING

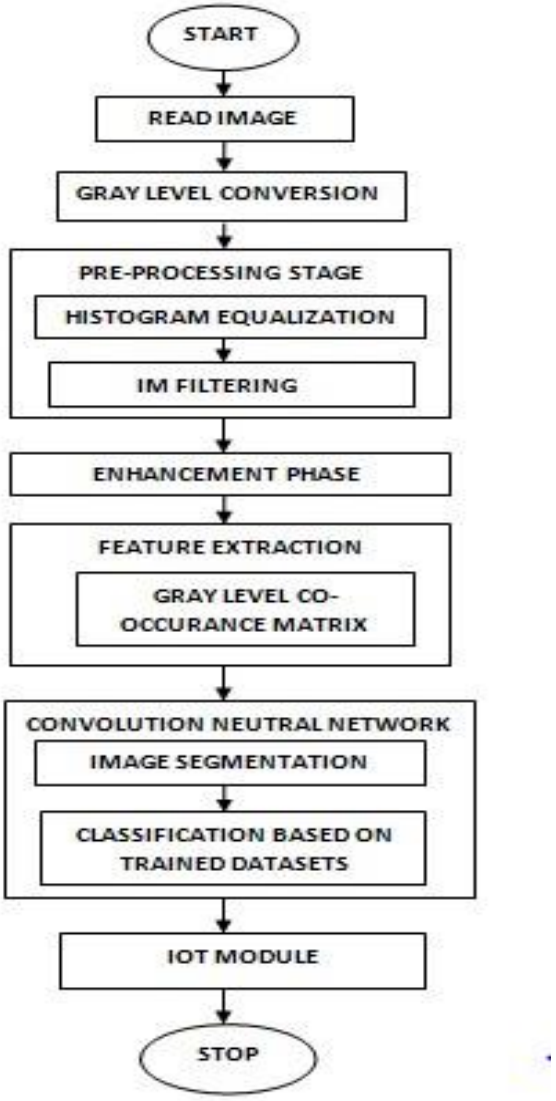


Fig. 2. Flow chart explaining the process steps.

VIII. WORKING METHODOLOGY

A. DATA ACQUISTION AND INPUT TEST IMAGE

The efficiency of the output is governed by the selection of precise and unique set of data sets (image). The datasets are very important in the deep learning prediction process, the more and precise the datasets, the more accurate the output of the neural network will be. The number of datasets (training images) forms the different layers of the Convolution Neural Network (CNN). The proposed network was trained using 600 MRI Images (300 each for malignant and Begin). The proposed algorithm is tested with 50 input test MRI images of the infant brain.

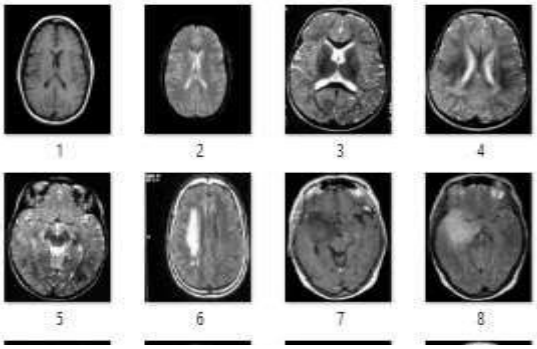


Fig. 3. Infant Brain MRI Test images for experimenting the proposed algorithm.

B. PREPROCESSING OF THE INPUT IMAGE

The improvement of the image (data) is dole out by pre-processing either by suppressing the unwilling distortions or enhancing some image options necessary for more process, though geometric transformations of pictures such as rotation, scaling, and translation are classified among pre-processing strategies here since similar techniques are used.

a) GREY LEVEL TRANSFORMATION

Grayscale or greyscale image is one within which the worth of every pixel may be a single sample representing solely associate degree quantity of light intensity, (i.e.,) it carries solely intensity data. Grayscale pictures, a form of black-and-white or grey monochrome, are composed completely of reminder grey. The distinction ranges from black at the weakest intensity to white at the strongest.

At the opposite finish of the dimensions, a dark image could have high distinction if the background is considerably totally different from the individual objects at intervals the image, or if separate areas at intervals the image have terribly totally different reflection factor properties.

C. ENHANCEMENT PHASE

Image improvement or enhancement is that the method of adjusting digital pictures in order that the results are additional appropriate for exibit or additional image analysis. as an example, you'll take away noise, sharpen, or brighten an image, creating it easier to spot key features. The aim of image improvement is to boost the interpretability or perception of data in pictures for human viewers, or to supply `better' input for different automatic image process techniques

a) HISTOGRAM EQUALIZATION Histogram effort is a digital image process technique wont to improve distinction in images. It accomplishes this by effectively spreading out the foremost frequent intensity values, i.e. stretching out the intensity vary of the image. This technique typically increases the worldwide distinction of images once its usable information is diagrammatical by close distinction values. this permits for areas of lower native distinction to realize the next distinction. the method of adjusting intensity values are often done mechanically by exploitation bar chart equalisation. bar chart

effort involves reworking the intensity values so the bar chart of the output image roughly matches such a bar chart. By default, the bar chart effort perform, histeq, tries to match a flat bar chart with sixty four bits, however you'll be able to specify a unique bar chart instead.

b) FILTERING

In signal processing, a filter may be a device or method that removes some unwanted parts or options from an image. Filtering may be a category of signal processing, the process feature of filters being the entire or partial suppression of some facet of the signal. Most often, this implies removing some frequencies or frequency bands. Filtering may be a neighborhood operation, during which the worth of any given picture element within the output image is set by applying some algorithmic rule to the values of the picture elements within the neighborhood of the corresponding input pixel. A pixel's neighborhood is a few set of pixels, outlined by their locations relative picture element.

*D. **FEATURE EXTRACTION***

In machine learning, pattern recognition and in image processing, feature extraction starts from an associate initial set of measured information and builds derived values (features)intended to be informative and non-redundant, facilitating the following learning and generalization steps, and in some cases resulting in higher human interpretations. Feature extraction is said to spatiality reduction.When the input data to associate formula is simply too massive to be processed and it's suspected to be redundant (e.g. an equivalent measuring in each feet and meters, or the repetitiousness of pictures given as pixels), then it will be remodeled into a reduced set of options (also named a feature vector). Determinative a set of the initial features is named feature choice. the chosen options ar expected to contain the relevant data from the input data, so the specified task will be performed by mistreatment this reduced illustration rather than the whole initial knowledge. Feature extraction involves reducing the quantity of resources needed to explain an outsized set of knowledge. once playacting analysis of complicated knowledge one in all the most important issues stems from the quantity of variables concerned. Analysis with an outsized variety of variables usually needs an outsized quantity of memory and computation power, conjointly it should cause a classification formula to over fit coaching samples and generalize poorly to new samples. Feature extraction may be a general term for strategies of constructing combos of the variables to induce around these issues whereas still describing the info with decent accuracy.

a) GREY LEVEL CO – OCCURRENCE MATRIX

A method of examining texture that considers the abstraction relationship of pixels is the gray-level co-occurrence matrix (GLCM), collectively spoken because the gray-level abstraction dependence matrix. The GLCM functions characterize the texture of an image by scheming but usually pairs of pixels with specific values and during a mounted abstraction relationship occur in a picture, creating a GLCM, then extracting applied math measures from this matrix. (The texture filter functions, delineated in Calculate applied mathematics Measures of Texture cannot supply information concerning type, that is, the abstraction relationships of pixels in a image.) GLCM could also be created by exploitation gray co-matrix and it'll derive several statistics from them mistreatment Graycoprops. These statistics supply information concerning the texture of an image. The subsequent table lists the statistics.

Statistic	Description
Contrast	Measures the local variations in the gray-level co-occurrence matrix
Correlation	Measures the joint probability occurrence of the specified pixel pairs.
Energy	Provides the sum of squared element in GLCM. It can be also known as angular second moment or uniformity.
Homogenity	Measures the closeness of distribution of elements of GLCM in the GLCM diagonal.

Fig. 4. Statistics Of GLCM.

E. CNN BASED SEGMENTATION

Many pc vision tasks need intelligent segmentation of an image, to grasp what's within the image and alter easier analysis of every half. Today's image segmentation techniques use models of deep learning for pc vision to grasp, at a grade out of the question solely a decade past, precisely that real-world object is portrayed by every constituent of a picture. Deep learning will learn patterns in visual inputs so as to predict object categories that form up a picture. the most deep learning design used for image process may be a Convolutional Neural Network (CNN).Image segmentation may be a vital method in pc vision. It involves dividing a visible input into segments to change image analysis. Image segmentation with CNN involves feeding segments of a picture as input to a convolutional neural network, that labels the pixels. The CNN cannot method the total image right away. It scans the image, viewing atiny low "filter" of many pixels whenever till it's mapped the whole image.

F. CLASSIFICATION USING CNN

The convolutional neural network (CNN) may be a category of deep learning neural networks. CNNs have an associate input layer, and output layer, and hidden layers. The hidden layers typically incorporates convolutional layers, ReLU layers, pooling layers, and fully connected layers

Convolutional layers apply a convolution operation to the input. This passes the data on to following layer.

- Pooling combines the outputs of clusters of nerve cells into one neuron within the next layer.
- Fully connected layers connect each nerve cell in one layer to each nerve cell within the next layer.

In a convolutional layer, neurons solely receive input from a subarea of the previous layer. during a absolutely connected layer, every nerve cell receives input from each part of the previous layer.A CNN works by extracting options from pictures. This eliminates the necessity for manual feature extraction. The options don't seem to be trained! They're learned whereas the network trains on a collection of pictures. This makes deep learning models very correct for pc vision tasks. CNNs learn feature detection through tens or many hidden layers. every layer will increase the quality of the learned options.

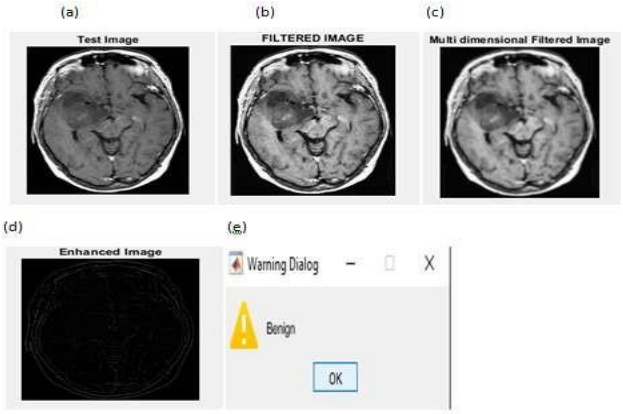


Fig. 5. Steps in the implementation of the proposed algorithm .

(a) Test image. (b) Filtered image after histogram equalization. (c) Multi-dimensional filtered image after IM Filtering. (d) Enhancement output. (e) Output after CNN Classification.

G. INTERFACING OF IOT MODULE

The result obtained from the algorithm is updated in an webpage for future references. The RC 232 connector and IC MAX 232 establish serial communication between PC and microcontroller. Connection is given between the ground and Vcc of the IC MAX 232 and ESP8266 IoT module which updates the data to the webpage through WiFi communication.

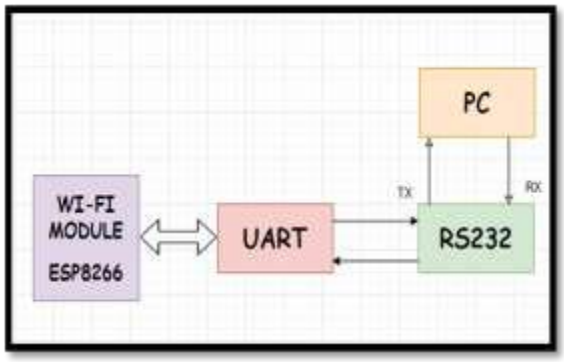


Fig. 6. Interfacing Architecture

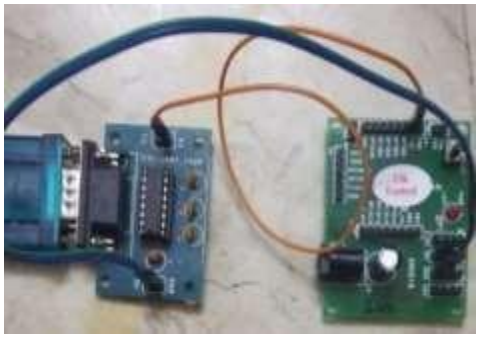


Fig. 7. Hardware IoT Modules for Data Transfer

IX. RESULT AND DISCUSSION

In this proposed paper, a methodology has been provided for infant Brain MRI detection which effectively uses Deep learning classification techniques. The proposed network was trained using 600 MRI images (300 each for malignant and benign). The result of the system along with the accurate time stamp is automatically updated in the webpage for remote monitoring using an IoT module which uses ESP8266 WiFi for Data transferring.

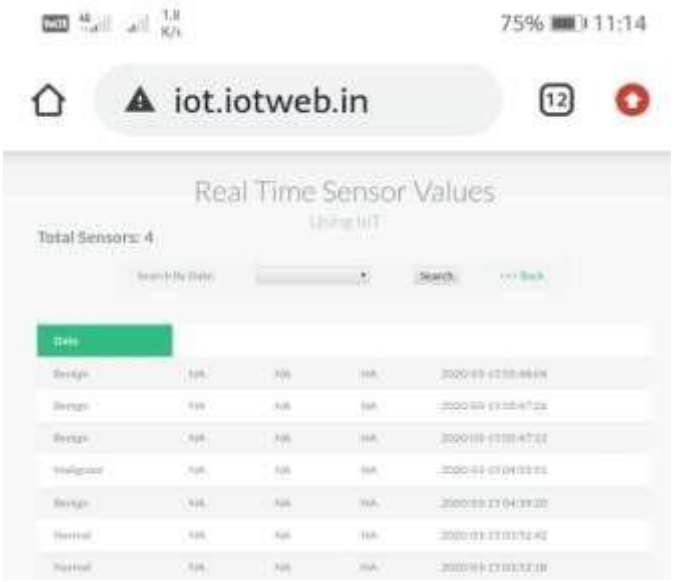


Fig. 8. Results updated in the webpage

The performance of this classification method can be measured by calculating its Accuracy (Acc) and Precision (Pre). For evaluating the classification Model using the metrics derived outcomes of the model needs to be considered. We include three outcomes termed as True Positive (TP), False Negative (FN) and False Positive (FP), as shown in the TABLE 1.
TP is an outcome value where the model accurately predicts the class – Positive. FP is an outcome value where the model incorrectly predicts the class- Positive and FN incorrectly predicts the class- Negative.

TABLE I. CALCULATION OF ACCURACY AND PRECISION FROM THE OUTCOME

Outcome Of the	Values Of the
TP	74
FP	4
FN	8

We consider two metrics for analyzing the performance of this model. Accuracy (Acc) is one metric widely used for evaluating the models used for classification. Informally, Acc is the fraction of predictions, which our model got right. Pre is another metric which refers to the closeness between the two or more measurements to each other.

$$Accuracy(Acc) = \left(\frac{TP}{TP + FN}\right) * 100 \quad (1) \qquad Precision(Pre) = \left(\frac{TP}{TP + FP}\right) * 100 \quad (2)$$

TABLE II. CNN ACCURACY RESULT OF OUR PROPOSED SYSTEM COMPARED WITH THE EXISTING METHODS

METHODS	ACCURACY *(Acc)*		PRECISION *(Pre)*
	SVM	CNN	
EXISTING	83.3%	86.4%	90.921 %
PROPOSED	90.361 %		94.936 %

From the results calculated from the table 2, our proposed system has better accuracy ***(Acc)*** and precision ***(Pre)*** values. The accuracy is achieved to 90.3 % (90 correct predictions out of
100 total examples) which is high compared to the other existing methods of SVM and CNN which is 83.3% and 86.4% respectively. Our model reaches a precision of 94.9% in other words when it predicts a tumor, it is correct the time 90 of the time.

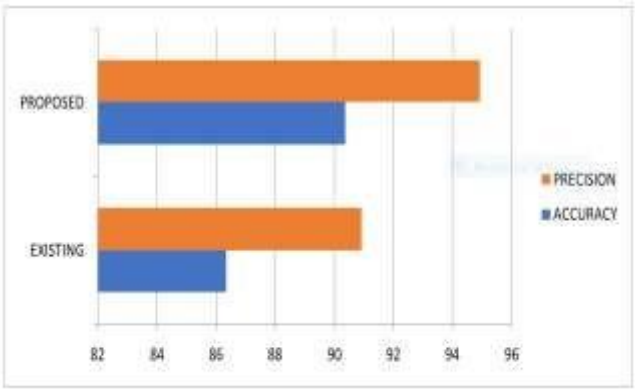


Fig. 8. Graph comparing the efficiency of the existing and proposed system.

X. CONCLUSION

An efficient method for categorizing and detection of brain abnormalities in infants has been proposed. The major contribution of this proposed paper is the CNN based segmentation and classification which is a well-established deep learning technology. The method has achieved high rate of accuracy and efficiency using simple implementation and low computational cost. The

working efficiency of our method has been compared with the other methods of segmentation and classification. The results displayed that this method of categorization outperform most of the other existing methods of classification and the results are promising. The future work will be focusing on the performance of the algorithm by increasing the more unique datasets and making the network transfer learning which is self learns by storing the knowledge acquired by solving previous problems which automatically deepens the layers of the neural network.

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