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AN INTEGRATED DEEP AUTO-ENCODER BASED 3D-CNN ARCHITECTURE TO ANALYSE BRAIN FUNCTIONAL UNITS IN DETECTING PREMATURE STAGE OF ALZHEIMER'S DISEASE

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ABSTRACT: Current generation research in neural networks has evidenced the wide usage of deep auto encoders for the diagnosis of brain functional networks in the context of feature extraction and dimensionality reduction. Diagnosing Alzheimer's disease in the very mild cognitive impairment stage is considered as a challenging task in the context of neuroimaging research. Despite several research studies, it is evidenced that still there is lose in time varying information of the feature aggregation matrix while analysing the matters in the gray and white matters in the brain. Addressing this problem this article presents an integrated Deep Auto-Encoder Based 3D-CNN Architecture to Analyse Brain Functional Units in Detecting Premature Stage of Alzheimer's disease. The simulation results depict the functional cognitive status of normal and very mild cognitive impairment subjects that helps in the early diagnosis of Alzheimer's disease.

KEYWORDS: Alzheimer's disease, Deep Neural networks, Auto encoders, Cognitive impairment, 3D-CNN

I. INTRODUCTION

Very Mild Cognitive Impairment (VMCI) relates to an improved risk of progression to possibly Alzheimer's disease (AZD) diagnosis. Progression rates vary in the context of some Individuals with VMCI are increasingly deteriorating; some remain stable for years, and some return to normal cognitive function. Enhanced predictability in patients with an imminent decrease risk. VMCI may aid in the efficiency of large-scale clinical trials and as aggressive for individual patient risk stratification would become increasingly necessary in the development of a new treatment that enhances the metrics for quantitative neuroimaging.

The term Dementia refers to the loss of memory for people after a certain age that is considered as the most common dementia type. Gunawardena et al . [1] clarified the impact of Alzheimer's disease on brain tissue collapse, which inevitably causes failure to an individual's memory. An individual loses himself as a result. Capability to accomplish daily tasks—the studies from Sahyoun et al.[2] have reported that Alzheimer's disease is considered as the world's sixth-largest cause of death by the World Health Organization (WHO). Steenland et al. in 1991 and Mortimer et al. in 2009. [4] has shown that about 5.7 million have been identified. American people have the disease of Alzheimer's. In 2018, the group of the Alzheimer researchers [5] predicted that the number of individuals in the United States with Alzheimer's cultivate up to 13.8 million by 2050. Brain damage can start in some cases where the Clinical symptoms even before they occur. Therefore, the treatment for treating Dementia is to be done at the preliminary stages. The symptoms demonstrated by the affected persons mostly include the declination of the cognitive functions that significantly affect their lifestyle and regular habitat.

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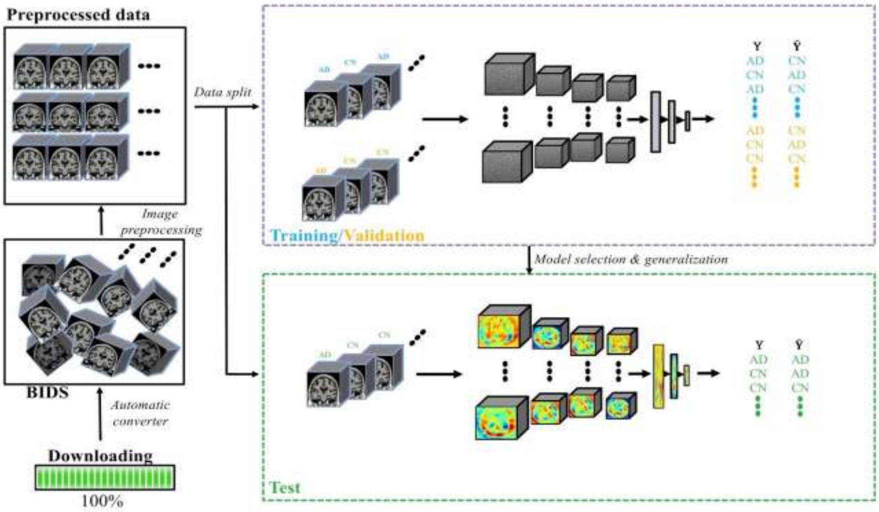

Figure 1. Generalized architecture for CNN based Neuroimaging

Few evidential pieces of research indicated the cost of people reporting AZD along with Dementia would be around 2.5 trillion by 2030 [3]. Henceforth design and development of the premature interventional strategies that aids and individual and a medical professional in the context of diagnosing, preventing and restrict the progressive symptoms related to Dementia are considered as a significant facet of research in the field of medical image processing as well as the clinical science research paradigms. MRI is considered as a primary modality for the diagnosis of VMCI and AZD in recent years [6]. During the process of the clinical analysis of the AZD, the MRI mode of diagnosing has depicted relatively satisfactory outcomes in terms of Classification of the MRI image from average to AZD. Despite in many cases of the clinical analysis, it is evidenced that MRI subsequently produces the insensitive outcomes during the analysis timeframe between the normal controls and the VMCI phase as depicted in figure 2. It is observed that the MRI image features of the AZD and VMCI are appeared to be relatively similar to each other the traditional image classifiers will not be able to analyze and classify the image features of the different age groups during two stages of AZD. Therefore, the main objective of the current study is to investigate and evaluate the prominence of applying Artificial intelligence and deep learning algorithms to address the limitation that is inferred from the pathological distinction that is involved across the various stages of AZD.

The main objective of this study is to develop an auto encoder integrated 3D CNN mechanism to identify the classification of brain functional units in the context of early diagnosis of AZD.The rest of the paper is organized as in section 2 study of various research articles related to deep auto encoders and 3D CNN are summarized, section 3 includes Integrated deep auto encoder model along with 3D CNN, section 4 includes the experimental analysis of the proposed method and section 5 details about the conclusion and future work along with the limitation of the proposed framework.

II. LITERATURE STUDY

A ton of study that is apparent in literature has sought a brief description of the brain's systemic MRIs AZD, slight cognitive disability, or regular examination [12-14]. Included VBM (voxel-based) most recent and previous methods. The predictive medical imaging application is also used [15] Class. It allows the study of variations in local grey and white matter concentrations. Forms details in Ref. [16] Sphere harmonic shape (SH) has been used as supporting characteristics Classification of the vector machine (SVM). Statistical models in Ref. [17] The heterogeneity of hippocampal modes was used to model (SSMs) between the people. The diagnosis of AZD was thus focused on photographs For the hippocampus study primarily. Cf. [18] writers may show the CSF quantity, and MRI biomarkers combination Give more robust forecasts, particularly for AZD versus MRI alone or CSF. Papers on the analysis discussed here are also available explained in three sections: AZD content-dependent image retrieval, AZD Segmentation and 3D Convolutional Neural Network, CapsNet Classification strategy for AZD.

Few papers are eligible for AD as an ongoing study subject using MRI static photos identification and image recovery CBIR, for sure. CBIR applications of medical science capacities The area is indeed doubtful and a big obstacle for science. The explanation is linked to the precise existence and subtlety of medical photos

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Modifications involving identification and analysis of this [19]. The key goal is to find a strong image of the Quality of the picture by using extraction techniques Properly reflect scientifically essential knowledge. It is afterwards allow the use of CBIR medical systems more relevant, more effective and relevant scientifically. A neural network was a multi-class network Ref. [20] marker to identify numerous AZD actions. At the first time. This, numerous methods exposing the shape and contour have been used extracted from MRI scans of the hippocampus area Used brain back regions to verify AZD [21] length. A multi-species. Technology[22] enabling experimental versatility Accuracy of 82.45 percent has different characteristics, including grouping, reviews, distribution, and rating. The Functionality is Input description not only contained the phases number Disease, but also led to a rating change.

In an earlier work, Several classifiers to be included in the identification and were tested AZD progression estimation, utilizing RIM photography, with the development of a More stable CBIR [23,24] method. The SVM was used for the early diagnosis of Dementia and Alzheimer's Stages by the application of biomarker brain function [23,24]. Three were included Sectional pictures cross-section, hippocampus, co-axial to the aspects of the cortex to classify From AZD. The outcome precision of this methodology amounted to 90.65%[21]. Deep learning algorithms were able to learn those depictions Data from CNN, in particular[28]. Another study recently carried out[22] The usage of deep CNNs for problems was investigated and used CAD in the world of pharmacy.

Multivariate model review is very widely used brain functional state extraction process (Dimitriadis et al. Nishida et al 2013). 2013. These methods of study are typically paired with algorithms for dimension reduction, such as clustering and dictionary education (DL), to address improvements in practical linkage during time series (Cao et al . 2019; Li et al. 2017). time period. Erik et al. Erik et al. (2015) suggested procedure for the assessment of functional magnetic resonance imaging (fMRI) of time-variable communication and used it for interactive dynamic analysis Normal individual networks and individuals with Schizophrenia. Li et al . (2014) used a DL and sparse mix Job Condition coding to examine PostTraumatic Stress Disorder (PTSD) Functional Connectomes in patients. Ouet al . (2014) derive and introduce hierarchical clustering of complex functional interface patterns it for the Mind Defcit Condition analysis (ADHD). Independent Part Bassettet.al (2011). Functional network dimensional analysis (ICA) Analyze their diverse functions. In the past years, the state of the brain activity is slowly getting hot EMCI testing sites. There is, still, no definite Conclusion on the main brain activity network Responsive state and efficient social contact this networks also have unexplained complex characteristics

CifarNet[30] has numerous types of dilemma teaching. Lymph nodules identification or recognition and different lung forms CT photos illnesses. You may increase the data collection Significantly, since they used implants instead of complete preparation pictures. They assumed that transfer learning was considerably carried out Higher than scratch testing [11] and Google Net more frequently than not Architecture has been seen as successful as a more dynamic network Capable of possessing secret data structure. There were plenty, too. Works on Alzheimer recognition utilizing neural networks. In res. In sec. [12], [16] [19] The writers used a packed AD / MCI auto-encoder Precise findings of up to 87.07% and 92.34% CapsNets have been established recently as a effective way to conquer The CNN [6] boundaries. The architecture of the 3D-CNN networks The human visual system functions encouraged. It's sort of Including classical neural networks primarily specifically built on the High-level picture extraction characteristics foundation. A recent research has applied the concept of CapsNet and analyzed numerous model effects variations from lining up to adjusting capsule layers Parameters and hyperparameters [14]. Experiments were done with reference [15] CapsNet and the writers have announced that CapsNet has been effective CNNs for the naming of brain tumors. They created an illustration

III. PROPOSED METHOD

3.1 Architecture of Deep Auto Encoder:

Deep learning integrated auto encoder framework is designed and developed in the context of learning deep neural network models for effective detection of WannaCry ransomware in IoT devices. Encoder runs automatically on the unsupervised model by which it understands and builds the input. In general complex data designed via deep learning methods are better than original data in the fields of speech recognition and computer vision. An auto encoder consists of three layers which are encoder layer, hidden layer and decoder layer. Any information through input layer comes out from encoder layer same is with decoder layer and hidden layer consecutively. Decoder and Encoder works together for a function as autoencoder with a mirrored architecture followed with a function mapping from $K^d \to K^d$ Output function.

$x = f(y) = \sigma(R * y + a)$……. (1)

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with a input variables y in relation with $\partial = (R, a)$. The defined function is Relu. When the defined function is compared with Relu it removes the unnecessary predefined values by keeping the model dislocated. (Lecun et al. 1998; Huang et al. 2017). Intention of auto encoder is to optimize the following function.

$\partial, \partial' = \min_{\partial,\partial'} \sum_{j=1}^{e} L(y, z)$ ……………(2)

By which the input layer can be organized by hidden ayer. We infer from Autoencoder method to excerpt information of training data from many available hidden layers. Autoencoder is even used for classification of widely used smartphone application.In Autoencoder model we have one encoding layer, two hidden layer, and one classification layer that infer from Figure 1. Detection of malware is possible with the function soft max applied on the classification layer function and obtained training data.

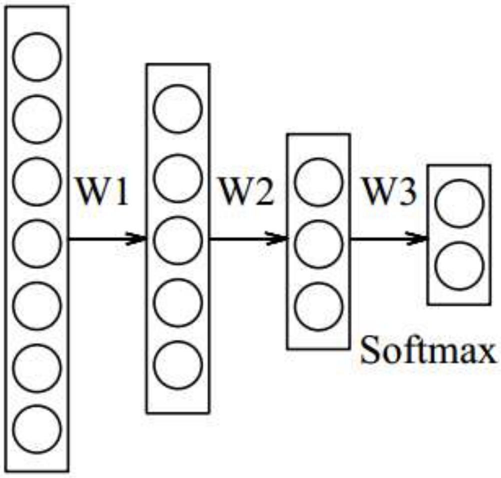

Figure 2: Layerd Autoencoder Mechanism using Softmax

3.2 CNN with different architectures:

The Slight variant of convolution neural networks i.e., CNN-S is depicted in Figure 2.There is a differentiation with CNN for CNN-S it is defined below.

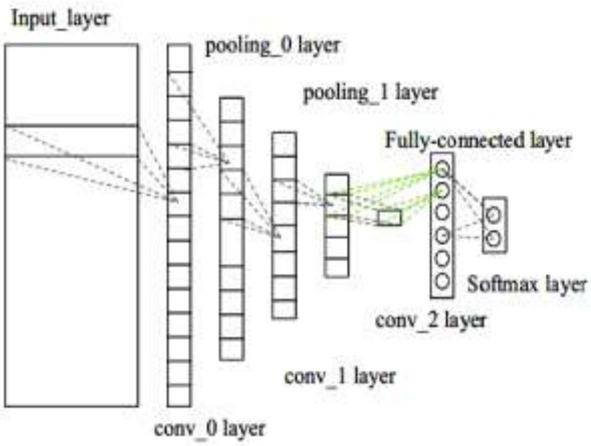

Figure 3: CNN-S architecture

All the distilled features of the input data from the application is for the Convolution layer. Length of an IoT devices is considered as

$x_i = f(R * y_{i:i+n-1} + a)$ ……………. (3)

In this $f(y) = \max(0, y)$ is considered as a Relu function with characteristics of non linear model .Condition $R \in W^{n*l}$ is used to excerpt a feature map
$y \in W^{(m-n+1)*1}$ for the features $\{y_{1:n}, y_{1:n+1}, \dots \dots . . y_{n-m+1:n}\}$…………… (4)

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In this f(y) = max (0, y) is a non linear function Relu which is biased with $a \in W$.The highest value $X = \max(x)$ is obtained from maxpooling layer to obtain the important features and reduce the dimension of the map obtained.With max pooling layer in between two layers CNN -S model is constructed. Each layer has a Relu function which acts as activation. Accuracy of CNN increases due to the small and non zero gradient. CNN-S is different from the original one based on the extraction between second pooling layer and third pooling layer which results with maximum redundancy. All neurons are interlinked completely in all previous layer. Later on we add dropout layer to fully connected layer to ensure no redundancy in the hidden neurons. The neurons which are expelled do not contribute in forward pass while in backward propagation neurons which are constant participate which ensures layer is built without any adaptation. Results exhibit overfitting when considered the non redundant neurons.

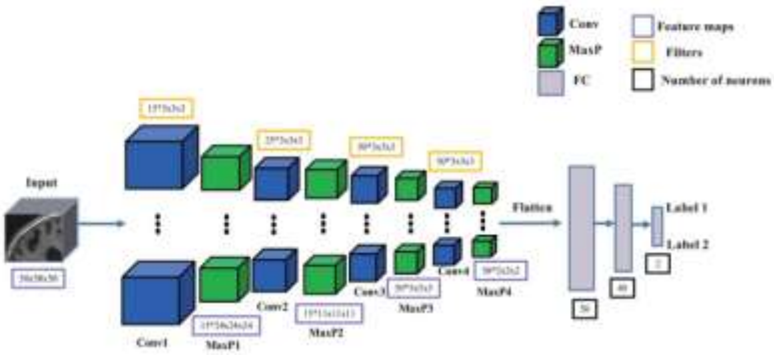

Figure 4. ROI- based 3D CNN architecture

Probability distribution over the layers is achieved when SoftMax layer is considered for the work in CNN- S model.When three windows with different sizes distills the multiple features it is a CNN-P architecture which is depicted in the figure 3.

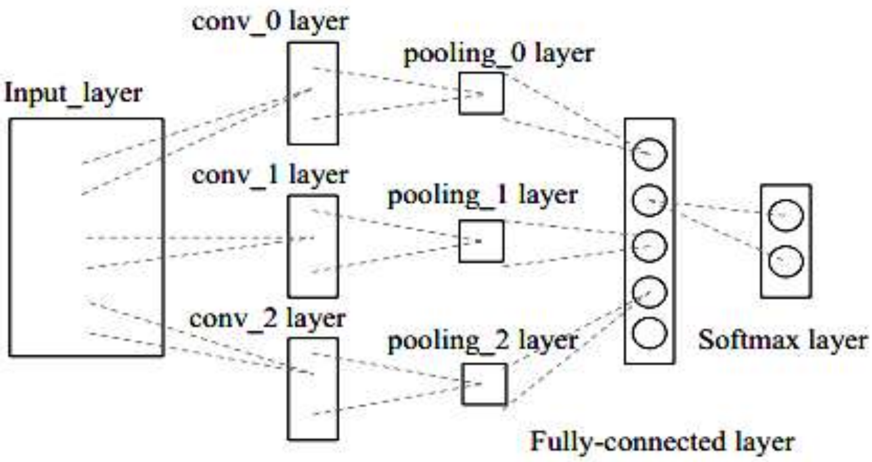

Figure 5: P-CNN Fully Connected Network

CNN-P model is the above features in distilling. As penultimate layer is constructed based on the defined features all are inherited to form a complete connected network. In the proposed models actual and network output has least error between them and they are reverted back in optimized manner. Later weights associated with CNN are adjusted.

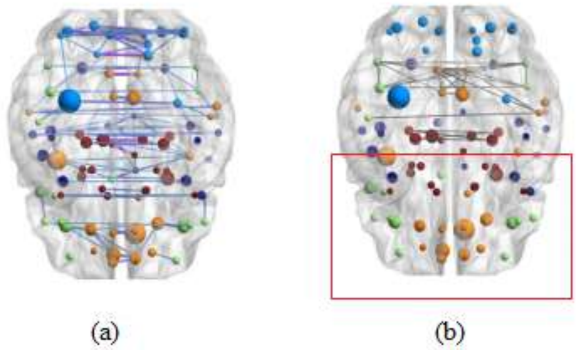

Figure 6: Auto-encoder based visualization for (a) normal brain functional unit (b) VMCI

Time complexity is the measured with model's training and testing time. When the complexity associated with time is high greater efforts has to be put in order to achieve the desired result . Due to which prediction and evaluation of a model takes a great effort .Time complexity in a model is affected due to input and output of channels, sizes of maps and kernel in a convolutional layer. Let us assume that the depth of the convolutional layer is E and T as the naming factor aligned in the convolutional network. K_p and M_p are the sizes of the kernel and feature maps respectively further Ci and Co denotes the input and output channels for communication finally the time complexity is computed as

$$Time \cong O\left(\sum_{T}^{E} M_p^2 * K_p^2 * C_{t-1} * C_t\right)$$

Time complexity gradually decreases with the dimensionality reduction of the above equation.

IV. RESULTS AND ANALYSIS

Our analysis incorporates evidence from three public datasets: the Neuroimaging program for Alzheimer's disease. The AIBL research and the Open Access Collection of the Australian Neuroscience, Biomarker and Lifestyle Tests. (ADNI) Studies in Photography (OASIS). Ses data sets are listed in eMethod 4 in addition. The T1w MRI was used. In both of these experiments, they are available. We will see comprehensive MRI protocols (Samper-González et al. 2018). Our studies have 1500 ADNI data sets for which a T1w MR picture is used. At least one visit had been possible. Conversion of the data sets obtained into a standard data structure is considered as a major task during the implementation.

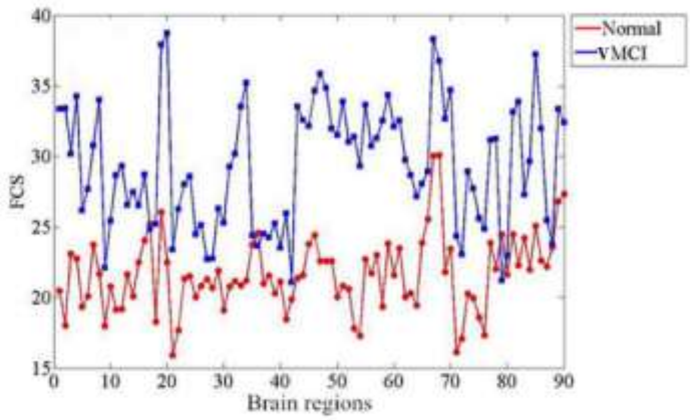

Figure 7. Functional cognitive analysis of Normal and VMCI patients

In theory, the capacity of CNNs to remove automatically requires just minimum preprocessing functions on medium to high standard. In AD, however, where data sets are minimal and therefore profound It is not obvious that networks may be hard to train, that they will gain from a larger network Preprocessing. In comparison, previous experiments used different preprocessing techniques but without them. Assessment of their effects routinely. So we contrasted two separate pictures in the current analysis Procedures for preprocessing: the

"Minimal" protocol and the more detailed. Both approaches contained racism Correction of field and rescaling (optional) pressure. The "Minimal" procedure was also a linear method The "Extensive" entailed non-linear registration and skull-strip registration. The functional cognitive strength between the normal and VMCI subjects are denoted in the figure 7.

BrainNet Viewer (https:/www.nitrc) in Matlab R2012a, Normal and VMCI (Jiao et al. 2018) are now shown in the.org/projects/bnv/) toolkit. There are a lot of individuals Full CFN relations and results are not Obviously they 're all visualized after that. That is why just the first 200 maximum association practical relations As seen in Fig 7. It is difficult to locate no apparent distinction between Normal was noticed VMCI and The important functional partnerships are largely stable and localized which demonstrates strong internal DMN coupling network.

V. CONCLUSION

The studies in this article present an integrated Deep Auto-Encoder Based 3D-CNN Architecture to Analyse Brain Functional Units in Detecting Premature Stage of Alzheimer's disease. Specific to this context, this research presents an integrated architecture of deep auto encoder in which a ROI-based 3D CNN is utilized for the purpose of extracting the grey and white matters in the brain for the functional analysis. Further, on analysing the ADNI data set related 1500 patients the simulation studies depicted the the functional cognitive status of normal and very mild cognitive impairment subjects that helps in the early diagnosis of Alzheimer's disease. Although the test results have shown the effectiveness of this method, certain considerations such as amount of network strata, secret matrix measurements and training parameters affect the reduction in dimensional characteristics and need more study. The experimental findings have been checked. In the meantime, it is worth further researching the robustness of this treatment in relation to derived features and its applicability to other brain disorders.

VI. REFERENCES

[1] J. P. Amezquita-Sanchez, N. Mammone, F. C. Morabito, S. Marino and H. Adeli, A novel methodology for automated differential diagnosis of mild cognitive impairment and the Alzheimer's disease using EEG signals, *J. Neurosci. Methods* **322** (2019) 88–95.

[2] Y. Sun, Z. Dai, Y. Li, C. Sheng, H. Li, X. Wang, X. Chen, Y. He and Y. Han, Subjective cognitive decline: Mapping functional and structural brain changes — A combined resting-state functional and structural MR imaging study, *Radiology* **281** (2016) 185.

[3] Y. Li, M. Mandal, S.N. Ahmed, Fully automated segmentation of corpus callosum in midsagittal brain MRIs, in: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2013, https://doi.org/10.1109/EMBC.2013.6610698.

[4] R. Duara, D.A. Loewenstein, E. Potter, J. Appel, M.T. Greig, R. Urs, Q. Shen, A. Raj, B. Small, W. Barker, E. Schofield, Y. Wu, H. Potter, Medial temporal lobe atrophy on MRI scans and the diagnosis of Alzheimer disease, Neurology (2008) http://dx.doi.org/10.1212/01.wnl.0000336925.79704.9f

[5] Yue Li, Huiquan Wang, Nizam Ahmed, Mrinal Mandal, Automated corpus callosum segmentation in midsagittal brain MR images, ICTACT J. Image Video Process. (2017).

[6] G.B. Frisoni, N.C. Fox, C.R. Jack, P. Scheltens, P.M. Thompson, The clinical use of structural MRI in Alzheimer disease, Nat. Rev. Neurol. (2010) http: //dx.doi.org/10.1038/nrneurol.2009.215.

[7] L. Younes, M. Albert, M.I. Miller, Inferring change point times of medial temporal lobe morphometric change in preclinical Alzheimer's disease, Neuro Image Clin. (2014) http://dx.doi.org/10.1016/j.nicl.2014.04.009

[8] T. Kurban, P. Civicioglu, R. Kurban, E. Besdok, Comparison of evolutionary and swarm based computational techniques for multilevel color image thresholding, Appl. Soft Comput. J. (2014) http://dx.doi.org/10.1016/j.asoc. 2014.05.037.

[9] X.S. Yang, S. Deb, Cuckoo search via Levy flights, in: 2009 World Congr. Nat. Biol. Inspired Comput. NABIC 2009 - Proc., 2009, http://dx.doi.org/10. 1109/NABIC.2009.5393690.

[10] S. Suresh, S. Lal, An efficient cuckoo search algorithm based multilevel thresholding for segmentation of satellite images using different objective functions, Expert Syst. Appl. (2016) http://dx.doi.org/10.1016/j.eswa.2016. 03.032.

[11] Oliva D, Cuevas E, Pajares G, Zaldivar D, Perez-Cisneros M (2013) Multilevel thresholding segmentation based on harmony search optimization. J Appl Math 2013:1–24 230.

ISSN- 2394-5125 VOL 7, ISSUE 15, 2020

[12] Oliva D, Cuevas E, Pajares G, Zaldivar D, Osuna V (2014) A multilevel thresholding algorithm using electromagnetism optimization. Neurocomputing 139:357–381

[13] Mousavirad SJ, Ebrahimpour-Komleh H (2017) Multilevel image thresholding using entropy of histogram and recently developed population-based metaheuristic algorithms. Evolut Intell 10(1–2):45–75

[14] Sarkar S, Das S, Paul S, Polley S, Burman R, Chaudhuri SS (2013) Multi-level image segmentation based on fuzzy-Tsallis entropy and diferential evolution. In: 2013 IEEE international conference on fuzzy systems (FUZZ). IEEE, pp 1–8

[15] Bhandari AK, Kumar A, Singh GK (2015) Modifed artifcial bee colony based computationally efcient multilevel thresholding for satellite image segmentation using Kapur's, Otsu and Tsallis functions. Expert Syst Appl 42(3):1573–1601

[16] Zhang J, Li H, Tang Z, Lu Q, Zheng X, Zhou J (2014) An improved quantum-inspired genetic algorithm for image multilevel thresholding segmentation. Math Probl Eng 2014:1–12

[17] Mala C, Sridevi M (2016) Multilevel threshold selection for image segmentation using soft computing techniques. Soft Comput 20(5):1793–1810

[18] Singh, V.K., Rashwan, H.A., Akram, F., Pandey, N., Sarker, M.M., Saleh, A., Abdulwahab, S., Maaroof, N., Torrents-Barrena, J., Romani, S., Puig, D. (2018) "Retinal Optic Disc Segmentation Using Conditional Generative Adversarial Network". CCIA.

[19] Gu, Zaiwang & Jiang, Shanshan & Lee, Jimmy & Xie, Jianyang & Cheng, Jun & Liu, Jiang. (2018)"Automatic Localization of Optic Disc using Modified U-Net". 79-83. 10.1145/3232651.3232671.

[20] Lu SY, Lu ZH, Zhang YD (2019) Pathological brain detection based on AlexNet and transfer learning. J Comput Sci 30:41–47

[21] Maleeha FS, Martin AL, Jay JP, Shruti A, Sachin KG, Ann SC, Brian C, Haris IS (2017) Dynamic functional connectivity states between the dorsal and ventral sensorimotor networks revealed by dynamic conditional correlation analysis of resting-state functional magnetic resonance imaging. Brain Connect 7(10):635–642

[22] Milne AMB, Macqueen G, Hall GB (2012) Abnormal hippocampal activation in patients with extensive history of major depression: an fMRI study. J Psychiatr Neurosci 37(1):28–36

[23] Mingjin Y, Keying Y (2007) Determining the number of clusters using the weighted Gap statistic. Biometrics 63(4):1031–1037 Muldoon SF, Bassett DS (2016) Network and multilayer network approaches to understanding human brain dynamics. Philos Sci 83(5):710–720

[24] Nishida K, Morishima Y, Yoshimura M, Isotani T (2013) EEG microstates associated with salience and front parietal networks in frontotemporal dementia, schizophrenia and Alzheimer's disease. Clin Neurophysiol 124(6):1106–1114