

Integrated Approach of Brain Disorder Analysis by Using Deep Learning Based on DNA Sequence

Ahmed Zohair Ibrahim^{1,*}, P. Prakash², V. Sakthivel² and P. Prabu³

¹Computer Sciences Department, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, P.O. Box 84428, 11671, KSA

²School of Computer Science and Engineering, Vellore Institute of Technology, Chennai, 600127, India

³Department of Computer Science, CHRIST (Deemed to be University), Bangalore, 560029, India

*Corresponding Author: Ahmed Zohair Ibrahim. Email: azibrahim@pnu.edu.sa

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Abstract: In order to research brain problems using MRI, PET, and CT neuroimaging, a correct understanding of brain function is required. This has been considered in earlier times with the support of traditional algorithms. Deep learning process has also been widely considered in these genomics data processing system. In this research, brain disorder illness including Alzheimer's disease, Schizophrenia and Parkinson's disease is analyzed owing to misdetection of disorders in neuroimaging data examined by means of traditional methods. Moreover, deep learning approach is incorporated here for classification purpose of brain disorder with the aid of Deep Belief Networks (DBN). Images are stored in a secured manner by using DNA sequence based on JPEG Zig Zag Encryption algorithm (DBNJZZ) approach. The suggested approach is executed and tested by using the performance metric measure such as accuracy, root mean square error, Mean absolute error and mean absolute percentage error. Proposed DBNJZZ gives better performance than previously available methods.

Keywords: Deep belief networks; zig zag; deep learning; mean absolute; percentage error; mean absolute error; root mean square error; DNA; genomics

1 Introduction

When any such gene is found to be pretentious and prone to some kind of ailment, it is denoted as genetic disorder. Genetic disorder diseases such as Alzheimer and Parkinson directly affects the human being by disrupting the brain functionality [1–3]. The medical imaging has been an essential parameter to present several modalities of images such as X-ray, MRI and CT [4]. Storage of delicate form of information regarding medical images and other associated data in a secure manner also holds a prominent role in medical field. Some of the conventional form of DNA based molecular cryptography scheme and its inscription methods to hoard its image in a secure form has become an interesting area of research. One such main issue seen in traditional means of approaches is that it could not resist the instinctive force attack and hence, this research work executes DNA sequence based JPEG ZIG ZAG encryption system.



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Conventional use of computational neuro-scientific systems have been known extraordinarily promising in comprehensive mental health trials. This multidisciplinary field of study could model the genetic systems prevailing the dynamic and diseased environments of the human brain and map these practices into identifiable clinical descriptions. In the previous age, the rapid rise in high-volume biomedical datasets, simultaneous with the advancements in machine learning, has unconstrained inventive prospects for assessment and prediction of neurodegenerative and neuropsychiatric complaints. From a computational viewpoint, this modern extension has fashioned the advance of tools that assimilate abundant patient-specific elucidations into assessments and rise the clinical effects of patients anguish from such circumstances. The crucial purpose of these neuro technical techniques is to magnify the introductory associate and complete the supervision impression of entities in high threat of Alzheimer's disease and alzheimer-related cognitive failure [5].

For the purposes quantified above, existing studies have engrossed on beginning enormously capable approaches that use ML systems to develop the examination of AD. The usage of intuitive structures proficient of discriminating extreme cases from normal cases centered on their magnetic resonance imaging scans will donate massively to the primary analysis of AD. This study examines notable elements that identify AD and use MRI data, ML and Deep Learning schemes with unbounded AD datasets.

Several kinds of algorithms and systems has been presented earlier for detecting the brain disorder and the limitations seen in them includes: pre-processign and feature extraction were not evidently described and ineffective manner of handling complicated form of genomic data [6–10].

The key contribution of current research is given as follows:

1. Analysis of brain disorder could be executed with the support of deep learning approach and describes how to hoard sensitive form of data in image setup by incorporating DNA based encryption system.
2. Evaluates accurateness of pre-processing of image with respect to image registration, image enhancement, normalization filtering and smoothening.

This research is structured as follows: Section 1 defines introduction of analysis of brain disorder. Section 2 mentions literature review of the research topic. Section 3 presents the outline for classification of status of water quality. Section 4 confers about the investigated outcomes and Section 5 determines the research work with forthcoming research guidelines.

2 Literature Review

In current era of rapid advancements in several tools and technologies, brain disorder disease and its analysis is becoming more effective. There exists several methods to tackle these anxieties and deep learning is the most popular methodology these days. Some of the brain related illness terms are Alzheimer, schizophrenia and Parkinson.

Current research work attempts to introduce DBN feature extraction of the disorder image for brain related illness and to progress overall value of performance. In Alzheimer disease, the database is collected from the ADNI dataset. This could validate and process the data of MRI, CT and PET images [11]. Deep learning approach is mainly deployed to identify Parkinson disease with the use of SPECT image dataset [12]. A new DBN based architecture model is considered which could discover statistical form of values from the perceived data and certainly identifies the pretentious area [13]

To enhance the speed level of processing geome data, DNA sequencing is mainly suggested [14] and the classification of DNA sequence is accomplished with the aid of machine learning algorithm. Here, the features are extracted and stored as vector format. Supervised form of learning is executed here and

the drawback found is that: it could not read by machine and moreover high dimensionality of data occurs [15].

Tab. 1. displays summary of assessment on exploration of brain disorder by incorporating deep learning process. Alzheimer is an advanced form of neuro degenerative ailment which could account for 70% dementia cases all wide and the predictions estimate that with 2030, 75 million of cases might exist worldwide. Even though there is no such cure for AD, the primary analysis could assist in helping to progress quality of life of patients and their relations . There are several drugs and medicines which are under research stage. It is expected that their effectiveness is confirmed once it is managed all through h the initial stage of the disease. These days, Alzheimer is treated with the aid of medical documents and appropriate inspection of the mental status. For suggestion based entities, the judgment is maintained by biomarkers resultant from cerebrospinal fluid and neuroimaging methods such as magnetic resonance imaging. During earlier times, several methods has described 3 major effects of Alzheimer and its progressive nature on rsEEG signals, explicitly, decay in synchronization and condensed intricacy. Moreover, modern form of tentative sign has suggested a neuro modulatory discrepancy in rsEEG signals, which might have its basis in the deduction of neurotransmitters owed to devastation in brain pathways prompted by alzheimer. To define these neuro-modulatory debits, amplitude modulation examination of rsEEG signals were projected lately. While these 4 effects were regularly perceived independently, they all developed from the loss of neurons that intrude anatomical brain connectivity at the level of functional networks. Stating these perceptions, several rsEEG biomarkers have been advised to either explore alzheimer to display disease progress.

Table 1: Analysis of brain disorder

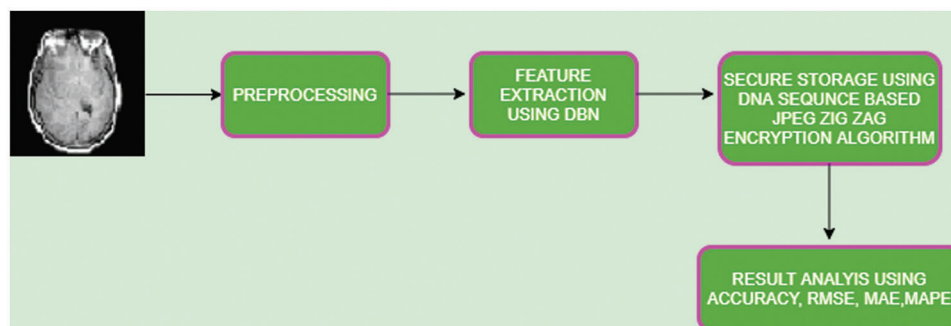
| Author | Process | Applications |
|--------------------------------|------------------|------------------------------------------------------------------------|
| Mahmud et al. (2020) [16] | Deep learning | Biological data mining |
| Fabiatti et al. (2020) [17] | Neural network | Artifact recognition in neural probes |
| Islam et al. (2020) [18] | “Deep learning” | GAN-based synthetic brain PET image generation. |
| Rabby et al. (2020) [19] | “Deep learning” | Tree-based unsupervised keyphrase abstraction technique |
| Lei et al. (2020) [20] | “Deep learning” | Neurodegenerative disease diagnosis by using adaptive sparse learning. |
| Chand et al. (2020) [21] | Machine learning | Neuroanatomical of schizophrenia |
| Ali et al. (2019) [22] | “Neural network” | Segmentaion of MRI image |
| Noor et al. (2019) [23] | “Deep learning” | Neurodegenerative disease in MRI |
| Basaia et al. (2019) [24] | CNN | Classification of alzheimer by means of MRI |
| Li et al. (2019) [25] | “Deep learning” | Prediction of alzheimer’s disease by using MRI |
| Spasov et al. (2019) [26] | “Deep learning” | Mild cognitive damage to alzheimer |
| Bohle et al. (2019) [27] | DNN | Layerwise propagation of alzheimer |
| Qiu et al. (2019) [28] | CNN | Classification of schizophrenia using MRI |
| Sivaranjini et al. (2019) [29] | “CNN” | Diagnosis of parkinson’s disease |
| Shinde et al. (2019) [30] | “DNN” | Predictive markers for parkinson’s disease |
| Kollias et al. (2018) [31] | “DNN” | Prediction in healthcare |

(Continued)

Table 1 (continued)

| Author | Process | Applications |
|----------------------------|------------------|-------------------------------------------|
| Zeng L et al. (2018) [32] | “Deep learning” | Classification of schizophrenia |
| Mahmud et al. (2018) [33] | “Deep learning” | Reinforcement learning of biological data |
| Litjens et al. (2017) [34] | “Deep learning” | Medical Image analysis |
| Dakka et al. (2017) [35] | “Neural network” | Neural markers of schizophrenia |
| Shakeri et al. (2016) [36] | “Deep learning” | Shape features for alzheimer |

Accurate means of diagnosis of Alzheimer shows significant changes in patient treatment during initial phase of disease as the threat alert alertness endures the patients to carry out protective approaches even afore incidence of irretrievable brain obliteration. Even though more than a few modern studies have used computers to detect alzheimer, extreme machine detection methodologies were controlled by inherited observations. Alzheimer could be diagnosed-but not predicted-at its primary phases, as prediction were only suitable formerly the disease manifests itself. Deep Learning has become a communal system for the principal analysis of alzheimer. At this point, briefly analyzes a number of the substantial works on alzheimer and determine how deep learning could help investigators ascertain the pattern at its initial points are described in Fig. 1.

**Figure 1:** Workflow of DBNJZZ

3 Proposed Method

Medical imaging is a way of essential tool to treat any disease and for examining brain disorder, this research work executes deep learning technique of DBN. Proposed approach contains 2 modules such as:

First Module: Pre-processing phase

Second Module: Feature Extraction of disorder image and DNA Sequence centered privacy Storage of Brain image using proposed method.

3.1 Pre-processing (Module 1)

CT, MRI, PET are the neuroimaging based modalities of the brain images and pre-processing is carried out to enhance the quality of images. Phases tangled in pre-processing steps are described in Fig. 2.

3.1.1 Image Registering

This is the form of acquiring 2 or more similar image features along with diverse variation time structure into distinct explanatory image. The linear regression based system is mainly deployed for image registration

which could entail function of image in rotation, transformation, scaling on x, y and z axes. The spatial correlation of image gets aligned in all such angles and generally, the image registration is specified by

$$I_b = R((I_{b'}), \{\beta\}) \quad (1)$$

where, $I_{b'}$ is the coordinate of value of image b, β is the set of parametric value of transformation.

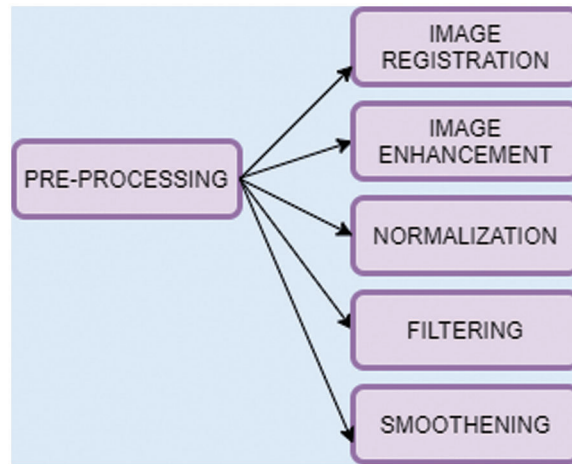


Figure 2: Pre-processing

3.1.2 Image Enhancement

The image enhancement step expands quality of images by means of filtering with “contrast limited adaptive histogram equalization (CLAHE)”. It could increase the brightness of image with its contextual background to enhance perceptibility.

3.1.3 Normalization

Normalization is method of alignment of image with respect to dimension and shape to infer them according to usual topographies of the image. It could map data point which is attained from discrete space rate to reference space value.

3.1.4 Filtering

With the support of Wiener filtering, it could remove the unnecessary features of image and reducing the noise of image.

$$R(u) = \frac{H(u)^*}{|H(u)|^2 + k} \quad (2)$$

where,

k denotes low frequency value of wiener filter. High pass filter assessment is mainly deployed for blurry form of images.

3.1.5 Smoothing

Smoothing is the criteria of minimizing noise from images and here, the spatial smoothing is executed which estimates average value of pixels from neighboring pixel features. This improves Signal-to-noise ratio value and decreases spatial resolution value.

3.2 Feature Extraction of Disorder Image and DNA Sequence

In proposed approach, Deep Belief Network could be deployed to abstract feature type of biomarkers of image. The biomarker could act as a specified tool for analytical purpose and it is mainly used for identifying anomalous state of image. DBN is mainly based on restricted boltzman machines design [37–40]. DBN is an unsupervised feature extractor which could extract major features of image for enhancing performance level [41–43]. This could abstract the typical structure topographies from brain image to recognize disorder of brain disease. Fig. 3 indicates that workflow of commending biomarkers.

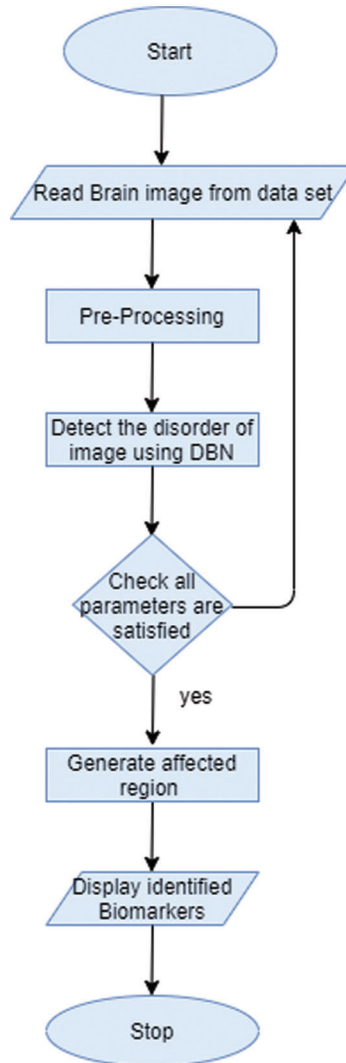


Figure 3: Work-flow of getting biomarker

The structural design of DBN is mainly composed of stacks RBM which contains a discernible layer and several hidden layers. Here, every layer comprises of nodes and association between input and hidden layers were by allocating weight value. Once after adjusting the weight vector value, the network gets trained and the arrangement of DBN is described in Fig. 4. The structural design of RBM is specified in the Fig. 5.

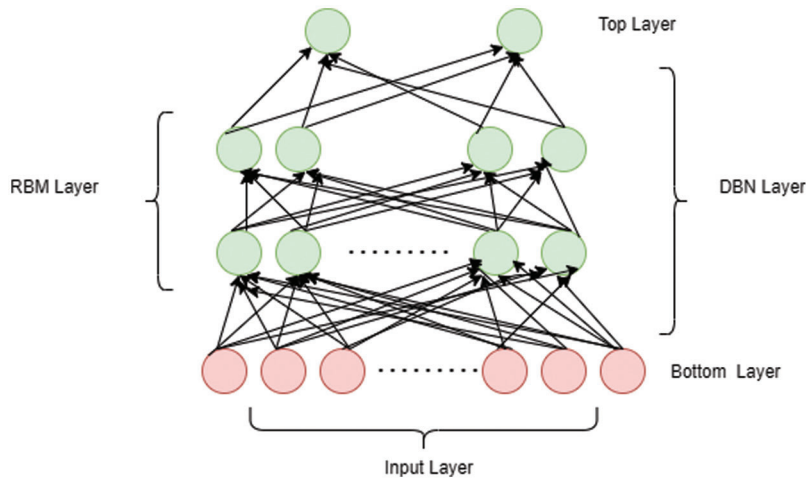


Figure 4: DBN layer

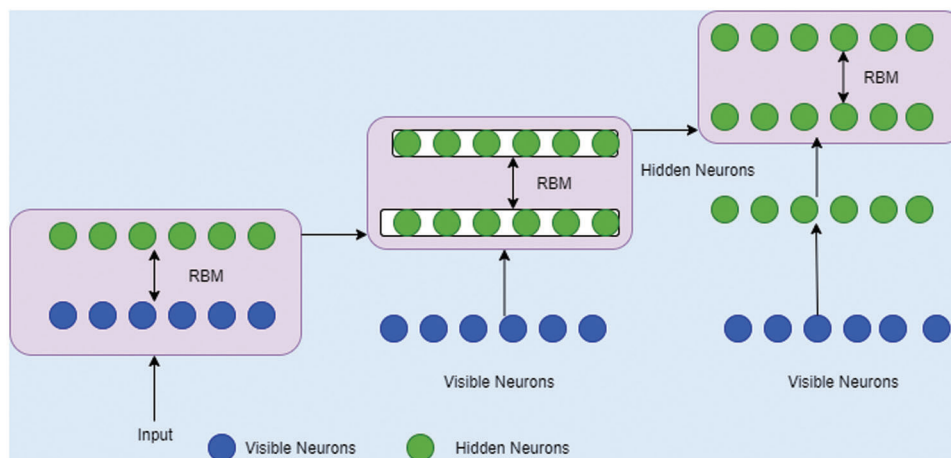


Figure 5: RBM design

The process involved for training DBN is mentioned as follows:

First Algorithm: Training DBN

The steps involved in first algorithm is given as follows:

- 1: Here, I_i ; $0 \leq i \leq N$ is the input neuron which covers binary values. N is the aggregate total of all input neurons.
- 2: Here, h_i ; $0 \leq i \leq K$ is hidden neuron which comprises binary values. K is the total number of hidden neurons.

- 3: Evaluate energy function $Er(i, j)$ among the input neurons and hidden neurons by

$$\text{Using the equation: } Er(I, h) = \sum_i b_i I_i - \sum_i a_i h_i - \sum_i \sum_j I_i W_{ij} h_j \quad (3)$$

- 4: Train RBM's initial layer with the support of input values to each neuron.
-

(Continued)

First Algorithm (continued)

5: Output of Step 4 could be used as the corresponding input of next layer (hidden layer).

$$6: D(I, h_i) = \frac{1}{F} e^{-Er(I, h_i)} \quad (4)$$

Pair values of evident and hidden values are summed up and it could produce F as a function.

7: Estimate unbiased value among visible and hidden neuron

$$D\left(h_{ij} = \frac{1}{I} = \sigma\left(b_{ij} + \sum_i I_i W_{ij}\right)\right) \sigma \text{ is sigmoid function.}$$

8: Reprise the steps 6 and 7 till all layers gets assessed.

9: Output Binary Values B_{ij}

The first algorithm trained the image to perceive the disorder of the image. Lastly, it could be stowed in a secured manner by using DNA sequence-based JPEG Zig Zag Encryption method.

DNA sequence-based JPEG Zig Zag Encryption algorithm:

DNA (Deoxyribonucleic acid) is made up of monomers in a polymer configuration and is known as Deoxyribonucleotides. The elementary constituents of nucleotide are phosphate, deoxyribosesugar, and nitrogenous base. Afterward execution of first system, output values were in the matrix arrangement and 4 base variable of DNA sequences are A, C, T, G nucleotides. The encoded value of A is [1, 0, 0, 0], C encoded value is [0, 1, 0, 0], T encoded value is [0, 0, 1, 0] and G's encoded value is [0, 0, 0, 1] and hence, disorder image value could be signified as corresponding DNA sequence of code [38]. The encryption key DNA sequence-based JPEG Zig Zag is demarcated by the Fig. 6.

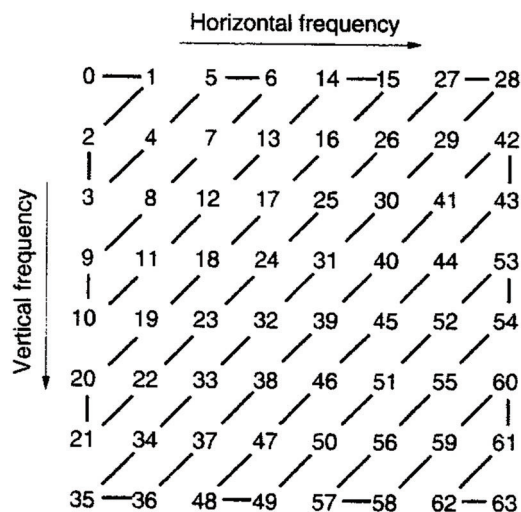


Figure 6: JPEG Zig Zag format

Currently, gene binary sequence value is measured as encrypted image and stowed in a secure manner. The encrypted DNA sequence JPEG Zig Zag process is mentioned below as follows.

Second Algorithm: DNA sequence JPEG Zig ZagEncryption

The steps involved in second algorithm is given as follows:

- 1: Call first algorithm
- 2: Transform B_{ij} to equivalent DNA Sequence value.
- 3: $A \leftarrow DNA(B_{ij})$ // Transform image into DNA image
- 4: $Z_A \leftarrow A$ // Interpret DNA image conferring to JPEG Zig Zag as in Fig. 5
- 5: Encrypted Image

Third Algorithm: DNA sequence JPEG Zig Zag Decryption

The steps involved in third algorithm is given as follows:

- 1: $B \leftarrow DNA$ sequence of binary file F
- 2: $B \leftarrow Reverse\ function\ of\ JPEG\ ZIG\ ZAG(B)$
- 3: Transform B into binary value and produce decrypted image as output.

Equally the sender and receiver are ought to have identical gene sequence value and stowed it as a binary format. For every DNA nucleotide sequence in B quadruple value, select it casually from the binary format file and substitute it by image. Fig. 7 displays consequence of storage of image by using JPEG Zig Zag pattern.

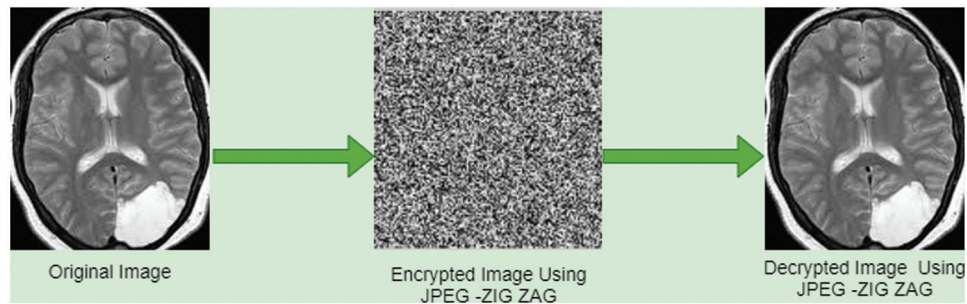


Figure 7: JPEG zig zag encryption algorithm

4 Results

To estimate exploration of DBNJZZ in perceiving disorder image, four performance metric measure is used such as root mean square error, Mean absolute error, Accuracy and mean absolute percentage error.

$$RSME = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - P_i)^2} \quad (5)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |O_i - P_i| \quad (6)$$

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{O_i - P_i}{O_i} \right| \quad (7)$$

$$Accuracy = 1 - \frac{\sum_{i=1}^N |O_i - P_i|}{\sum_{i=1}^N O_i} \quad (8)$$

where,

O_i is observation value,

P_i is estimate value and

N is sum of interpretations.

Tab. 2 displays diverse disorder disease and its dataset.

Table 2: Disorder diseases and its appropriate dataset [39]

| Recognition of disorder | Datasets |
|-------------------------|--------------|
| Alzheimer | ADNI, OASIS |
| Schizophrenia | COBRE, FBIRN |
| Parkinson's disease | NTUA, PPMI |

In neurological disorder of Alzheimer, it is exaggerated to older people. It will degrade them emotionally and makes disorder function of brain in specific area. Using Eq. (8) accuracy actions for pre-processing actions of Alzheimer are mentioned in the Tab. 3 by using Tab. 2 datasets.

Table 3: Accuracy of neurological disorder of Alzheimer

| DL | Image registering | Contrast enhancement | Normalization | Wiener filter | Smoothing |
|-------------------------------|----------------------|-------------------------|---------------|------------------|-----------|
| CNN + JPEG ZIG-ZAG | 92.74% | 80% | 89.47% | 85% | 93.84% |
| DNN + JPEG ZIG-ZAG | 85% | 78.12% | 88.30% | 80.25% | 90.21% |
| DBN + JPEG ZIG-ZAG (Proposed) | 97.52% | 89.56% | 92.67% | 88.89% | 98.56% |

In the above Tab. 3, displays that proposed work has created enhanced performance. Using Eq. (8) Tab. 4 depicts that accuracy for neurological disorder of Schizophrenia disease. It is a psychiatric ailment and it deviates patient's behaviour corresponding to emotion and cognition.

Table 4: Accuracy of neurological disorder of Schizophrenia

| DL | Image registration | Contrast improvement | Normalization | Wiener filter | Smoothing |
|-------------------------------|-----------------------|-------------------------|---------------|------------------|-----------|
| CNN + JPEG ZIG-ZAG | 89.47% | 82.34% | 85.74% | 81.20% | 90.84% |
| DNN + JPEG ZIG-ZAG | 87.45% | 84.12% | 86.67% | 84.53% | 91.45% |
| DBN + JPEG ZIG-ZAG (Proposed) | 96.25% | 91.56% | 94.76% | 90.45% | 99.21% |

In the above [Tab. 4](#), shows that proposed research has fashioned a superior performance. Using [Eq. \(8\)](#) [Tab. 5](#) displays the accuracy for neurological disorder of Parkinson's disease. It is a disorder in neurodegenerative and affects voluntary movements.

Table 5: Accuracy of neurological disorder of Parkinson's disease

| Deep learning | Image registration | Contrast augmentation | Normalization | Wiener filter | Smoothing |
|-------------------------------|--------------------|-----------------------|---------------|---------------|-----------|
| CNN + JPEG ZIG-ZAG | 87.89% | 86.43% | 88.78% | 84.20% | 89.48% |
| DNN + JPEG ZIG-ZAG | 88.54% | 87.21% | 88.67% | 86.36% | 90.54% |
| DBN + JPEG ZIG-ZAG (Proposed) | 98.25% | 92.67% | 95.89% | 92.65% | 98.90% |

The experimental outcome of [Tab. 5](#) displays that in accuracy metric measures for Parkinson's disease, suggested research by incorporating DBN gives better performance. By using [Eqs. \(5\) & \(6\)](#) root mean square error, Mean absolute error is given in the [Figs. 8, 9 and 10](#). [Eq. \(5\)](#) is intended as square root of mean of the squared variances among actual results and expectations. [Eq. \(6\)](#) is total difference between the actual or true values and the values that are anticipated. In the total difference, if outcome has an adverse sign, it is unnoticed.

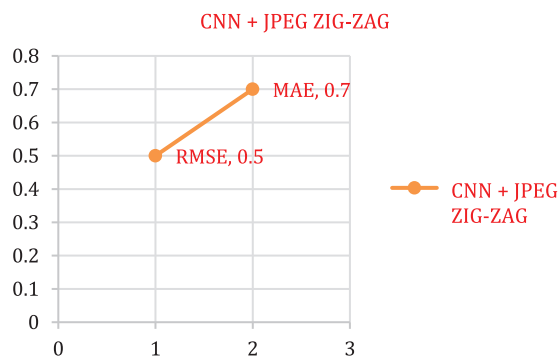


Figure 8: Error rate-CNN + JPEG ZIG-ZAG

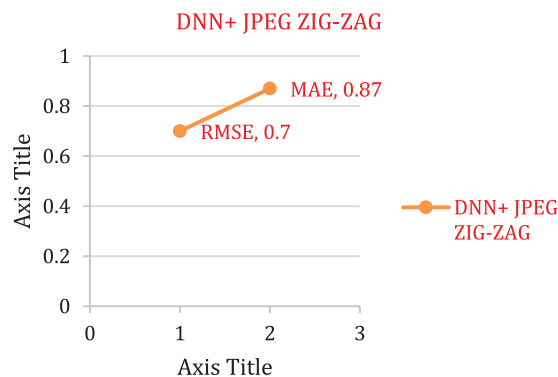


Figure 9: Error rate using DNN + JPEG ZIG-ZAG

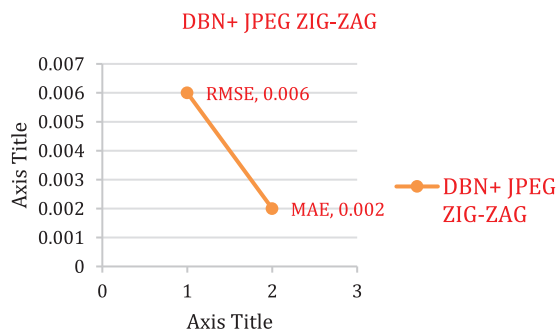


Figure 10: Error rate using DBN + JPEG ZIG-ZAG

The experimental results shown in the Figs. 8–11 implies that the suggested work DBN + JPEG ZIG-ZAG achieves enhanced prediction performance than associated with other prevailing algorithm in deep learning criteria. In the current research analysis, the accuracy metric is deployed for estimating brain disorder diseases of Alzheimer, Schizophrenia, Parkinson's disease with deep learning classification algorithms. Recommended research work exposes improved performance in the accuracy metric.

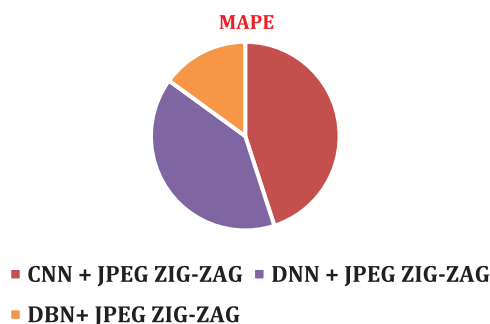


Figure 11: MAPE using DBN + JPEG ZIG-ZAG

To visualize performance impact of systems with respect to error rate, lower error rate of DBN system and results were predicted correctly.

5 Conclusion

The proposed research incorporated deep learning technique along with the CNN, DNN. DBN is estimated by using secure means of stowage of image in JPEG Zig Zag encryption system. When coming to unsupervised form of feature extractor for extracting biomarker of disorder image and tested on brain disorder of Alzheimer's disease, Schizophrenia and Parkinson's disease, DBN is predominantly suggested.

This DBNJZZ system could fulfil the features of image and shared this image in a safe manner. This could also be capable of providing prompt prediction of disorder of images. This current research focused on 3 diseases and the future work could examines more case studies with diverse DNA sequence.

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