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DIAGNOSIS OF IMAGES OF HUMAN BEHAVIOUR

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Abstract. An analysis of single photon emission computerized tomography (SPECT) images was carried out. The purpose is to determine the activities of the different lobes of the brain to classify human behaviour. Pulse-Coupled Neural networks (PCNNs) were used to get the signature of activity in each lobe. This was then used by a k-NN classifier and fuzzy-like rules for diagnosis. Genetic programming was used to evolve a diagnostic grammar which is used for syntactic and semantic diagnosis. Several test cases were used to verify the proposed scheme giving high diagnosis accuracy.

1. Introduction

SPECT is an acronym for Single Photon Emission Computerized Tomography. It is a sophisticated nuclear medicine study that looks directly at cerebral blood flow and indirectly at brain activity (or metabolism). In this study, a radioactive isotope is bound to a substance that is readily taken up by the cells in the brain. A small amount of this compound is injected into the patient's vein where it runs throughout the blood stream and is taken up by certain receptors sites in the brain. The patient then lies for 14-16 minutes while a SPECT gamma camera rotates slowly around his head. The camera has special crystals that detects where the compound has gone. A supercomputer then reconstructs 3-D images of brain activity levels. The elegant brain snapshots that result offer a sophisticated blood flow/ metabolism brain map. With these maps, physicians are able to identify certain patterns of brain activity that correlate with psychiatric and neurological illnesses. [1]

SPECT studies can be displayed in different kinds. One kind is a 3D 'surface images', looking at the blood flow of the brains cortical surface. These

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images are helpful for picking up cortical surface area of good activity as well as low-active areas. They are helpful to look at strokes, brain trauma, effect of drug abuse, etc. A normal 3D surface scan shows good, full, symmetrical activity across the brain's cortical surface. The other kind is a 3D 'active brain image'. These images are helpful for picking up areas of HIGH activity, as seen in active seizures, obsessive compulsive disorder, anxiety problems, certain forms of depression, etc. A normal 3D active scan shows increased activity in the back of the brain (cerebellum or occipital cortex) and average activity everywhere else. Physicians are usually altered that smoothing is wrong in one of three ways:

a. HIGH activity in certain area
b. LOW activity in certain area
c. Asymmetrical area of activity which ought to be symmetrical.

In this paper, intelligent techniques for classification, diagnosis, imaging and understanding were used for the purpose of diagnosis and analysis of images of human behaviour. Similar decision support systems for medical image diagnosis can be found in [2, 4, 5, 6, 10, 15, 16].

2. A prologue to SPECT Imaging

2.1. **Anatomy of Brain.** The human brain is anatomically divided into four main lobes namely: the Frontal lobe, the Parietal lobe, the Occipital lobe, and the Temporal lobe and the cerebellum (Fig.1). The SPECT brain radiologist looks for levels of activity in these lobes mainly. [3]

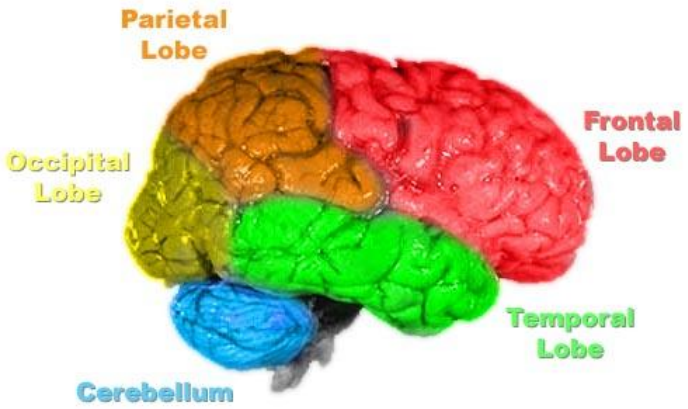

Figure 1. Brain Anatomy

2.2. **Brain SPECT Views.** There are three main views for SPECT imaging: [3]

a. Horizontal View (transaxial)
The brain is viewed in horizontal slices, cut from top to bottom. It is as if you are looking down from a bird's eye view. Fig 2(a)

b. Coronal View (front on view)
The brain is viewed in vertical slices, cut from front to back. It is as if you are looking face on or front on to the brain. Fig 2(b)

c. Sagittal View (side to side)
The brain is viewed in vertical slices, cut from side to side. It is as if you are looking at brain from the side. Fig 2(c)

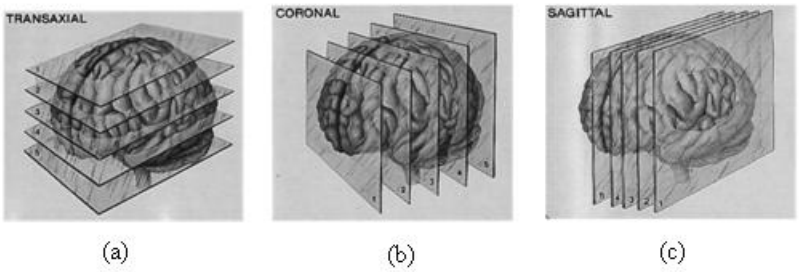

FIGURE 2. (a) horizontal view (Transaxial). (b) Coronal View (Front on View). (c) Sagittal View (Side to Side)

2.3. **Normal 3D Brain Images.** As stated above, there are two main brain SPECT views: the surface view and the active view. For a normal brain, the surface view shows smooth distribution of dye in the top-down, front-on, underside and side surface views. Fig 3

The active view shows the regions of activity in anatomical brain lobe with a 3D reconstruction of the images. Fig 4

3. Proposed SPECT Diagnosis Schemes

Two schemes are adopted in this paper. The first uses fuzzy rules to correctly classify the symptom. The second evolves a diagnostic grammar.

The first scheme goes through several phases of image processing and pattern recognition to correctly diagnosis the disorder.

First, the input image whether surface or active view is resized to a particular size. Then the 3D resized coloured image is converted into a 2D grayscale

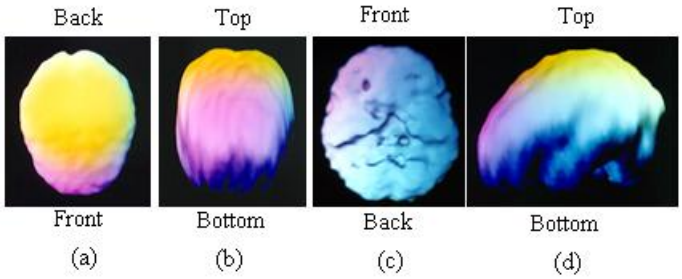

FIGURE 3. (a) Top - Down Surface View. (b) Front - On Surface Views. (c) Underside Surface View. (d) Side Surface View.

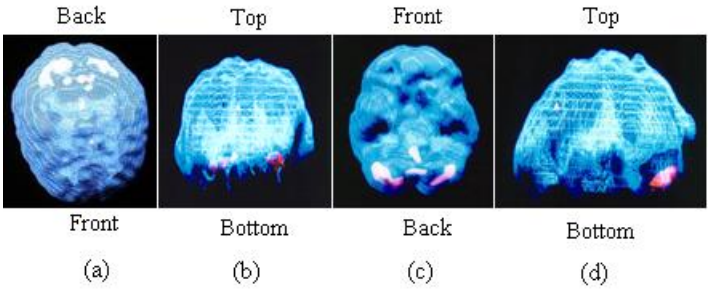

FIGURE 4. (a) Top - down active view. (b) Front - on Active View. (c) Underside Active View. (d) Side Active View

image. The features of the image are determined using the freeman chain code to clarify the brain orientation (horizontal, coronal, or Sagittal). These features are passed to a k-NN classifier [13] for exact determination of the orientation. A 'mask' image is then 'ANDed' to the original image to separate the particular brain lobe. Next, a matrix for each lobe's image and run through a pulse-coupled Neural Network [11] for 100 iterations, so as to get a unique 'signature' that is then used by the k-NN classifier again to identify the state of the brain lobe, whether low, high or normal activity. A set of diagnostic fuzzy-like rules are induced for classification of the brain disorder. To summarize the scheme:

1. Surface or active view input image is resized.
2. Convert 3D color image to 2D grayscale image.
3. Apply freeman- chain - code for feature extraction.
4. Classify features using k-NN classifier.
5. 'AND' a mask image to input image for lobes' separation.
6. Apply PCNN to get signature of each lobe.
7. Classify signature using k-NN again (Low, High, Normal).

8. Build fuzzy - like rules for disorder diagnosis.
9. If image disorder set is finished then stop else goto 1.

The second scheme adopted genetic programming (GP) [8, 9, 12] to evolve an image-understanding diagnostic grammar [12, 14]. It goes through the same steps as above, but replaces step 8 by the application of GP as will be explained.

3.1. **Feature Extraction of SPECT Views.**

3.1.1. *Freeman Chain Code.* To determine the brain orientation whether top-down, side, underside or front-on view, contour information is needed. This is performed by Freeman Chain Code. It is an ordered sequence of n links C_k, where C_k is a vector connecting neighbouring contour pixels. The directions of C_k are coded with integer values k = 0, 1, ..., k-1 in a contour clockwise sense. A simple example is depicted in Fig 5. Fig 5(a) shows the directions of the eight connected chain code (K = 8). Fig 5 (b) is a sample object with chain code presentation in Fig 5 (c).

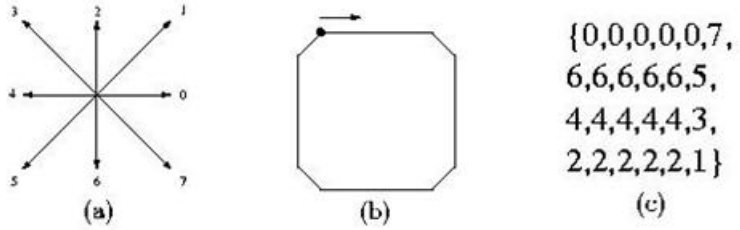

FIGURE 5. (a) The directions of the eight Connected chain code (K=8). (b) A sample object, a square. (c) Chain code presentation of the square

The pseudocode for the Freeman Chain Code is as follows:

1. For i = Starting _ row _ index +1 till image's matrix rows no.
2. For j = Starting _ column _ index +1 till image's matrix columns no.
3. Get the coordinates (i, j) of the first pixel that is not black.
4. End For
5. End For
6. Get the contour from the resulting coordinates.
7. Initialize 8 counters for 8 directions by 0.
8. For k = 1 till the number of rows of the contour
9. Get the direction of the pixel by comparing its coordinates to the coordinates of its following pixel
10. Increment the contour of the resulting direction by 1
11. End For

12. Normalize contours
13. Return a vector of normalized contours.

3.1.2. *k-NN Classifier.* The k-NN (K-Nearest Neighbour Algorithm) is a method for classifying objects based on closest training examples in the feature space [13]. In our case, the feature space is 8-dimensional since the number of features from chain code is 8. The training examples are vectors in multi-dimensional feature space. The space is partitioned into regions by locations and labels of the training samples. The algorithm pseudocode is as follows:

1. Load the training samples in vectors
2. Get feature vector of image
3. MinDist = 100 000
4. For i = 1 till number of rows of sample vector
5. For j = 1 till number of columns of sample vector
6. Get a training feature vector
7. End For
8. Get the Euclidean distance between image's feature vector and training vector
9. if distance < MinDist
10. MinDist = distance
11. Class = i
12. End For
13. According to the ordering of training samples, class will indicate corresponding view

3.2. **Pulse-Coupled Neural Network (PCNN).** The Eckhorn model of PCNNs is used. It is based on the cat visual cortex. The model can be abstracted into the following five time dependant equations: [11]

1. $F_{xy}(t) = F_{xy}(t-\Delta t)e^{-\alpha_F \Delta t} + S_{xy} + \sum_{x'y'} W^F_{x'y'\to xy}\ Y_{x'y'}(t-\Delta t)$
2. $L_{xy}(t) = L_{xy}(t-\Delta t)e^{-\alpha_L} + \sum_{x'y'} W^L_{x'y'\to xy}\ Y_{x'y'}(t-\Delta t)$
3. $U_{xy}(t) = F_{xy}\ (t)\ \ (1+\beta\ L_{xy}\ (t))$
4. $Y_{xy}(t) = \begin{cases} 1 & \text{if}\quad U_{xy}(t) > \theta_{xy}(t-\Delta t) \\ 0 & \quad otherwise \end{cases}$
5. $\theta_{xy}(t) = \theta_{xy}(t-\Delta t)e^{-\alpha_\theta} + W^\theta\ \ Y_{xy}(t)$

The F, L, U, Y and θ are the activations of the five different neuron - types in the model. The α_F, α_L and α_θ are the decaying constants of the respective neuron - types; the W^F, W^L and W^θ are the feedback weights from the output Y to the feeding neurons (F), linking neurons (L) and dynamic threshold neurons (θ) respectively.

For the feeding and linking neurons the weights are four-dimensional matrices and finally the S is the stimuli or image input. The signal-flow between the processing elements (neurons) is illustrated in Fig 6.

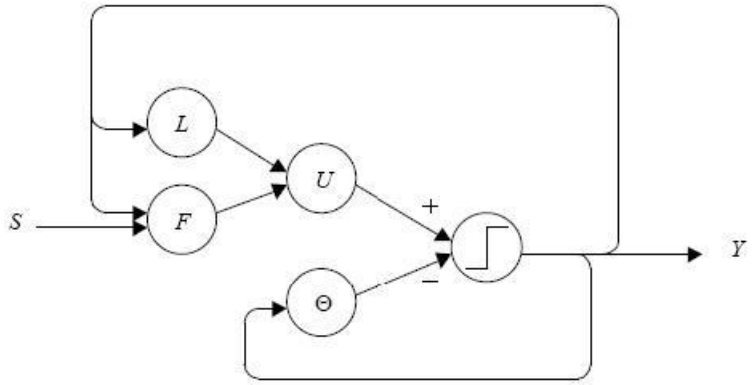

FIGURE 6. Pulse-Coupled Neural Network

Normally, one feeding neuron per pixel is used. Five matrices of the same dimensions of the image store intermediate results for discrete time steps t = 0, 1, ..., K. the output of the PCNN is a series of binary images. When an output neuron goes high or 'fires', its dynamic threshold θ is significantly increased, then decays exponentially and after a couple of iterations the neuron can fire again. This pulsating behaviour is characteristic of the PCNN. The signature of a lobe image is a series of 100 elements each is the number of ones in binary output images for K iterations.

3.3. **Genetic Programming Evolution of Diagnostic Grammar.** The problem of grammar induction involves recognizing patterns existing in a sequence of data.

In summary, the genetic programming paradigm breeds grammars to solve problems by executing the following three steps:

1. Generate an initial population of random compositions of grammars.
2. Iteratively perform the following substeps until termination criterion has been satisfied.

(a) Execute each grammar in the population and assign it a fitness value
(b) Create a new population of grammars by applying the following two primary operations:

(i) Copy existing grammars to new population
(ii) Create new grammars by genetically recombining randomly chosen parts of two existing grammars.

3. The best grammar that appeared in any generation (i.e. the best-so-far individual) is designated as the result of genetic programming.

4. ANALYSIS AND RESULTS

4.1. **Fuzzy Rules for Diagnosis.** The following fuzzy rules are deduced and used for diagnostic purpose:

1. IF Frontal _ lobe _ activity = H AND
Parietal _ lobe _ activity = N AND
Temporal _ lobe _ activity = N AND
Occipital _ lobe _ activity = N AND THEN Diagnosis = Stroke.

2. IF Frontal _ lobe _ activity = L AND
Parietal _ lobe _ activity = L AND
Temporal _ lobe _ activity = L AND
Occipital _ lobe _ activity = N AND THEN Diagnosis = Trauma_Induced_ADD.

3. IF Frontal _ lobe _ activity = H AND
Parietal _ lobe _ activity = N AND
Temporal _ lobe _ activity = H AND
Occipital _ lobe _ activity = N AND
Gyrus activity = H THEN Diagnosis = Ring_of_Fire_ADD.

4. IF Frontal_lobe_activity = L AND
Parietal_lobe_activity = N AND
Temporal_lobe_activity = L AND
Occipital_lobe_activity = N AND THEN Diagnosis = Marijuana_Abuse.

5. IF Frontal _ lobe _ activity = H AND
Parietal _ lobe _ activity = H AND
Temporal _ lobe _ activity = H AND

Occipital _ lobe _ activity = H AND THEN Diagnosis = Heroin_Abuse.

6. IF Frontal _ lobe _ activity = L AND
   Parietal _ lobe _ activity = L AND
   Temporal _ lobe _ activity = L AND
   Occipital _ lobe _ activity = L AND THEN Diagnosis = Alcohol_Abuse.

7. IF Frontal _ lobe _ activity = L AND
   Parietal _ lobe _ activity = L AND
   Temporal _ lobe _ activity = N AND
   Occipital _ lobe _ activity = L AND THEN Diagnosis = Schizophrenia.

8. IF Frontal _ lobe _ activity = N AND
   Parietal _ lobe _ activity = N AND
   Temporal _ lobe _ activity = H AND
   Occipital _ lobe _ activity = N AND THEN Diagnosis = Anxiety.

4.2. **Grammars for Diagnosis.** The following grammars were evolved using Genetic Programming:

1. SYMPTOM → STROKE
   STROKE → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → H
   PARITAL_LOBE_ACTIVITY → N
   TEMPORAL_LOBE_ACTIVITY → N
   OCCIPITAL_LOBE_ACTIVITY → N

2. SYMPTOM → TRAUMA_INDUCED_ADD
   TRAUMA_INDUCED_ADD → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → L
   PARITAL_LOBE_ACTIVITY → L

TEMPORAL_LOBE_ACTIVITY → L
OCCIPITAL_LOBE_ACTIVITY → N

3. SYMPTOM → RING_OF_FIRE_ADD
   RING_OF_FIRE_ADD → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → H
   PARITAL_LOBE_ACTIVITY → H
   TEMPORAL_LOBE_ACTIVITY → H
   OCCIPITAL_LOBE_ACTIVITY → N
   GYRUS_ACTIVITY → H

4. SYMPTOM → MARIJUANA_ABUSE
   MARIJUANA_ABUSE → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → L
   PARITAL_LOBE_ACTIVITY → L
   TEMPORAL_LOBE_ACTIVITY → N
   OCCIPITAL_LOBE_ACTIVITY → N

5. SYMPTOM → HEROIN_ABUSE
   HEROIN_ABUSE → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → H
   PARITAL_LOBE_ACTIVITY → H
   TEMPORAL_LOBE_ACTIVITY → H
   OCCIPITAL_LOBE_ACTIVITY → H

6. SYMPTOM → ALCOHOL_ABUSE
   ALCOHOL_ABUSE → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY

and OCCIPITAL_LOBE_ACTIVITY

FRONTAL_LOBE_ACTIVITY → L
PARITAL_LOBE_ACTIVITY → L
TEMPORAL_LOBE_ACTIVITY → L
OCCIPITAL_LOBE_ACTIVITY → L

7. SYMPTOM → SCHIZOPHRENIA
   SCHIZOPHRENIA → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → L
   PARITAL_LOBE_ACTIVITY → L
   TEMPORAL_LOBE_ACTIVITY → N
   OCCIPITAL_LOBE_ACTIVITY → L

8. SYMPTOM → ANXIETY
   ANXIETY → FRONTAL_LOBE_ACTIVITY
   and PARITAL_LOBE_ACTIVITY
   and TEMPORAL_LOBE_ACTIVITY
   and OCCIPITAL_LOBE_ACTIVITY

   FRONTAL_LOBE_ACTIVITY → N
   PARITAL_LOBE_ACTIVITY → N
   TEMPORAL_LOBE_ACTIVITY → H
   OCCIPITAL_LOBE_ACTIVITY → N

4.3. **Test Cases.**

4.3.1. *Test case 1.*

1. Inputs SPECT image in Fig 7(a)
2. Processing
   (a) Converting the 3D image into gray scale 2D image Fig 7 (b)
   (b) Determining the brains orientation → Result: Top-Down
   (c) According to given view and orientation, extract the appropriate lobes of the brain
   Result: Extracted lobes in fig 7 (c), (d), (e)
   (d) Get the time signature for each lobe

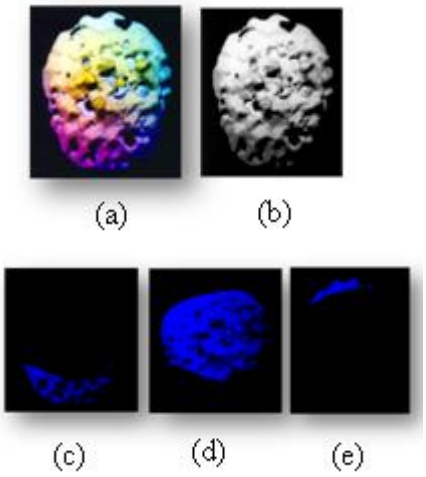

FIGURE 7. (a) SPECT image (View Type: Surface). (b) Gray Scale Image. (c) Occipital lobe. (d) Parietal lobe (e) Frontal lobe

Result for Occipital lobe:
130000 0 1315 1471 165 2308 617 1867 943 2028 851 2263 880 2206 889 2098 1200 1839 1312 1666 1702 1609 1999 1650 1738 1690 1953 1637 1937 1529 2079 1890 2364 2250 2507 2472 2584 2621 2947 2620 2757 3034 3161 3150 3106 3222 3133 3161 106275 4461 1785 1740 1851 1575 1851 1596 1900 1857 1683 1773 1743 1908 2056 2013 2145 2218 2205 2442 2297 2352 2449 2481 2539 2514 2674 2502 2631 2623 2837 2904 2745 2913 2904 2866 2888 2879 2952 2883 2962 3222 3125 3195 3353 3149 3258 3184 92807 4452 2182 2273
Result for Parietal lobe:
130000 0 11398 21342 6811 22759 14532 19795 15426 24249 12567 26529 12643 26270 17750 20624 20820 21350 19881 19640 22214 22081 21409 21695 18515 24196 24141 18772 22918 20247 24311 22484 22349 23206 24939 21533 25598 22042 26207 24252 21279 25309 27040 21616 26374 24257 22876 27154 61187 23650 24696 20439 23147 20789 21632 23095 22984 22115 23057 22514 21124 21429 23608 23769 22153 23133 24627 23510 22108 23333 23341 24636 23338 22436 26678 23127 22314 23732 24311 24486 24017 24280 24082 24234 23143 23242 24736 24755 22467 24881 24527 24928 26135 22689 24459 25034 42342 24864 24090 23546
Result for Frontal lobe:

130000 0 56 3315 2533 1491 3394 2098 2677 3402 2867 3591 3663 3809 3349 2735 3137 4214 2345 4141 2765 3430 4155 3669 3091 4128 3562 3621 3147 3923 3920 4276 4584 4348 4692 5112 4740 5137 5971 4698 4489 5835 5587 5212 5344 5787 5209 5681 89031 6127 3926 3779 3473 3604 3340 3263 4319 4114 3580 3727 3072 4079 4792 3800 3869 4459 4695 4991 4317 4446 4147 5178 4490 5184 5321 4288 4422 4453 5320 5005 4968 5208 5065 5355 4718 5130 5596 5037 4721 5777 5257 5859 6132 5409 5127 5267 73489 6173 4694 4282

(e) Compare time signatures' values of existing data to determine their abnormality level
Result:
Occipital : Low
Parietal : Low
Frontal : Low

(f) Apply the rules that identify the disorders.
Result: Schizophrenia

3. The result of the test case
Success in detecting the abnormalities then the disorder accordingly

4. Parse Tree of test case 1
As shown in Fig (8)

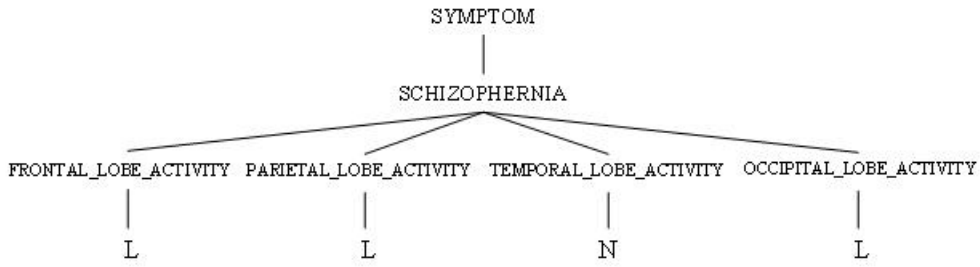

FIGURE 8. Parse Tree of Test Case 1

4.3.2. *Test case 2.*

1. Inputs
SPECT image 1 in Fig 9(a)
SPECT image 2 in Fig 9(b)

2. Processing
   (a) Converting the 3D image into gray scale 2D image Fig 9 (c), (d)
   (b) Determining the brain's orientation
   Result: For the first image fig 9 (c): Side
   For the second image fig 9 (d): Top-Down

   For the first image 9(a)
   According to given view and orientation, extract the appropriate lobes of the brain.
   Result: Extracted lobes in Fig 9 (e), (f), (g), (h)

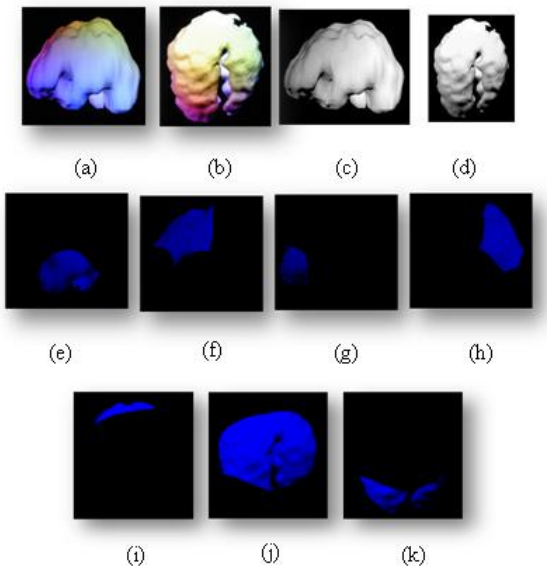

FIGURE 9. (a) first input image. (b) Second Input Image. (c) Grayscale image for first input image. (d) Grayscale image for second input image. (e) Temporal lobe for first image. (f) Parietal lobe for first image. (g) Frontal lobe for first image. (h) Occipital Lobe for first image. (i) Frontal lobe for second image. (j) Parietal Lobe for second image. (k) Occipital Lobe for second image.

   (c) Compare time signatures' values of existing data to determine their abnormality level
   Result:
   Temporal :Low
   Occipital :Normal

Parietal :Normal
Frontal :Low

For the second image 9(b)
According to given view and orientation, extract the appropriate lobes of the brain.
Result: Extracted lobes in fig 9 (i), (j), (k)

(d) Compare time signatures' values of existing data to determine their abnormality level
Result:
Occipital: Normal
Parietal : Low
Frontal : Low

(e) Apply the rules that identify the disorders.
*Result:*Trauma Induced ADD

3. The result of the test case
Success in detecting the abnormalities then the disorder accordingly

4. Parse Tree of test case 2
As shown in Fig (10)

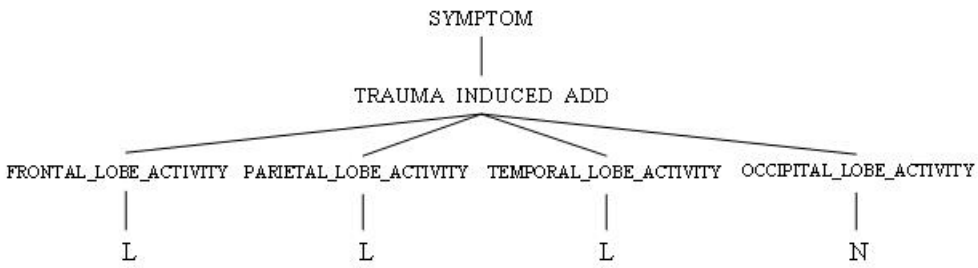

FIGURE 10. Parse Tree of Test Case 2

4.3.3. *Test case 3.*

1. Inputs SPECT image in Fig 11 (a)
2. Processing
   (a) Converting the 3D image into gray scale 2D image Fig 11 (b)
   (b) Determining the brains orientation → Result: Underside

(c) According to given view and orientation, extract the appropriate lobes of the brain
Result: Extracted lobes in fig 11 (c), (d), (e)

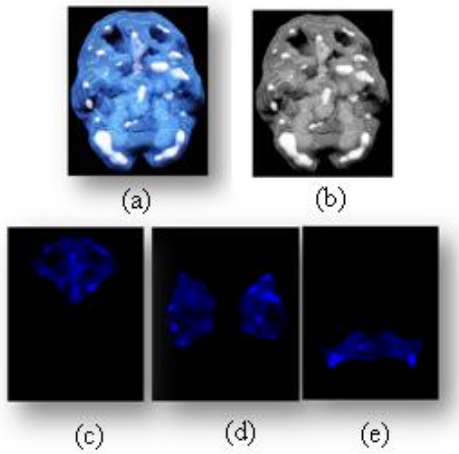

FIGURE 11. (a) SPECT Image (View Type: Active). (b)Grayscale Image. (c)Frontal lobe. (d)Temporal lobe. (e)Occipital lobe

(d) Compare time signatures' values of existing data to determine their abnormality level
Result:
Temporal : High
Frontal : Normal
Occipital : Normal

(e) Apply the rules that identify the disorders.
Result: Anxiety

3. The result of the test case
Success in detecting the abnormalities then the disorder accordingly

4. Parse Tree of test case 3
   As shown in Fig (12)

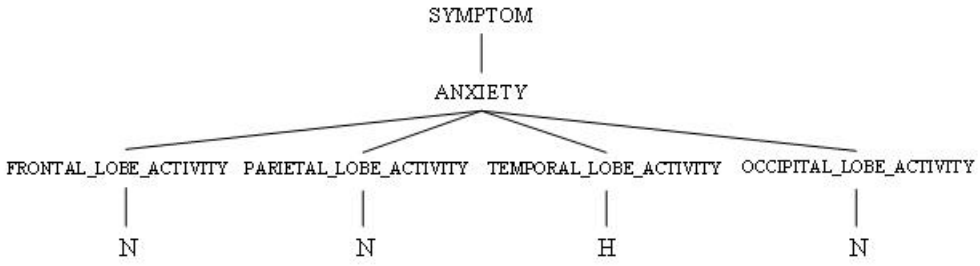

FIGURE 12. Parse Tree of Test Case 3

5. Conclusion

A classification and analysis scheme for human behaviour images is proposed. The analysis is dependant on the determination of activities in different brain lobes fuzzy-like rules and grammars were used for diagnosis. Pulse-Coupled Neural Networks were adopted to generate signatures of lobes' activities. Genetic Programming was used to evolve diagnostic grammars. The proposed scheme proved to be accurate and efficient in diagnosis human behaviour.

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