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Brain Disease Diagnosis Prediction Model for Fuzzy Based Generic Shaped Clustering and HPU-Net

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Abstract: A current fuzzy logic based medical imaging rendering system for conferences on brain diseases. Lectures use MRI (Magnetic Resonance Imaging) images to present various noises and brittle boundaries, images based on artistic facts. Here the general pattern matching algorithm is improved. Brain imaging processing and brain disease prediction based on the Generic Shape Clustering (GSC) algorithm and HPU-NET (Hybrid Pyramid U-NET Model for Brain Tumor Segmentation) predict performance reliably. We collected a model image based on brain disease prediction from a Kaggle data set and simulated the prediction result and performance. The simulation results are compared with various predications-based algorithms. Then simulate the networks performance fast and the result performance based on mostly lower energy consumption and other model compared to stable changes. Faster data transfer performance and overall network throughput. Basically faster 4.6 data transmission per second is better than other models. The future prediction performance reaches the maximum level of DSC accuracy and its classification accuracy is better than other models. To further validate the proposed system, CNN (convolutional neural network), RNN (recurrent neural network), FCM (fuzzy C-means), LDCFCM (local density clustering fuzzy C-means) are included in the simulation tests for comparison. The algorithm stops when the power consumption is determined. Results may provide evidence for feature recognition and predictive brain imaging diagnostics.

Keywords: *Fussy system, brain image, image segmentation, Generic shaped Clustering algorithm, more transparent noise.*

1. Introduction

A critical danger to human wellbeing and Cerebrum tissue is a complex useful framework. The sporadic shape and design of mind pictures give rich and important data to exact division in clinical practice. Now that the economy is developing fundamentally, wellbeing has turned into a central issue, influencing individuals' assumptions for regular solaces. As a typical infection that influences human wellbeing, mind sicknesses are sorted in view of their seriousness. Mind cancers are without a doubt the cerebrum infections that represent the most serious gamble to human wellbeing. Cerebrum tissue is a useful arrangement of tumultuous design.

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Exact division of brain images gives important and critical data to clinical practice. Be that as it may, clinical imaging of cerebrum tissue is in many cases subject to snags, for example Commotion, grayscale inclination, encompassing volume impacts and antiques. In the meantime, there are phenomenal troubles in understanding and fragmenting mind pictures because of feeble differentiation at the edges of the picture and the tumultuous design of cerebrum tissue.

The assortment of medical images is troublesome on the grounds that the assortment and comment of clinical data has become both a data security concern and an essential for troublesome essential explanation. Of two normal remedial ways, one includes gathering more data, for instance, openly underwriting or changing existing clinical reports. Another way is to zero in on an additional proficient manner to broaden the introduction of a little informational index, which is essential on the premise that the data acquired from the trial can be moved to concentrate on bigger informational collections.

In view of the above issues in clinical brain imaging processing, this work involves the data from marked and unlabeled information limits in medical brain imaging as clinical space information to additionally work on the symptomatic and division impact of imaging. Cerebral. Moreover, a semi-regulated acknowledgment strategy is presented and a deep learning calculation in view of semi-managed learning is coordinated. In various situations, the attractive reverberation picture of the human brain becomes fragmented. At long last, a clinical picture division framework for cerebrum infections is planned in view of the better calculation.

Medical imaging hardware keeps on getting better as PC innovation progresses. Clinical picture division is a significant assistant to clinical picture examination and an essential and basic innovation for clinical medical procedures. In any case, because of individual contrasts and the intricacy of human tissues, for example, the mind, division results for clinical imaging, particularly for cerebrum cancers, are not acceptable. Subsequently, endless scientists in this field all over the planet have concentrated on examining this subject.

With present day medical imaging innovations, how much data contained in pictures keeps on expanding, requiring clinical faculty to embrace a more prominent responsibility during clinical picture examination. Nonetheless, the pictures seem to have low differentiation, contrast between tissues, obscuring between various tissues or among tissues and sores because of contrasts in medical imaging standards and tissue attributes.

An outline of medical image processing, including different imaging modalities, medical image processing utilizing various methods is talked about here. Medical image alludes to the showcase of the human body or body parts for demonstrative and clinical purposes. It produces various sorts of clinical pictures that are exposed to medical image processing. Handling is applied to clinical pictures and valuable data is extricated from the pictures and in light of this data, dissects are played out that assist with distinguishing the pictures to foresee sicknesses.

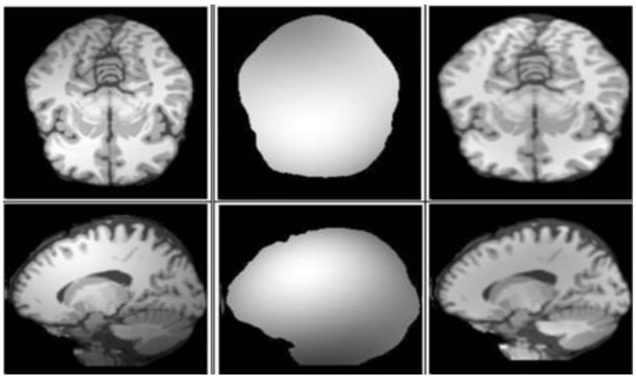

Fig.1. Brain Disease Images

Figure.1 characterize the brain images, in this brain image processing and information to specialists, understudies, researchers, doctors, and others to distinguish, analyze, or analyze sickness and study typical life structures and physiology. Due to the steadily expanding size of patient data sets, medical care divisions require precise and efficient data sets and data recovery; it tends to be effortlessly controlled with the assistance of appropriate clinical imaging procedures.

Since it is key for the examination and visualization of specific sicknesses or conditions, mind imaging has been the subject of a lot of exploration in the writing. Digital image processing techniques are utilized for clinical work that spotlights on mind acknowledgment in light of the fact that extricating the cerebrums from patient image for medical examination can give helpful data to determination and guess. [1].

2. Related Works

Imaging genomics is a proficient strategy to find likely biomarkers of Alzheimer's disease in hereditary and imaging information. Most hereditary imaging methods utilized today look at the connection between hereditary data acquired from cerebrum imaging and quantitative traits [2].

Neurodegenerative diseases can likewise cause different mental side effects, the improvement of which isn't straightforwardly connected with the visual examination performed by radiologists, since they can't identify efficient contrasts, and the computerized morphometric investigates of the mind that play out this estimation contribute very little to this estimation[3].

The capacity to accurately distinguish specific examples of sickness from individual sweeps is one of the essential objectives of clinical imaging. But since of the changeability in shape and appearance, brain imaging is troublesome. As a result of the utilization of populace based investigates principally fit to looking at the impacts of gathering implies, conventional imaging-based approaches have generally neglected to recognize differential sickness disease. [4].

With propels in clinical imaging innovation, multi-methodology imaging procedures like positron emission tomography (PET) and attractive reverberation imaging (X-ray) can identify unobtrusive underlying and practical changes in the mind, assisting with diagnosing problems. like Alzheimer's disease. Multimodality imaging doesn't necessarily in every case incorporate PET because of restrictive expenses or absence of genuine accessibility. The example size was diminished with the greater part of the accessible methodologies, which eliminated patients with missing information. Besides, the extraction and blend of multimodal highlights stays troublesome. [5].

Mechanized brain determination is made conceivable by multimodal neuroimaging methods like positron emission tomography (PET) and attractive reverberation imaging (X-ray), which can give point by point primary and utilitarian understanding of the cerebrum. In multimodal neuroimaging research, missing information because of patient dropout as well as low quality of information are unavoidable. Missing information subjects are much of the time avoided by traditional methodologies, diminishing the extents of preparing tests. [6].

Diffusion kurtosis imaging (DKI) has been demonstrated to be helpful in different neurological and clinical applications. Notwithstanding, commotion frequently subverts exact assessment of DKI tensors, particularly on account of the kurtosis tensor (KT). In this article, we present a system for troupe assessment and extraction that consolidates information from a few more established sources, like nonlocal structural self-similarity (NSS), neighborhood spatial perfection (LSS), actual fit, and DKI model scaling. Clamor highlights. Diffusion magnetic resonance (DMRI) permits more exact assessment of TKI tensors [7].

Their cutters commonly follow at least one chart books that are promptly accessible and considered fitting for the pictures being referred to. We present an information driven probabilistic framework that at the same time sections X-ray mind pictures into homogeneous subgroups, produces separate probabilistic map books for each gathering, and performs chart book directed division of the subgroups. [8].

Clinical information examination is focusing harder on multimodality picture information combination since it can add more data for more precise investigation. Primary and useful multimodality imaging information are progressively being consolidated to analyze cerebrum problems like epilepsy. The greater part of the at present involved strategies center around the mix of various modalities in the element space while disregarding the associated discriminative highlights for examining and arrangement. [9].

The fuzzy relational picture division engineering can consider earlier data because of another procedure. As a result of this forecast, likelihood conveyances of highlights and size maps, a decent physical position, and force signs can slant the circulation of power properties of client chose highlights. This information area is connected to fuzzy relational correspondence. [10].

The grouping of histogram spikes might be because of the fuzzily granular data in histograms. Recognition of power histogram tops got from MR images permits programmed assurance of power limits for division of a subject's entire mind. The whole mind can be perceived when these edges are evaluated by a procedure called region traversing. 50 human mind MRI image were utilized in a division test. A measurable investigation uncovered that the consequently and physically divided blocks were similar. [11].

To adjust for surface-initiated critical heterogeneity (/SPL AP/80%), we fostered an original methodology called nearby entropy minimization with a Bicubic spline model (LEMS), which utilizations dim voxel values to depict sickness. Without the requirement for characterization, this entropy-based approach really resolves a few critical issues in mind imaging, including commotion, unexpected polarizing field, aversion to blood vessel wall voxel edge varieties, and blood vessel wall voxel edge varieties [12].

Urate condition, at this point not thought about an uncommon or intriguing illness, is the most serious quake in kids. Early finding of Tourette disorder and persistent spasm problems is troublesome yet significant in light of the fact that improper medical treatment can deteriorate a youngster's condition whenever taken too early. The amine oxime of technetium-99m hex methyl propylene is utilized in mind perfusion figured tomography to separate these two diseases. [13].

Image segmentation, the most common way of distinguishing objects in image, stays perhaps of the most difficult issue in picture handling, notwithstanding many years of endeavors. Until now, there are a ton of normal techniques to tackle this issue. Fuzzy Connection is another system that has as of late shown a great deal of potential. By definition, pictures are foggy. [14].

One of the most pursued research regions in the field of medical imaging is the division of mind tissue. It gives a total quantitative investigation of the cerebrum, permitting problems to be precisely recognized, analyzed and characterized. Assumes a significant part in the separation among sound and disease tissues. Accordingly, just the presentation of the division technique utilized can decide the exactness of the determination and treatment plan. [15].

In numerous biomedical imaging applications, image segmentation is basic for the analysis of different deformities by doctors or other medical care experts utilizing proof based methodology. Nonetheless, the huge computational intricacy restricts its utility and is tedious. Division of biomedical pictures is upheld by explored equal handling models. [16].

Since the PVA exists at the limits between tissues, the PVA was at first displayed with the confined edge force estimation. This guide is determined in 3D and changed to a worldwide portrayal to build heartiness to clamor. Significant advantages compare to the PVA voxels, which are utilized to decide the PVA α portion (how much each tissue present in the composite voxels). The consequences of the reproduced and genuine FLAIR images show the superior presentation of WML division against reality in the field. [17].

Scaling conduct is innate in essential natural designs, and the level of such a property must be recognized at a specific degree of perception. Thusly, the properties of parts and power-regulation scaling became appealing for research in science and medication, because of their capacity to distinguish examples and properties of brain boggling biological morphologies. [18].

Human health management the executives is the principal level of everyday development for a solid human. Rest identification and observing innovation is a specific center since rest quality and amount fundamentally affect wellbeing. Besides, a SoS is broke down in clinical imaging. This part presents the clinical utilization of attractive reverberation MRI scanners to analyze specific infections. [19].

A finding is the name of an individual's conceivable medical condition, disease, disorder, or other condition. Some of the time creating a determination can be very straightforward, while at different times it tends to be somewhat more troublesome. There are enormous informational indexes, however there are a wide range of innovations that can precisely recognize examples and make expectations. This condition is as of now identified utilizing manual, blunder inclined systems. [20].

Because of this impediment, conventional systems can't gain trans cranial data from erratic areas in the skull. This article depicts Tran’s cranial environment, which permits specialists to concentrate on cerebrum harm and mind issues, for example, epidural or subdural hemorrhages and skull breaks from any point, from any review point of the mind's surface. Assemble a comprehension of the life systems of the human head and use dispersion surmising to distinguish cranial and cerebral surfaces. [21].

Spatial normalization is frequently used to relegate information to a standard direction framework by eliminating multi-purpose morphological contrasts and permitting bunch investigation to be performed. The work introduced was inspired by the requirement for a robotized cortical surface standardization method that would naturally recognize homologous cortical milestones and guide them to similar directions on a standard complex [22].

One of the most broadly involved techniques for looking at causal impacts in unambiguous mind districts is Granger causality (GC), which has created momentous discoveries in the investigation of cerebrum networks utilizing utilitarian attractive functional magnetic resonance imaging(fMRI). Ordinary GC indicators and succession choices, notwithstanding, depend on straight models, which has disadvantages, remembering unfortunate nonlinearity identification for the application. [23][24].

3. Proposed System

The proposed system was used for fuzzy logic-based general pattern clustering algorithm and HPU-Net method-based brain tumor image segmentation for confident prediction performance. A dataset of at least 1,000 records and 10,000 images was collected to analyze the prognosis of brain tumor disease.

As computer technology develops, medical imaging equipment is continuously being updated. Medical image segmentation is a vitally important fundamental technology for clinical practice as well as an essential supplement to clinical image analysis. As a result, a huge amount of effort has been invested by numerous researchers in this discipline in exploring this subject broadly.

Medical professionals must exercise extreme caution when analyzing medical images because of the growing amount of information they contain. However, due to variations in imaging standards and tissue properties of clinical images, the images have low contrast, changing tissue, blurry between different tissues, or tissues and lesions. As a result, processing and analyzing medical images accurately has been made extremely difficult by the sophistication and classification of medical images. In order to diagnose and treat disorders, it is crucial to use computer technology for the detection of brain images and the forecasting of brain diseases.This study analyzes the assortment of unlabeled and marked data in medical cerebrum imaging, making the previously mentioned difficulties in medical brain imaging and clinical information space for additional work on the effect of cerebrum imaging on division and conclusion.

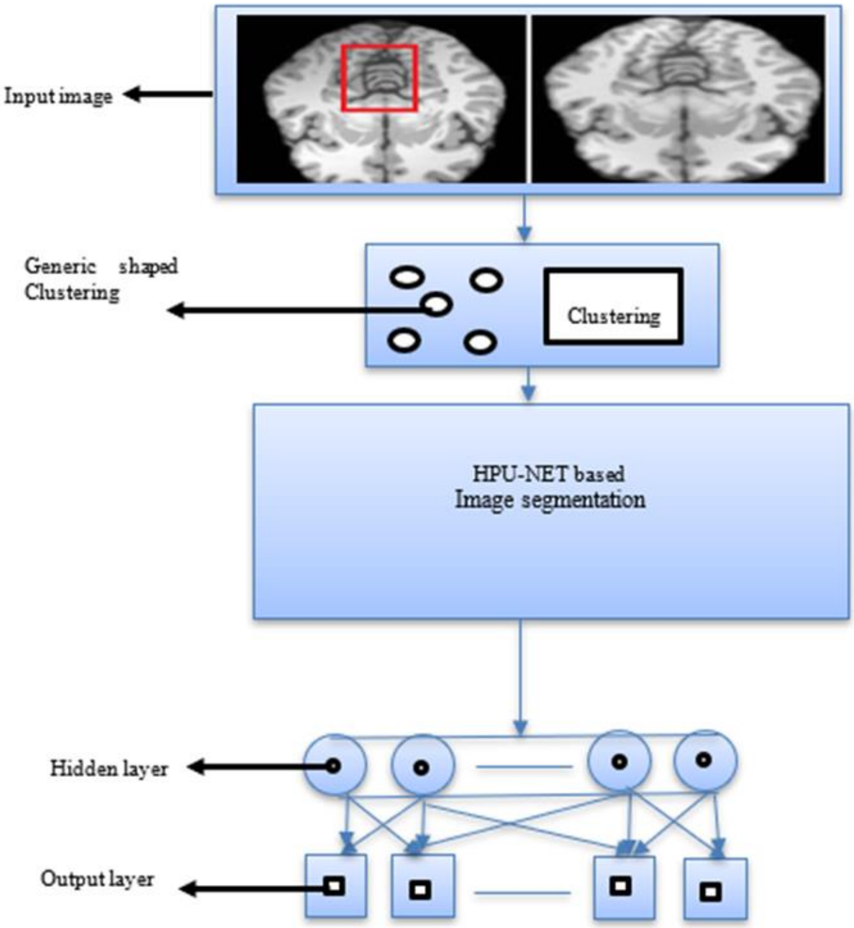

Fig.2. Proposed Architecture

Figure.2 define the proposed architecture for brain tumor disease prediction performance. It is four step process of predications, first step collect the input images and step-2 process for Generic shaped Clustering algorithm and clustering the images. Step-3 HPU-NET model used image segmentation process. Step-4 hidden layer is used provide higher precision, more transparent noise reduction effect and finally output layer predict the disease performances.

The complicated imaging component of human cerebrum tissue presents MRI images with shifting levels of clamor, feeble edges, and ancient rarities. In this manner, a fuzzy clustering calculation is created to extricate the elements of the procured cerebrum imaging information. Then, at that point, a cerebrum diagnostics and mind imaging handling expectation model in view of a typical example bunching calculation in light of cutting edge fluffy rationale and HPU-Net is planned, while guaranteeing the security execution of the model Figure.2.

Further developed discourse execution with a summed up design fuzzy logic based Generic shaped Clustering (GSC) algorithm in view of fuzzy logic. This calculation has been utilized to totally noise lesson images. Our most memorable investigation of C is bunching. A dataset X is gathered into classes C. C is the gathering set X1, X2, XC are associated. The accompanying bunch condition (1)

$$\begin{cases} X_1 \cup X_2 \cup \ldots \cup \ X_c = X \\ X_i \cap X_k = \emptyset, 1 \leq i \neq k \leq c \\ X_i \neq \emptyset, X_i = X, 1 \leq i \leq c \end{cases} \quad (1)$$

The fuzzy C area can decide the vulnerability level of each model in the dataset across all classes. This will assist with seeing better and depict the elements in the brain images. As far as division results, fuzzy logic can allude to the division border, availability, and scattering among various division blocks. Subsequently, it can mine definite data about the brain image.

The GSC algorithm limits the weighted amount of the squares of the good ways from the arranging testing point to each arranging community. Weight is the participation capability of each example point for every grouping place, which is a typical measures in bunching calculations. The characterization objective capability (2) is acquired as follows:

$$J_{min} = (U,V) = \sum_{i=1}^{c} J_i$$
$$= \sum_{i=1}^{c}\sum_{i=1}^{c} u_{i,j} d_{ij}^2 \quad (2)$$

Equation (2) here U is the classification of matrix, C denote the number of samples and V is the classification vectors.

$$\sum_{i=1}^{c} u_{i,j} = \forall j$$
$$= 1 \ldots .1 \quad (3)$$

Here equation (2) and (3), to define the process of Generic shaped Clustering (GSC) algorithm is best combination of U and V. so the minimum values find the constrain equation (4)

$$F = J\big(U, U_{1,\ldots} U_{c,} \lambda_1, \ldots\ldots \lambda_n\big)$$
$$= (\sum_{i=1}^{c} \lambda_1 \sum u_{i,j} - 1) \quad (4)$$

Here eqn(4), $\lambda_1, \ldots\ldots \lambda_n$ is LaGrange operator. The main request streamlining important condition for the fractional subsidiary of equation (4) is:

$$\frac{\delta F}{\delta}$$
$$= \sum_{i=1}^{c} \lambda_1 - 1$$
$$= 0 \quad (5)$$

$$\frac{\delta F}{\delta u_{i,j}} = m(u_{i,j})^{m-1}(d_{i,j})^2\text{-}\ \lambda =$$
$$0 \quad (6)$$

Finishing Equation (6) can obtain Equation (7):

$$(u_{i,j} = \left[\frac{\lambda}{m(d_{i,j})^2}\right] \quad (7)$$

Equation (7) into (3) can get Equation (8)

$$\sum_{i=1}^{c} u_{i,j} = \sum_{i=1}^{c} \frac{\lambda}{m}\left[\frac{1}{(d_{i,j})^2}\right]$$
$$= \frac{\lambda}{m}\left\{\sum_{i=1}^{c}\left[\frac{1}{(d_{i,j})^2}\right]\right. \quad (8)$$

$$\frac{\lambda}{m} =$$
$$\frac{1}{\frac{\lambda}{m}\left\{\sum_{i=1}^{c}\left[\frac{1}{(d_{i,j})^2}\right]\right.} \quad (9)$$

Substituting Equation (9) into (7) can get Equation (10):

$$u_{i,j}$$
$$= \frac{1}{\sum (d_{i,j})^2} \quad (10)$$

This algorithm has higher division precision and the capacity to hold detail upset by high fixation clamor, and picture edges have more noteworthy perfection after division. This calculation is recorded as a Summed up Generalized Form Clustering (GSC)model depicted as equation(11):

$$\boldsymbol{J}^{\mathrm{GSC}} = \big(U, U_{1,\ldots} U_{c,} \lambda_1, \ldots\ldots \lambda_n\big) = 2\sum_{i=1}^{c}\sum_{j=1}^{n}(u_{i,j})^2\,(1 - \|x_i - x_j\|) +$$
$$2\sum_{i=1}^{c}\sum_{j=1}^{n}(p_i)^2\,(1 - \|x_i - v_i\|) \quad (11)$$

In Equation (11), signifies sifted mean mind picture or separated mean cerebrum picture. The principal thing here is that the conventional GSC articulation piece changes from the distance metric, which doles out examples to a higher layered space and boosts the contrast between tests.

Here, the third component, the area spatial requirement component, is expected to reinforce the strength of the calculation for creating commotion pictures. Finally, the spatial capability is incorporated into the enrollment capability u_{ij}

$$u'_{ij} =$$
$$\frac{u_{ij}^p u_{ij}^q}{\sum u_{ik}^p S_{ik}^q}\ \boldsymbol{J}^{\mathrm{GSC}} \quad (12)$$

Here S_{ik}^q is similar to the enrollment capability, which addresses the chance of a pixel having a place with a classification, and the boundaries p and q are the weight boundaries that control the enrollment capability and the spatial relationship capability. Here u'_{ij} is the final membership function. Demonstrates the improved fuzzy clustering GSC algorithm.

$$\delta_\beta^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_\beta)\ \hat{}2 \quad (13)$$

Next, data in the current batch are normalized as Equation (14):

$$x_i = \frac{x_i - \mu_\beta}{(\delta_\beta^2 + \epsilon)}\ \boldsymbol{J}^{\mathrm{GSC}} \quad (14)$$

Equation (14) seems to be somewhat contrary to the previous operation; however, it can restore the original input. Besides, parameters β shall meet Equation (15):

$$\begin{cases} \gamma^k = \sqrt{var(x^k)} \\ \beta = E(x^k) \end{cases} \boldsymbol{J}^{\mathrm{GSC}}$$
(15)

The total model could conceivably change the info circulation of the ongoing layer. The general impact is to keep the element dispersion steady to settle the model during preparing and learning. In the interim, the GSC algorithm assists accelerate the union with timing during model preparation, forestalls dispersing or blasting of slopes, and further develops the preparation exactness.

4. Result and Discussion

Simulation result prediction performances discuss about brain disease. The performances is improved using fuzzy based Generic shaped Clustering (GSC)) algorithm and HPU-Net. The brain images are get from large dataset of haggle. In this performance analysis using following algorithm CNN, RNN, FCM are selected to compare to proposed system. The simulation result will demotion using python with Tensor flow as the back end.

DSC (Dice Similarity Coefficient), which goes from 0 to 1, addresses the level of comparability between the test division result and the master mark. The higher the DSC esteem, the higher the similitude of the division. The Jacquard coefficient and the DSC are characterized as Conditions (16) and (17):

$$DSC = (T, P) = \frac{2|T^{\wedge}P|}{T+P} \quad (16)$$

$$\text{GSC algorithm}\ (T, P) = \frac{|T \Lambda P}{|TVP|} \quad (17)$$

In (16) and (17), D addresses the first locale of the cancer and P addresses the division aftereffect of the proposed calculation. P and T ought to be viewed as exhaustively while assessing the division aftereffects of the ongoing model. The better the impact of the fluffy based GSC bunching calculation, the bigger the enrollment distinction of a similar pixel having a place with various classifications, the bigger the got division coefficient, and the lower the division entropy.

$$V_{pc} = \frac{\sum_{i=1}^{c} u_{i,j})}{n} \quad (18)$$

$$V_{pe} = \frac{[\sum_{i=1}^{c} \sum_{j=1}^{c} u_{i,j}]}{n} \quad (19)$$

A Cluster formation

Dissected different models utilizing nodes development and bunch arrangement and functional hubs and reproducing complete networks power utilization execution. The gathering looks at each networks model. In this model, the hour of complete energy utilization of the networks is limited. A bunch is utilized which lessens the power utilization of the networks and decreases the time utilization and inertness of the networks.

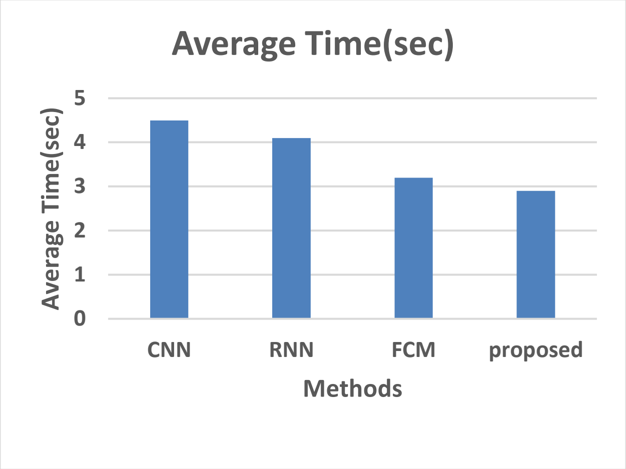

Fig.3. Average Time (sec)

Figure3. Discuss about the average time performance to compared to various methods, the methods of CNN average is 4.5 time per sec and RNN average is 4.1 time per, and FCM average is 3.2 time per sec and proposed average is 2.9 per sec.

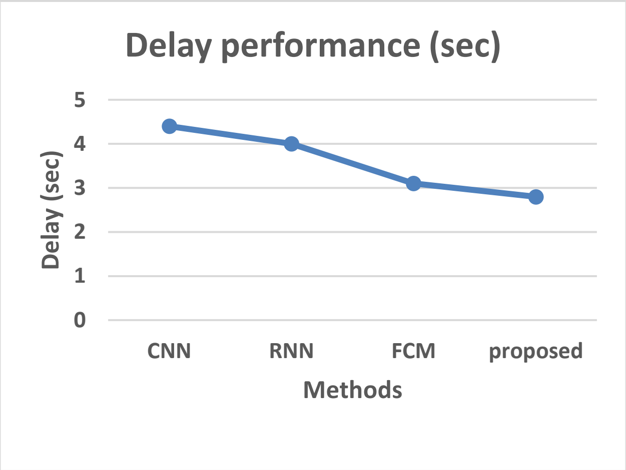

Fig. 4. Delay performance (sec)

Figure 4. Discuss about the time delay performance to compared to various methods, the methods of CNN average is 4.4 time per sec and RNN average is 4.4 time per, and FCM average is 3.1 time per sec and proposed average is 2.8 per sec.

B PSNR (Peak Signal-to-Noise Ratio)

The PSNR is the noise ratio has been calculate and reduce the noise for various percentage levels 30%, 60% 80%. The below average calculate the noise level is 30 % for figure.5 of evaluation performance.

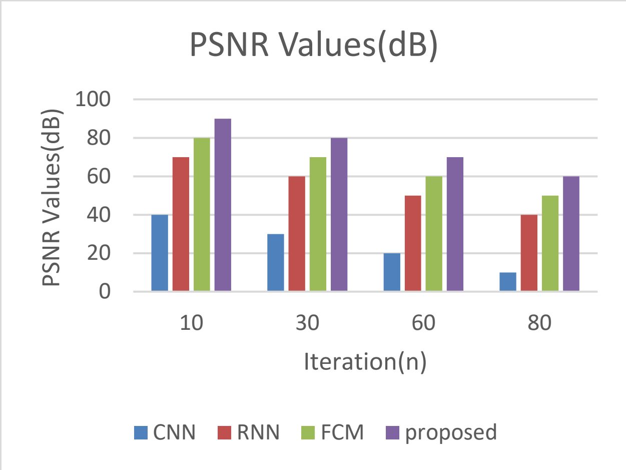

Fig. 5. PSNR Values radio for 30 %

Figure.5 discuss about the noise radio levels are compared to various methods. The first level of 30% noise performance method of CNN is 30% and RNN is 60 % noise level and FCM is 70 % of noise level and proposed level is 80%.

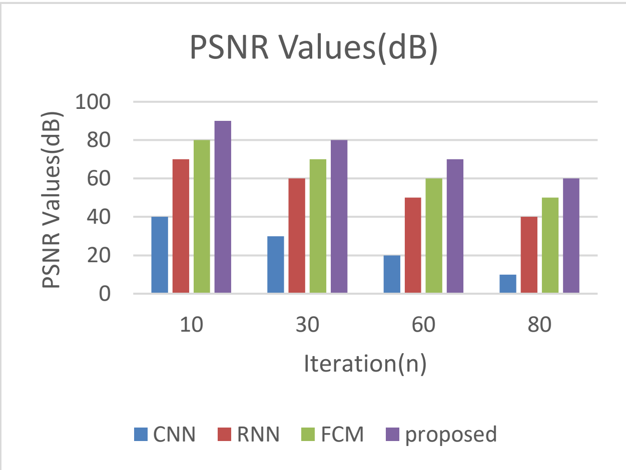

Fig. 6. PSNR Values radio for 60 %

Figure.6 discuss about the noise radio levels are compared to various methods. The first level of 60% noise performance method of CNN is 20% and RNN is 50 % noise level and FCM is 60 % of noise level and proposed level is 70%.

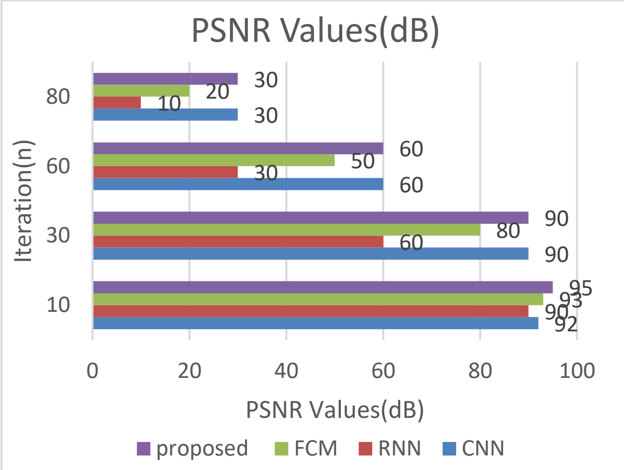

Fig. 7. PSNR Values radio for 90 %

Figure.7 discuss about the noise radio levels are compared to various methods. The first level of 80% noise performance method of CNN is 60% and RNN is 30 % noise level and FCM is 50 % of noise level and proposed level is 60%.

C Evaluation performance for different models

The table.1 discuss about the evaluation of performance compared to various methods. The methods CNN, RNN, FCM, Generic shaped Clustering (GSC) is the proposed level approaches

Table 1 Changes in evaluation functions of different models (%)

Models	$\mathbf{V_{pc}}$	$\mathbf{V_{pe}}$
proposed	0.958	0.055
RNN	0.923	0.069
FCM	0.888	0.113
CNN	0.853	0.167

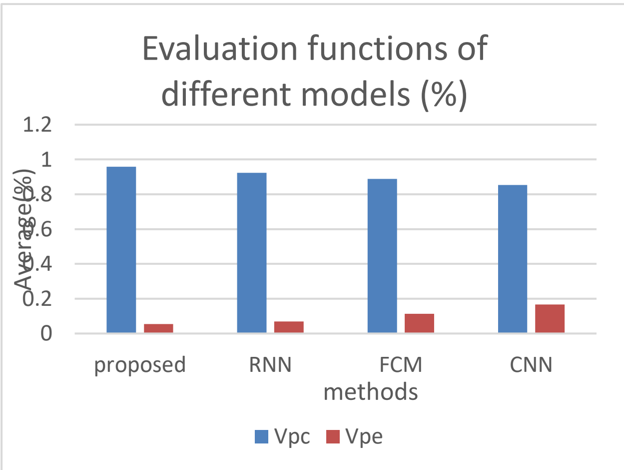

Fig. 8 Evaluation functions of different models performance (%)

Figure.8 discuss about the evaluation model performances, the performance of CNN is 0.853 %, and the performance of FCM is 0.888% and the performance of RNN is 0.923% and proposed system of Generic shaped Clustering (GSC) algorithm is 0.958%

Table 2. Variation of each model with the Jaccard coefficient (%).

models	The white matter	The gray matter
proposed	0.858	0.799
RNN	0.823	0.743
FCM	0.788	0.713
CNN	0.753	0.667

The table.2 discuss about the evaluation of the Jaccard coefficient performance compared to various methods. The methods CNN, RNN, FCM, Generic shaped Clustering (GSC) is the proposed level approaches

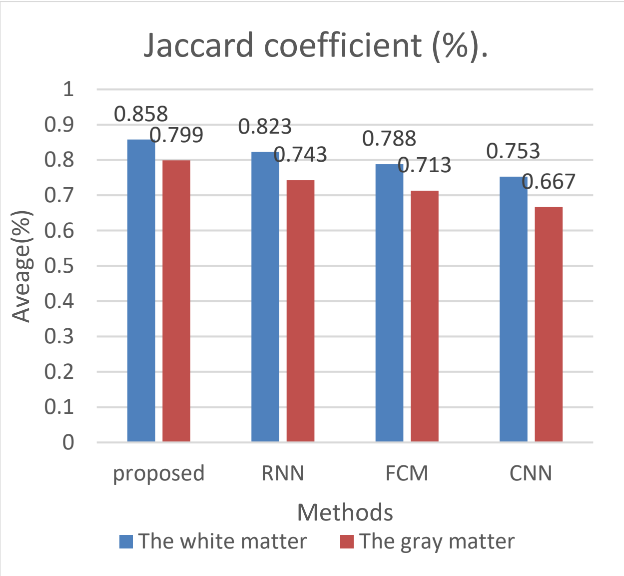

Fig. 9 Evaluation of different Jaccard coefficient performance (%)

Figure.9 discuss about the evaluation Jaccard coefficient performances, the performance of CNN is 0.753 %, and the performance of FCM is 0.788% and the performance of RNN is 0.723% and proposed system of Generic shaped Clustering (GSC) algorithm is 0.858%

5. Conclusion

Brain tumor is the most common disease in the world. Our discussed proposed system for brain disease prediction analysis. First, we collect X-ray images of brain tumor datasets. Our critical area is to analyze brain disease prediction and assessment performance of the entire dataset. Evolution based on noise, weak boundaries, and artifacts in brain images. Improved brain imaging prediction performance using Generic Shape Clustering (GSC) algorithm and HPU-NET models. The Generalized Shape Clustering (GSC) algorithm and HPU-Net are proposed structure extraction and reconstruction, better noise reduction and higher segmentation efficiency as a result. The highest prediction accuracy for DSC reaches 0.958%, and the Jacquard coefficient reaches 0.858, providing a test basis for the brain imaging characteristic and prognostic diagnosis of brain diseases.

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