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استكشاف جدوى الاستفادة من تحسين سرب الجسيمات لتحسين الشبكات العصبية التلافيفية العميقة في تحديد أورام الدماغ في الصور الطبية

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الخلاصة

تسعى هذه الورقة إلى تحليل كيفية تطبيق **PSO** لإجراء الطي الأمثل لشبكات **DCNN** الصفائحية في تشخيص أورام المخ من الصور السريرية. ويناقش طرقًا أخرى لحساب **PSO** للنمط فيما يتعلق بتقسيم وتقطيع صور **MR.**لغرض إنجاز الصورة، يتم اقتراح تقنية **PSO** الذكية، بينما يتم استخدام تقنية-**K-Means/SBM** **PSO**لتحديد صور **MR** للفصل. يقومون بتقييم تنفيذ **PSO** في تجزئة الصور وتعزيز خوارزمية التجميع **K-Means**مع صور **MR** من قاعدة بيانات متنوعة. طريقة البحث النوعية **PSO** هي مزيج من سلسلة من الأساليب المستخدمة في تصنيف صور الرنين المغناطيسي على أنها طبيعية أو غير طبيعية اعتمادًا على نوع الورم الموجود وفي تقييمها اعتمادًا على المقياس الذي تعطيه منظمة الصحة العالمية لأورام المخ . يثبت التحليل أن نتائج التقسيم المعزز بمعنى أنه إذا كان شخصان قريبان من بعضهما البعض من حيث القيمة النسبية المعطاة، فيجب أن يكونا في مجموعات مختلفة بينما يجب أن يكون الأشخاص الذين لديهم قيمة أكبر نسبيًا بينهم في نفس المجموعة. وبالتالي، فإن تهجين **PSO** مع **K-Means** يعزز موثوقية ودقة المصنفات. كما أنه يميز مستويات **PSO**العالية جدًا للزيادة في التصميم المعماري **DCNN** لتشخيص أورام المخ بشكل خاص مع الإشارة إلى حقيقة أن نماذج **PSO-k-means** المقترحة تظهر أعلى معدلات تجزئة وتصنيف جديدة ممكنة.

الكلمات المفتاحية: نموذج **PSO-K-Means** الهجين، تحسين سرب الجسيمات**(PSO)** ، تشخيص أورام الدماغ، الشبكات العصبية التلافيفية العميقة**(DCNNs)** ، تجزئة الصور الطبية،

Exploring The Feasibility To Utilize Particle Swarm Optimization For Improving Deep Convolutional Neural Networks In Identifying Brain Tumors In Medical Images

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Abstract

This paper seeks to analyze how PSO can be applied to perform an optimal folding of laminar DCNNs in the diagnosis of brain tumours from clinical images. It discusses other ways to compute PSO of pattern regarding MR images sectioning and chunking. For the purpose of accomplishing an image, an intelligent PSO technique is proposed Whereas for the identification of the MR images for segregation a K-Means/SBM-PSO technique is utilized. They assess the implementation of PSO in image segmentation and enhancement of K-Means clustering algorithm with MR images from a varied database. The qualitative PSO method of research is a combination of a series of methods that is used in classifying the MR images as normal or abnormal depending with the type of tumor found and in evaluating them depending with a scale that is given by the WHO for brain tumors. The analysis proves enhanced division results in the sense that if two people are proximal to each other in terms of the given relative value, they must be in different

bunches while those with a relatively larger value between them should be in the same bunt. Hence, the hybridization of PSO with K-Means enhances the reliability and accuracy of the classifiers. It also distinguishes PSO's very high levels of increase to the DCNN architectural design for the diagnosis of brain tumors especially pointing to the fact that the proposed PSO-k-means models show the highest new segmentation and classification rates possible.
Keywords: Hybrid PSO-K-Means model, Particle Swarm Optimization (PSO), Brain tumor diagnosis, Deep Convolutional Neural Networks (DCNNs), Medical picture segmentation,

1. Introduction

A growth of tissue that has cells reproducing at rates that seem to be outside the normal controlling mechanisms of the standard cellular cycle is known as an intracranial growth or brain cancer. Despite the existence of over 150 distinct types of brain tumors, brain cancers are primarily classified into two main categories: Especially, different types of intracranial tumors, primary, and metastatic.

Intracranial tumors can be classified into primary brain tumors and secondary brain tumors and the former is further sub categorized into tumors that develop from the tissues of the brain and those that develop from the tissues neighboring the brain. These are tumors that may be benign or malignant and are separated as glial tumors (made up of glial cells) or non-glial (found in or on other structures present in the brain, for example nerve, indications of blood vessels or glands.

On the other hand metastatic brain tumor starts from other organs such as breast or lungs but it reaches the brain; commonly through circulation in the blood stream. Such tumours are as a result considered malignant and are termed as cancer.

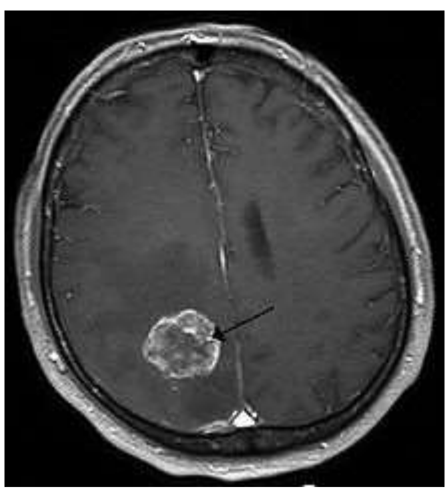

Figure 1: Brain Tumors

About forty five years ago researchers estimated that around 150000 patients each year, or nearly 25% of cancer patients, get brain metastases from their primary tumors. Among all the individuals who are diagnosed with lung cancer, it is believed that forty percent of them experience tumor spread in the brain area. Historically, the folks diagnosed with these cancerous growths had dismal outlooks with average life expectancies ranging about for weeks. On the other hand, with a boost in early diagnostic tools and adopting sophisticated surgeries and radiation therapies the life expectancy has gone up to years and also the life has become better even after diagnosis of the cancer.

1.1 Classification of Brain Tumors Brain tumors

may be classified based on many factors, including the cellular origin, location within the brain, and whether they are cancerous (malignant) or non-cancerous (benign). The following are few common types of brain tumors:

1. Gliomas
2. Meningiomas are a kind of brain tumor.
3. Pituitary tumors.
4. Medulloblastomas are a kind of brain tumor.
5. Schwannomas are a kind of tumor.
6. Craniopharyngiomas are a kind of brain tumor.
7. Hemangioblastomas are a kind of tumor.
8. The main part of the nervous system that includes the brain and spinal cord. Lymphomas

These are just a few of the many different types of brain tumors that may form. Each kind may display unique symptoms, need specific therapy approaches, and result in different results. Precise diagnosis and classification are crucial for selecting optimal care approaches for individuals affected by brain tumors.

1.2 Brain Tumor Symptoms

The symptoms may vary depending on the location of the brain tumor, while other forms of brain tumors might also result in the following symptoms:

• Nocturnal awakenings due to headaches or increased intensity of headaches in the morning
• Seizures or epileptic fits
• Difficulty in speaking, thinking, or expressing oneself
• Changes in one's individuality
• Paralysis or weakness in a specific part or side of the body

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• Feeling disoriented or lightheaded
• Changes in vision
• Sensory changes
• Numbness or tingling in the face
• Symptoms of nausea or vomiting, and difficulty swallowing
• Confusion and disorder.

Treatment for Brain Tumors

Whether a brain tumor is primary, metastatic, benign, or malignant, it is usually treated with

1. surgery,
2. radiation therapy, and/or chemotherapy, either alone or in combination.

- proton beam treatment
- standard external beam radiation
- stereotactic radiosurgery

3. chemotherapy
4. laser interstitial thermal therapy (LITT)
5. investigative therapies

Although the data confirm that radiation and chemotherapy are more frequently used to treat hazardous, residual, or intermittent growths, the choice of therapy is made based on a single assumption and a variety of models. Every type of treatment has some risks and unfavorable side effects.

2 Literature Review

In the work of Amin et al. (2020), traditional MRI data is used to enhance brain tumor classification through the combination of CNN with DWT. Clinical imaging input data pose the greatest difficulty in correctly categorizing the brain tumours, that the researchers wanted to address. The networks employed DWT techniques in conjunction with X-ray sequences and fed these reconstructed images to the CNN model, which yielded both high accuracy in classification. This particular technique uses deep learning and fused images for brain tumor detection which has steady time implication on patient care and clinical diagnostics.

Similar to Amayo et al. (2018), Kamath et al. (2019) also proposed a new method of K-infers clustering with neural networks for deformation of objects. Selecting the method in a way that they group the similar frameworks, the researchers opted for the neural network cluster for the organization and the K-means cluster for the segmentation. Their strategy was shown to localize distortions of the shape of the brain tumor in the clinical images through testing and analyzing the output and the same was done to map local minimums and maximums. For clinical image

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assessment, this work would be of significant in presenting a solution for the matter concerning the identification of diseases and their type for diagnosing pathological conditions in the early stages and formulating appropriate treatment methods in health care.

Utilizing this fact, Kaur et al. (2018) proposed an enhanced method for distinguishing between different objects properly, and this method actually targets mental images. Thus, their approach perfects the match between the closer perspective and the institution in mental reference frames, hence improving the definable spatial resolution of recognized objects. The advanced decisions and incorporation of availability dependent data enabled better practical implementation of recognizing significant patterns and abnormalities in priority images. The findings are also very relevant as the nurse can contribute to designing more accurate and efficient algorithms for medical image analysis that may be employed in diagnosing neurological diseases and categorization of therapy types.

Khan et al. (2020) developed a framework to examine gastrointestinal problems using computer-assisted remote case endoscopy. Experts concentrate on selecting optimal traits in order to enhance the accuracy of disease diagnosis. The framework aims to enhance the reliability and accuracy of case endoscopy findings by incorporating sophisticated component protection measures. This study presents a purposeful approach to focusing on gastrointestinal disorders using remote capsule endoscopy, which advances the disciplines of clinical imaging and computer-assisted diagnosis.

Recently, Khan et al. (2019) have initiated an approach for brain tumor identification and classification system with the help of need feature selection and marker-based watershed algorithm. The task was to apply contemporary methods in image processing in order to improve accuracy and efficiency of analysis of brain development. Thus, the researchers constructed a highly comprehensive framework for the identification and characterization of digital brain development by virtue of advanced algorithms and dynamic determination methods. Therefore, the work offers definitive confirmation for the precise and sustained identification of tumors within the brain that can positively impact the field of clinical imaging and diagnosis.

3 Particle Swarm Optimization

The assumptions that basis bird behavioral intercourseity Bird behavioral patterns is the ground for swarm intelligence optimization method referred to as Particle Swarm Optimization (PSO). It further defines expertise in terms of fine-tuning specific processes or actions, for offering information on modes of behavior, and, invoking the field of cognitive neuroscience. The application of PSO has been done in different fields of computing recently including face detection and recognition, in field of communication and in other field including imaging, classification, designing, and in training of artificial neural networks.

PSO has an edge over all other optimization approaches due to its relative simplicity and ease of use. Particle Swarm Optimization (PSO) and evolutionary computation techniques such as Genetic Algorithms (GA) exhibit significant similarities. The framework employs a population of random configurations and updates them by renewing ages in order to look for optima. However, PSO requires development administrators who possess hybrid and transformation skills, rather than relying on GA. The process involves the pursuit of the current optimal particles, which are hypothetical solutions, also known as particles, as they navigate around the problem space.

A problem arises in the fundamental Particle Swarm Optimization (PSO) algorithm, and a fitness function is used to assess a proposed solution. Furthermore, a social network or communication framework is created, enabling interactions among individuals and their neighbors. Subsequently, a population of individuals is generated, characterized as random conjectures regarding the potential solutions to the given challenges. The individuals in question are sometimes referred to as the candidate solutions. The phrase "particle swarm" is derived from their alternative moniker, "the particles." In order to enhance these prospective solutions, an iterative process is initiated. A multitude of individuals inundates the search area.

A molecule's configuration is not solely determined by its current position and the insights it has gained. It is also influenced by the arrangement of surrounding particles in its vicinity. The term "worldwide best molecule" refers to the optimal location within the entire range of a molecule. The resulting approach is referred to as a "g best PSO." The calculation is sometimes referred to as the particle swarm optimization (PSO) performance of each particle, particularly when smaller regions are employed. A wellness metric that varies based on the optimization problem is used to measure the proximity of the particle to the global optimum. The following features encompass each individual molecule within the many.

3.1 PSO based Image Clustering Algorithm

The identification of elements in this model of X-ray images is assumed where types of elements produce different pixels value since they have different spectral reflectance and emissivity. Monstrous example confirmation is a discipline that entails the use of supernatural data that is quantified at a pixel level. The many

2024 آب العدد 14
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المجلة العراقية للبحوث الإنسانية والإجتماعية والعلمية
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components and the definitions relative to the proposed computation are shown in Table 1 below.

Table 1: Variables employed in the Particle Swarm Optimization (PSO) based Image Clustering method

Variable	Meaning
Pi	Particle, Pi= (mil, mi2,,,, min ... , miN) : Represents *N* cluster centroids.
mik	k111cluster centroid of t1 particle
xi	Pattern matrix of i111 particle
f()	Fitness function f(pi) = w1dmax(Xi ,Pi) +w2(Xmax - dmin(pi))
dmax, dmin	Maximum and minimum Euclidean distances
xi	a matrix representing the assignment of patterns to the clusters of particle i.
Ne	Number of clusters
W1,W2	User defined constants(weight factors)
Si	Silhautte validity index

Based on PSO, we suggest the following picture clustering technique:

While ((S_i -1 $\geq \delta$)

1. ***For each particle i***
   a. For each pattern X_p
      Compute the Euclidean distance $d(X_p, m_{i,k})$ for all clusters $C_{i,j}$.
      Assign y to C_{ij}. Such that d-value is minimized.
   b. Calculate fitness of the particle, $f(p_i)$
2. ***Compute the personal best and global best solution y'(t)***
3. ***Update the cluster centroids.***

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Algorithm 6.1: Particle Swarm Optimization (PSO) based Image Clustering Algorithm

Evaluation metric:

According to the specification of the fitness function, a small deviation indicates that the clusters are well-separated. The concept of Quantization, which is represented by the term "The Blunder of Quantization," can also be employed to characterize the quality of a clustering algorithm.

$$Q_e = \frac{\sum_{k=1}^{K} [\sum_{\forall x_p \in C_k} d(x_p, m_k)] / n_k}{K}$$

The kth cluster, that is, the cluster number K is represented by Ck, and the pixel's count by n[sub]k[/sub].

In this context, the optimization goal of the fitness function is to f= dmin, which in turn results in minimizing the value of dmax. Hence for the best grouping, it is preferred to have a smaller dmax while a bigger dmin. Apart from the feature selection, group legitimacy that measures how well a grouping algorithm performs is also assessed. Cluster validation is a crucial step in clustering analysis because it ascertains the accuracy of the clustered results with regards to the various uses that are intended to be put into practice. Normally, the number of clusters used in clustering algorithms is another parameter which is input to the algorithm by the user. It is still possible to calculate the number of clusters in many ways depending on the chosen criteria. The measure of Silhouette Validity Index was employed in this study to evaluate the quality of clustering; it estimates how close an object is to its cluster members compared to members of other clusters.

$$S_i = (b_i - a_i) / \max(a_i, b_i)$$

Bi represents the direction in which all the I-particles are split away to the balance of the particles in the other set or the nearest group. However, the intelligence based on computers works the sum out depending on the relative difference of the I-particles from the other particles in the same cluster which are regarded as eq=y. Because this depicts a good clustering work done, then the approach of silhouette value increasing towards 1 is a proper indicator that all the pixels were properly clustered. On the other hand if silhouette value comes to zero or nearly zero than it signifies that the sample distance is 'a good likelihood of distance from nearest cluster'. The silhouette value of a sample is less than 0, but more than -1 the sample is referred as 'misclassified,' which suggests that the point belongs to the boundary between two clusters. The numbers are then averaged out because the silhouette-coefficients are in relation to the specific objects in the dataset. From the resultant equation that represents the allowable tolerance intended by the user, 5 is understood as a float type value 0. 04. Buy regarding the silhouette index and the fitness function, they are actually calculated and used at each stage of the process, not only the computation of Qe.

3.2 A model for segmenting images using a combination of K-Means and PSO algorithms.

K-Means is self-learning technique that is used to divide information into different groups. To do this, the following should characteristics of the institution; It should limit the presentation list. In each instance, the example is grouped with the cluster with the nearest distance to each one of the K randomly chosen center points. It is then renewed in the community of groups with the updated standard of the characteristics of each cluster of the new model. Pixel vectors are a collection of indexes in the data set within the image processing applications. As such, this often means that the pixels in the image will be clustered. Below is a summary of the means used in the K-Means algorithm:Below is a summary of the means used in the K-Means algorithm:

- Step 1: We can least select k initial values manually or randomly or else we can give a sample of the set of K initial values for clusters.
- Step 2: For each pixel in the image, calculate the Euclidian distances between the exact pixel more each cluster centroid and then categorize the exact pixel to the field that is related to the shortest distance.
- Step 3: Next up, determine the new cluster Centre by summing the pixel values of means of the different clusters that have been formed.
- Step 4: Steps 2 and 3 needs to be performed iteratively until either clustering process achieved the desired iteration or it stopped and formed new clusters.

An apparent drawback of the K-Means approach is its inability to explore global optimal solutions, but instead provides solutions within reasonable proximity of the true optimals. The result is more preferable when both the underlying group's communities are chosen at a moderate range distance. Weaknesses of K-Means algorithm With the use of the above explanation, the K-Means algorithm is rather ineffective in the identification of the basic clusters in the unsupervised manner if there exist clusters near to one another in the feature space. Improvement techniques are usually used for improving the ability and effectiveness of the K-Means algorithm. In addition, overlapping data, unclear borders, and averages are often in average clusters that require use of the Fuzzy CMeans method (FCM). The FCM indicates that there are fewer dependency issues with the initial conditions governing the process of bunching.

This paper proposes two effective variants of Particle Swarm Optimization (PSO) for the aim of optimization: GCPSO and FDR-PSO, where the performance of FDR-PSO is more satisfying than GCPSO.

3.2.1 GCPSO - K-Means algorithm:

The recommended GCPSO-K-Means method is built as follows:

• Step 1: With regard to the mathematical notational system, let m equal the number of particles; the number of clusters on the other hand would be represented by K.

• Step 2: Generate m sets of K randomly chosen center clusters that will be employed by m particles.

• Step 3: where, for each pixel, it can be mapped to the cluster having a least Euclidean distance.

• Step 4: Not go to the next step and update the new cluster center until a reasonable distance between the new cluster center and the old cluster center is achieved. If not, they branch off to step 3 in the process of the system.

• Step 5: Because of this, it is still important to ensure that the best solution that each of the particles has produced is maintained. Replace it with your individual or highest answer.

• Step 6: Of the 'm' personal best responses you have identified, retain only the 'm' best of the lot. It should be aptly named the "global best solution" or "gbest."

• Step 7: By applying the equtions, probabilistically modify the cluster center according to new solutions of the pbest and gbest.

• Step 8: Experts' recommendation such as: If the termination condition is met, then proceed to the next step is an efficient idea. In the latter case, proceed to the next step.

• Step 9: For these reasons, it is logical to require that the winners be capable of delivering the best solutions.

3.2.2 FDR-PSO- K-Means algorithm:

The PSO-C-K-Means method is introduced in the following manner:

Except for Step 7, the Al1 steps are identical to those described in S.3.1.

Step 7: Utilize equations to modify the cluster center of each particle based on the pbest and gbest results.

3.3.3 Three A model for classifying images Derived from a combination of kNN and PSO algorithms

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Iraqi Journal of Humanitarian, Social and Scientific Research
Print ISSN 2710-0952 Electronic ISSN 2790-1254

This chapter introduces an algorithm for the layout of :MR. ls is partially dependent on the and ironic fully on the PSO. K-nearest neighbour (kNN) is one of the methods which is applied for the placing objects according to their distance to the nearest training samples in the feature space. kNN is one of the forms of lazy learning or case learning; all calculations are made at the time of classification, and the ability is estimated locally. Specifically, the k-nearest neighbor (KNN) approach is perhaps one of the simplest in the broadly understood artificial intelligence field. It classifies an item to the class which has maximum vote from its neighbors and the nearest neighbors of an item to a considerably small positive integer k are considered. If k = 1, the item is placed into the class of its nearest neighbor or nip.

One of the known items selected in a legal order is a type of variety of known items. While there is no absolute necessity in having a certain preparation step here, it might be considered as the preparation set of an algorithm. Another observation one would make about the k-nearest neighbor method is the fact that the origin of the creation of the data impacts the functioning of the algorithm. The oldest n-nearest neighbor rules define the perimeter of the decision space using provable methods. However, it is be achieved in a clear and efficient manner and thus the complexity of the computational work will be only the complexity of the boundary.

The value of k is necessarily dependent on the data; higher values of k will in fact minimize the impact of noise on classification but at the same time tend to smoothen out the classifier by washing out the margins between the classes to some extent. The cross-validation is the other method is used to estimate on an appropriate value of k Cross validation When k=all the nearest neighbor algorithm is used Two neighbors and 28 neighbors three neighbors and 34 neighbors four neighbors and 37 neighbors Another problem arises from selecting a set of features that contains noisy or irrelevant features, or feature scales of which are inapposite to their importance toward the kNN algorithm. Another common area of focus is feature selection or scaling for better categorization, and it remains a hot topic for research. The inclusion of new features for the suggested model involves the use of PSO in the element scaling.

This means that in pattern recognition utilizing an unbalanced dataset for the training of the model, it is possible to arrive at a biased classification where the model completely disregard samples from the minority class and focus largely on the majority class. The data sampling approach tries to overcome the imbalance problem by either increasing the ratio of the minority class or decreasing that of the majority class. But those that alter the sample distribution through a greedy mode may compromise the impartiality of the results. Data sampling in this work was improved through feature selection techniques within a hybrid system enhanced through

2024 آب العدد 14
No.14 Aug 2024
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Particle Swarm Optimization (PSO). I have drawn the schematic flow of the proposed hybrid system as represented in the image below.

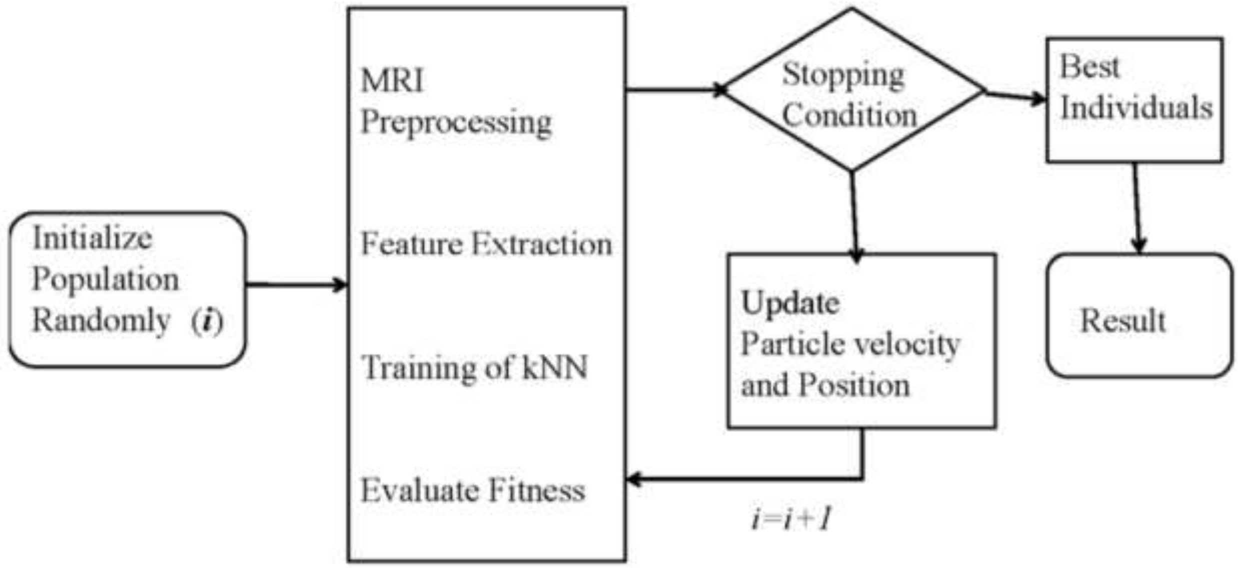

Figure 2: The suggested hybrid system, based on Particle Swarm Optimization (PSO) and k, follows a schematic flow.

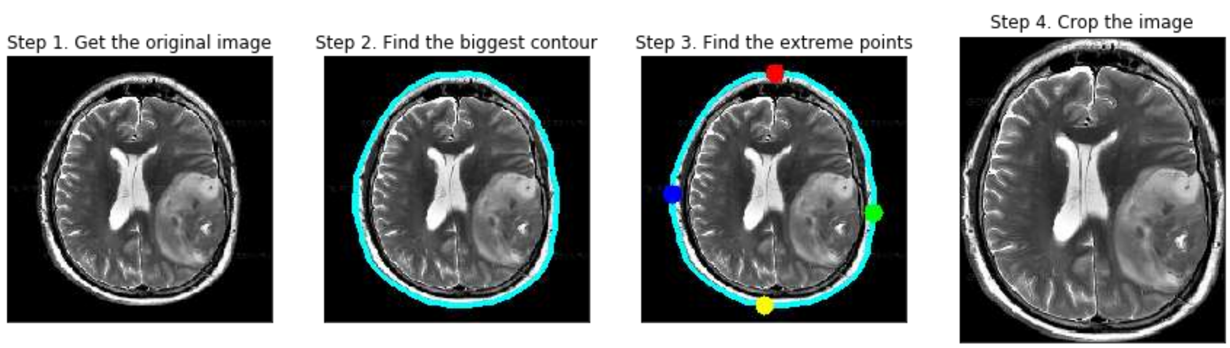

Figure 3: Brain imaging with X-ray technology

4 Results And Performance Analysis

All of the approaches based on PSO used all pictures listed in the table Image data set. Outlined in the figure are quite many findings related to segmentation. The mean values of Qe, dmax, and dmin computed from the two PSO models used in the above clustering methods, viz., K-Means and PSO-K-Means Hybrid, are shown in Table 2.

Table 2: Displays the values of Qe, dmax, and dmin acquired for the GCPSO, K-Means, and PSO-K-Means Hybrid algorithms..

Algorithm	Qe	drnax	drrun
GCPSO	9.3265	12.2356	20.2356
FDRPSO	8.8862	11.2354	19.8857
K-Means	5.6689	20.2356	12.5742
GCPSO-K-Means Hybrid	5.5246	17.5832	14.2568

Alleviating effects of the strategies based on the K-Means can be described by Table 2 where the parameter Qe is maximized. On the other hand, it is much more evident through the values dmax and d111111 that denotes the effectiveness of the PSO-based approaches towards the existing approaches. In the subsequent table 3, a summary of the comparative outcomes of the three quantitative evaluations of accuracy, recall, and precision for all the three models is presented. From the result presented in Table 3, it clearly shows that the Hybrid model of PSO-kNN is comparatively performing very badly in terms of both accuracy and training/testing time than both the PSO model and the Hybrid PSO kMeans model. Therefore for the deeming the PSO-kNN Hybrid model will be further excluded from the experiement.

Table 3: Results of the classification for the three methods that were suggested

Classifier	Precision	Recall	Accuracy
GCPSO	92.76	96.24	94.42
Hybrid PSO kMeans	93.33	95.28	96.71
PSO kNN Hybrid	91.12	90.24	91.15

4.1 Effect of PSO parameters

PSO requires modification to optimize results. Various values of the swarm size, velocity, inertia weight, and acceleration constants were employed during the execution of the PSO-based clustering algorithms. The results for Qe, dmax, and dmin are presented in Figures 4(a), (b), and (c) respectively, showcasing their variations with varied swarm sizes, denoted as s. The GCPSO and PSO-K-classification accuracy refers to the average level of correctness in classifying data using the GCPSO and PSO-K algorithms. The pictures display plots of hybrid techniques in relation to different swarm sizes and iteration counts. The plotted figures demonstrate that the highest level of performance is attained when the swarm size falls between the range of 35 to 45. Moreover, the data clearly indicates that a minimum of 500–700 repetitions is required in order to obtain improved outcomes. Table 4 presents the various PSO parameter values that were employed.

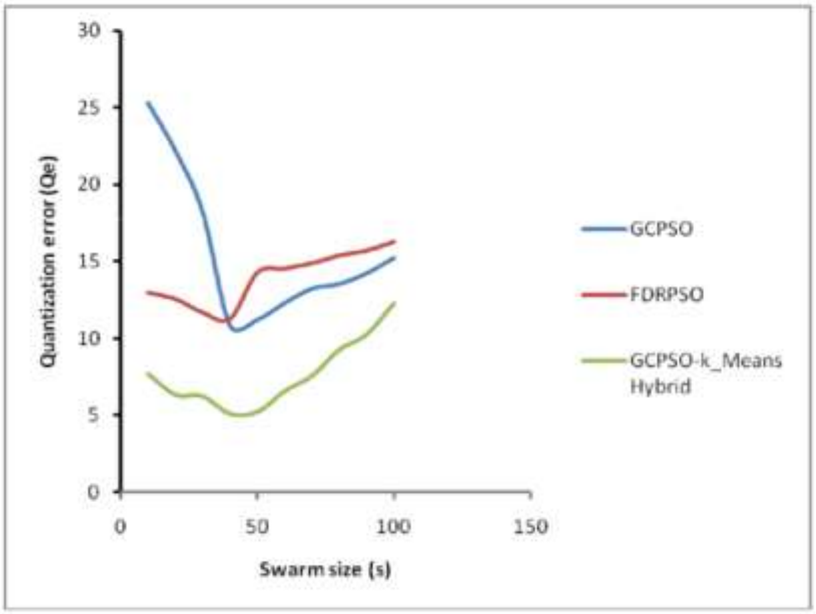

Figure 4 (a): The impact of the number of individuals in a swarm on the level of quantization error.

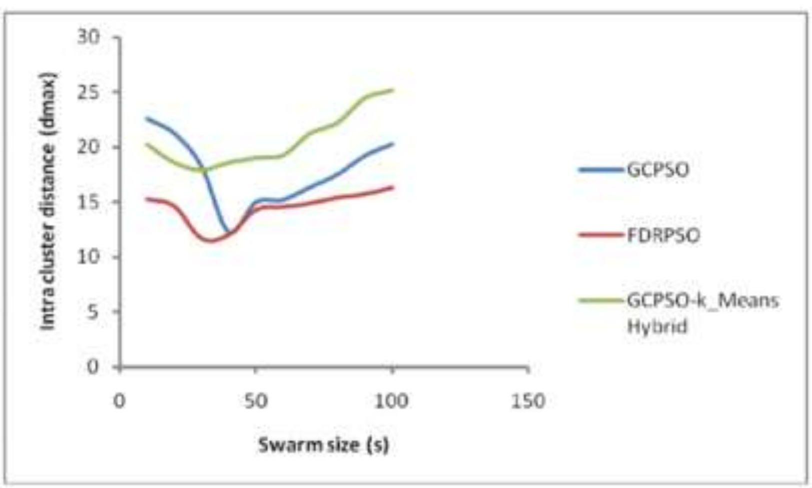

Figure 4 (b): The impact of the number of individuals in a swarm on the distances between individuals within the same cluster.

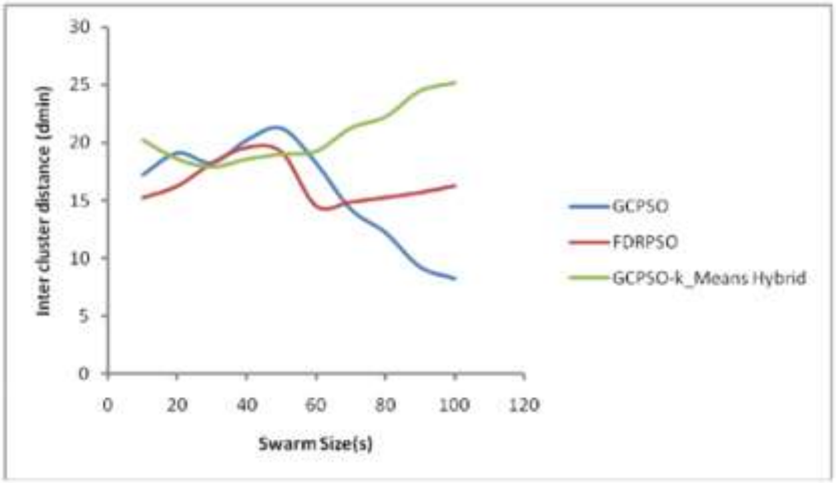

Figure 4 (c): Impact of swann size on distances between clusters.

Table 4: Optimizing the parameters for Particle Swarm Optimization in the detection of brain tumors.

Parameter	**Value**
Size of Particle Population	40
Iteration	500
Update Rule	Sigmoid Function
Cognitive Constant	1.6
Social Acceleration Constant	1.5
Inertia Weight	0.7
Velocity Range	0.2-1.1
Fitness Weight	0.34

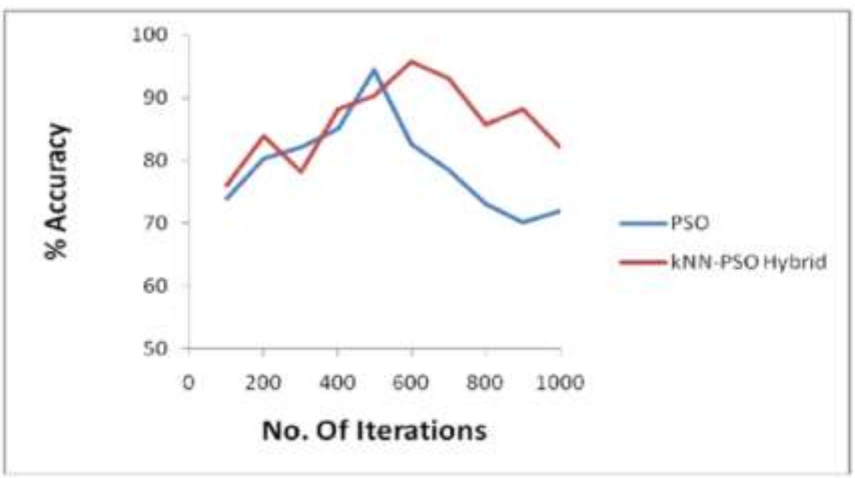

Figure 5 (a): The percentage classification accuracy of Particle Swarm Optimization (PSO) and Hybrid PSO is evaluated for various iterations.

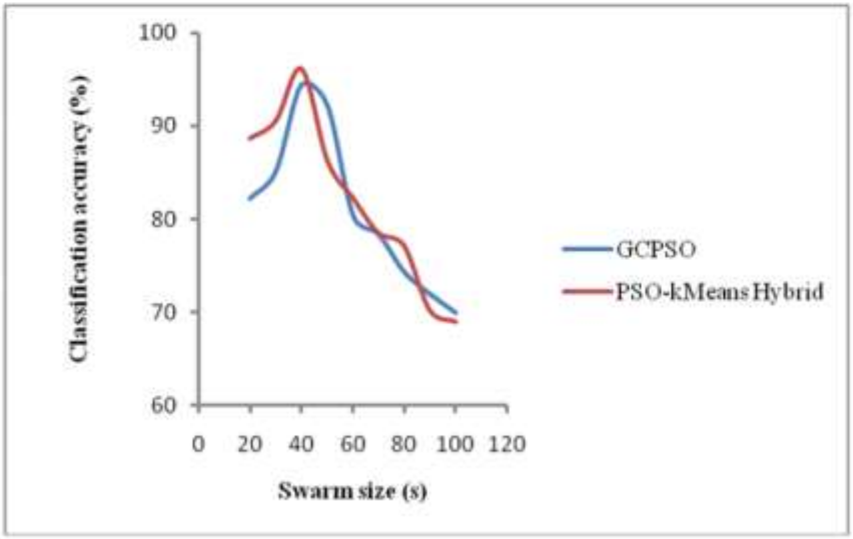

Figure 5 (b): Classification accuracy percentages of PSO and Hybrid PSO were evaluated for various swarm sizes.

4.2 Grading of Tumors

The main obstacle in creating an automated tumor grading tool is that traditional MR imaging often does not offer enough data to accurately establish the grade of the tumour. Thus, in order to determine the grades of tumors, medical experts rely on further examinations such as biopsies. This study examines several characteristics of Multiple MRI findings may indicate the presence of a certain grade of brain tumor. Subsequently, a model is developed to autonomously assess the severity of tumors. In order to assess the severity of the tumors, we do the following steps:

1. The term ROI stands for Return on Investment.
2. Feature extraction
3. Selecting characteristics
4. Classification is performed using a combination of k-PSO (Particle Swarm Optimization) and Leave One Out cross-validation.

Firstly, the diverse regions of brain tumors are examined by combining imaging data from many modalities. The importance of each element is subsequently evaluated in terms of organization based on morphological and textural characteristics, such as pivot invariant surface elements derived via Gabor filtering. For the purpose of identifying the three most common types of brain tumors - glioma (grade II, III, and IV), meningioma (often grade I), and metastasis - multiclass classification is employed.

4.2.1 Feature Extraction:

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First, the suitable returns on invested capital were examined with an emphasis made on the fact that suitable here meant only those returns that had been consciously selected for extraction. The characteristics used included the geometric representation of the growth's shape, the image force encompassed within various areas of interest, and the Haralick surface descriptors table.

1) Tumor morphology and statistical properties:
2) Intensity profile of the image.
3) Haralick textural characteristics.

4.2.2 Grading Implementation and Results

Thus, the totality of 156 pictures was evaluated, and the needle biopsy procedure was used to confirm the grades assigned to the images. As per the rules set by the World Health Organization (WHO), the brain masses were classified into four distinct categories: It includes four types- grade I, grade II, grade III, and grade IV. Several studies have shown that MR can detect various kinds of tumors. The grading results are as follows: The grading results are shown in the table below Table 5.

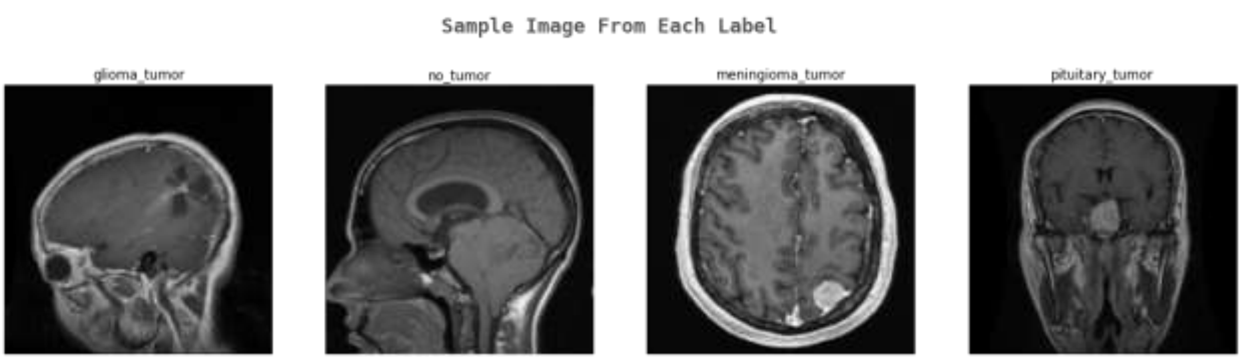

Figure 6: One representative image from each label

Table 5: Metrics for Evaluating the Performance of Brain Tumor Classification

Tumor Type	No. of Samples	TP	TN	FP	FN	Precision	Recall	Accuracy
Glioma	88	82	10	10	14	89.1	85.4	79.3
No Tumor	50	44	16	12	16	78.5	73.3	68.1
Meningioma	94	78	22	14	22	84.7	78.0	73.5
Pituitary	80	72	16	12	18	85.7	80.0	74.5

5 Conclusion

Purposing the study, an exploration of several muted versions of the PSO algorithm in segmenting and classifying MRI was underwent. For the intention of picture grouping, an algorithm has optimized using Particle Swarm Optimization (PSO). Finally, a system known as K-Means and SBM PSO was designed for segmentation of the MR image. All the proposed methods were applied, and their performance analyzed, based on magnetic resonance (MR) images from different resources. Therefore, according to the present paper, the benefits of PSO have been evidenced both in the process of applying to the photo segmentation and in the attempt to enhance the cluster solution, employing the K-Means clustering algorithm. Last but not the least, a compound PSO model was demonstrated, which was used to classify MR scans as abnormal or non-abnormal based on the presence or absence of the brain tumors. PSO-K-Means hybrid model was employed for the grading of MR images based on the classification system outlined by World Health Organization-WHO for tumor. Such proofs derived from the trial show that the solutions put forth possess less intra-group variance and we get enhanced division results with more between-group variance. By analyzing the results attained in the trial, it may be deduced that the PSO approach holds the likelihood to improve the performance of the K-Means algorithm. The integration of both PSO and K-Means algorithms differentiated significant performance improvements with better reliability against utilizing the PSO based technique or merely the K-Means algorithm. Analyzing the grading data it is becoming evident that the present MRI grading technology is not optimal for grading.

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