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Investigate the Application of Particle Swarm Optimization to Fine-Tune the Architecture and Parameters of Deep Convolutional Neural Networks for Enhanced Accuracy in Brain Tumor Detection from Medical Images



Abstract: - This study researches the use of Particle Swarm Optimization (PSO) to adjust the design and boundaries of Deep Convolutional Neural Networks (DCNNs) for improved precision in cerebrum growth recognition from clinical pictures. Different PSO calculation variants are investigated for division and grouping of MR pictures. A clever PSO-based strategy for picture gathering is presented, alongside a half and half K-Means/SBM-PSO approach for MR picture division. The proposed methods are assessed utilizing MR pictures from assorted sources, uncovering the adequacy of PSO in both picture division and advancing the K-Means grouping strategy. A half breed PSO approach is exhibited for characterizing MR pictures as typical or strange in light of the presence of mind growths, and for evaluating MR pictures as per the WHO characterization framework for cerebrum cancers. The exploratory outcomes demonstrate that the proposed techniques lead to more modest intra-bunch distances and bigger between-bunch distances, bringing about superior division results. Eminently, the reconciliation of PSO with K-Means shows improved strength and execution contrasted with individual methodologies. The reviewing discoveries recommend impediments in the ongoing X-ray approach for growth evaluating. Overall, this study highlights the potential of PSO in optimizing DCNN architectures for accurate brain tumor detection from medical images, emphasizing the effectiveness of hybrid PSO-K-Means models for improved segmentation and classification outcomes.

Keywords: Particle Swarm Optimization (PSO), Deep Convolutional Neural Networks (DCNNs), Brain tumor detection, Medical image segmentation, Hybrid PSO-K-Means model

1. Introduction

An unusual mass of tissue wherein cells multiply and replicate uncontrolled, apparently unregulated by the cycles that control typical cells, is called an intracranial growth, or mind cancer. In spite of the fact that there are more than 150 unmistakable kinds of mind growths known to exist, essential and metastatic cerebrum cancers are the two principal classes.

Cancers that emerge from the mind's tissues or the cerebrum's encompassing tissues are alluded to as essential mind growths. Essential growths can be named harmless or dangerous, glial (comprised of glial cells) or non-glial (framed on or in the cerebrum's designs, like nerves, veins, and organs).

Cancers that begin in different pieces of the body, similar to the bosom or lungs, and spread to the mind, as a rule through the circulation system, are alluded to as metastatic cerebrum growths. Metastatic growths are named harmful and as disease.

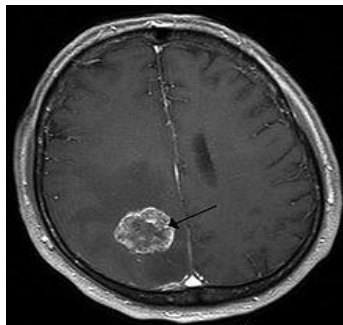


Figure 1: Brain Tumors

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An estimated 150,000 people annually, or almost one in four cancer patients, get brain metastases from their tumours. It is estimated that up to 40% of lung cancer patients will experience brain tumour metastases. Patients with these tumours used to have extremely poor prognoses, with normal survival rates of only a few weeks. Along with cutting-edge surgery and radiation techniques, more advanced diagnostic tools have contributed to survival rates rising to years and improved quality of life for patients after diagnosis.

1.1. Types of Brain Tumors

Brain tumours can be categorized according to a number of criteria, such as the type of cell they originate from, where they are in the brain, and whether they are malignant or benign. These are a few prevalent kinds of brain tumours:

1. Gliomas
2. Meningiomas
3. Pituitary Tumors
4. Medulloblastomas
5. Schwannomas
6. Craniopharyngiomas
7. Hemangioblastomas
8. Primary Central Nervous System (CNS) Lymphomas

These are but a handful of the numerous varieties of brain tumours that can develop. Every kind may exhibit distinct symptoms, necessitate certain therapeutic modalities, and have disparate outcomes. In order to choose the best management plans for those who are impacted by brain tumours, accurate diagnosis and categorization are critical.

1.2. Symptoms of Brain Tumor

The location of the brain tumour affects the symptoms, although other brain tumour types can also cause the following symptoms:

- Headaches that could wake the patient up at night or be more intense in the morning
- Convulsions or fits
- Having trouble speaking, thinking, or articulating
- Individuality shifts
- Paralysis or weakness in a single bodily portion or side
- Disorientation or lightheadedness
- Modifications in vision
- Sensing alterations
- Numbness or tingling in the face
- Symptoms of nausea or vomiting, difficulty swallowing
- Bewilderment and disarray.

1.3. Brain Tumor Treatment

Surgery, radiation therapy, and/or chemotherapy are typically used alone or in combination to treat brain tumours, regardless of whether they are primary, metastatic, benign, or malignant.

- ✓ Surgery

- ✓ Radiation Therapy
 - Standard External Beam Radiotherapy
 - Proton Beam Treatment
 - Stereotactic Radiosurgery
- ✓ Chemotherapy
- ✓ Laser Interstitial Thermal Therapy (LITT)
- ✓ Investigational Therapies

While the facts confirm that dangerous, leftover, or intermittent growths are all the more habitually treated with radiation and chemotherapy, the decision of therapy is picked on a singular premise in light of various models. Each kind of treatment conveys a couple of dangers and unpleasant effects.

2. Literature Review

Amin et al. (2020) proposed a methodology for characterizing mind cancers that consolidates convolutional neural networks (CNN) with the discrete wavelet transform (DWT) combination of magnetic resonance imaging (X-ray) arrangements. The creators set off on a mission to tackle the issue of accurately classifying mind cancers from clinical imaging information. They got great grouping exactness results by combining DWT methods with X-ray successions and afterward taking care of the consolidated pictures into a CNN model. This strategy offers an original utilization of deep learning and picture combination procedures for the ID of mind growths, possibly working on quiet consideration and clinical direction.

Arunkumar et al. (2019) proposed a clever methodology that joins K-infers grouping with brain networks for object ID and bending discovery. The designers had the option to find and sort mind growths by joining two compelling procedures: brain networks for request and K-infers clustering for division. Their proposed technique effectively isolated twisted cerebrum malignant growth districts from clinical pictures, as shown by careful testing and examination. The assessment adds to the progression of clinical picture assessment by illustrating qualities for a trustworthy system for robotized disease recognition and gathering. In clinical settings, this has significant implications for early end and treatment arranging.

Kaur et al. (2018) put out a more successful system for recognizing unmistakable items that functions admirably for concentrating on mental pictures. Through the union of the organization between the establishment and the closer view, their strategy improves the position accuracy of recognizable articles in mental pictures. upgraded execution in recognizing significant plans and irregularities as a main priority pictures was conceivable in light of the fact that to improved calculations and the mix of accessibility based information. This work adds to the advancement of additional exact and solid calculations for clinical picture translation, which may be utilized for the finding and arranging of medicines for neurological problems..

Khan et al. (2020) planned a framework to inspect gastrointestinal issues utilizing PC-upheld remote case endoscopy. Specialists focused on choosing the best characteristics with an end goal to further develop illness conclusion precision. The framework intends to work on the dependability and precision of case endoscopy discoveries by including complex part assurance techniques. The work gives a deliberate technique to concentrating on gastrointestinal diseases utilizing remote container endoscopy, which progresses the fields of clinical imaging and PC supported conclusion.

Khan et al. (2019) given a system to the recognizable proof and classification of mind cancers using staggered need include determination and a marker-based watershed calculation. The objective of the task was to utilize state of the art picture handling techniques to build the accuracy and adequacy of mind growth analysis. A far reaching structure for computerized mind growth ID and characterization was worked by the scientists by consolidating state of the art calculations and element determination methods. The outcomes give areas of strength for a to dependably and unequivocally recognizing cerebrum growths, which progresses the field of clinical imaging and diagnostics.

3. Particle Swarm Optimization

The way of behaving of bird runs filled in as the model for the swarm knowledge optimization procedure known as particle swarm optimization (PSO). A kind of knowledge adds to specialized applications, offers experiences into social way of behaving, and is established in friendly brain science. The utilization of PSO in an assortment of registering spaces, including organizing, picture handling, characterization, planning, and preparing counterfeit neural networks, has filled essentially over the most recent couple of years.

The relative simplicity and ease of use of PSO gives it an advantage over all other optimization techniques. PSO and evolutionary computation methods like genetic algorithms (GA) are quite similar. The framework searches for optima by refreshing ages in the wake of beginning with a populace of irregular arrangements. Be that as it may, PSO needs development administrators like hybrid and transformation, as opposed to GA. By pursuing the current optimum particles, the hypothetical solutions, also referred to as particles, fly through the issue space.

An issue is presented in the fundamental PSO, and a fitness function is one means of evaluating a suggested solution. Additionally, a social network or communication structure is established, facilitating interactions between each person and their neighbours. Next, a population of people is initialized that are described as random guesses at the solutions to the problems. We refer to these people as the candidate solutions. The term "particle swarm" comes from their other name, "the particles." To make these potential answers better, an iterative procedure is started. The group of people swarms across the search area.

A molecule's not entirely set in stone by the best position it has at any point visited (i.e., by its own insight) and the best molecule's situation in its nearby area (i.e., by the encounters of neighboring particles). The expression "worldwide best molecule" alludes to the place that is best inside a molecule's area, which is the whole multitude. The method that results is known as a "g best PSO." The calculation is regularly known as the PSO execution of every molecule (for example how) when more modest areas are utilized. A wellness capability that fluctuates in light of the enhancement issue is utilized to gauge how close the molecule is to the worldwide ideal. The accompanying highlights address every molecule in the multitude.

3.1. PSO based Image Clustering Algorithm

This model's characterization of X-ray pictures is predicated on the possibility that different element types display dissimilar pixel values as indicated by their separate otherworldly reflectance and emittance qualities. Ghostly example acknowledgment is the term used to depict this sort of order that depends on unearthly data estimated pixel by pixel. The rundown of factors and their definitions in the proposed calculation are shown in Table 1.

Table 1: Variables used in PSO based Image Clustering algorithm

Variable	Meaning
Pi	Particle, $P_i = (m_{i1}, m_{i2}, \dots, m_{iN})$: Represents N cluster centroids.
m_{ik}	k^{th} cluster centroid of i^{th} particle
x_i	Pattern matrix of i^{th} particle
$f()$	Fitness function $f(p_i) = w_1 d_{max}(X_i, P_i) + w_2 (X_{max} - d_{min}(p_i))$
d_{max}, d_{min}	Maximum and minimum Euclidean distances
x_i	a matrix representing the assignment of patterns to the clusters of particle i .
N_c	Number of clusters
W_1, W_2	User defined constants (weight factors)
S_i	Silhouette 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_{ij} .

 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.

Algorithm 6.1: PSO based Image Clustering Algorithm

Performance measure: As per the fitness function definition, well-separated clusters are indicated by a tiny value off. The Blunder of Quantization, which is given by, can likewise be utilized to describe the nature of a bunching calculation,

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

wherein the k th bunch is meant by C_k , and its pixel count is demonstrated by n_k .

The objective of the wellness capability in 1 is to augment the between distance between any sets of bunches, or d_{min} , and limit the intra-distance among designs and their group centroids, or d_{max} . For ideal grouping, a more modest d_{max} esteem and a higher d_{min} esteem are consequently liked. The group legitimacy, a measurement for assessing the nature of a bunching calculation, is likewise utilized in this methodology. Since most applications require the validation of the clustered result, cluster validation is a critical topic in clustering analysis. The number of clusters is typically set as a user parameter in clustering algorithms. Numerous methods exist for determining the ideal number of clusters. This study employed the silhouette validity index, which is provided by,

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

Where b_i is the base of normal divergence of I -particles to all particles in other group (in the closest bunch), and computer based intelligence is the typical difference of I -particles to any remaining particles in a similar bunch. A silhouette value that is near to one indicates that the pixels have been allocated to the proper cluster, indicating a good clustering. Conversely, if the silhouette value is close to zero, the sample may also belong to the next closest cluster, and its distance from both clusters is equivalent. The sample is "misclassified" if the silhouette value is near to -1, meaning it is simply in the middle of the clusters. The average of the S_i for every object in the dataset is the total average silhouette width for the plot. The user-defined acceptable tolerance is 5. In this study, the 5 value was set to 0.04. While silhouette index and fitness function are computed and employed in the algorithm itself, Q_e is only calculated after segmentation is complete.

3.2. An Image Segmentation Model Based on Hybrid of K-Means and PSO

One of the most fundamental unaided learning strategies for information examination and classification is the K-Means calculation. Its establishment is the presentation list's minimization. Each example is relegated to a bunch by the calculation in light of the most limited distance between every one of the K haphazardly chosen group communities. The new normal of the qualities in each bunch is then refreshed in the group communities. An

assortment of pixel vectors would be the informational index in picture handling. Accordingly, the picture's pixels will be generally sorted into bunches. The following is a rundown of the K-Means calculation's means:

Step 1: Select K starting cluster centres at random or using samples.

Step 2: Determine the distance between each pixel and the centres of each cluster, then assign the pixel to the cluster whose centre is the least far from it.

Step 3: Incorporate the average pixel values from each cluster into the newly created cluster centre.

Step 4: Up until the clustering converges, repeat steps 2 and 3.

Nearby ideal arrangements are regularly found by the K-Means technique instead of worldwide ideal ones. The result is more okay when the underlying group communities are chosen moderately far separated. The K-Means procedure neglects to recognize the fundamental bunches in the unaided mode assuming that they are near one another in the element space. To improve the K-Means algorithm's exhibition, enhancement methods are normally used. Moreover, information bunches with fuzzy limits and means must be isolated utilizing the Fuzzy CMeans algorithm (FCM). The FCM is less dependent on the bunching's beginning state.

For optimization purposes, two effective PSO versions, GCPSO and FDR-PSO, are proposed in this work.

3.2.1. GCPSO - K-Means algorithm:

Here is how the suggested GCPSO-K-Means algorithm is put together:

Step 1: Set the number of particles to m and the number of clusters to K.

Step 2: Set up m sets of K random cluster centres so that m particles can use them.

Step 3: Assign every pixel to a cluster whose Euclidean distance is as small as possible.

Step 4: Determine the new cluster centre and go to the next step if the new cluster centres converge to the old ones. If not, proceed to Step 3.

Step 5: Save the optimal solution that every particle was able to find. Refer to it as your personal or best answer.

Step 6: Save the top answer out of the m personal top answers that you found. Call it the "global best solution" or "gbest."

Step 7: Using equations, update each particle's cluster centre in accordance with the values of the pbest and gbest solutions.

Step 8: Proceed to the following step if the termination requirement is met. If not, proceed to Step 3.

Step 9: Provide the best possible outcome.

3.2.2. FDR-PSO- K-Means algorithm:

The proposed PSO-C-K-Means algorithm is presented as follows:

With the exception of Step 7, the All steps are exactly the same as those outlined in S.3.1.

Step 7: Using equations, update each particle's cluster centre in accordance with the values of the pbest and gbest solutions.

3.3. An Image Classification Model Based on Hybrid of kNN and PSO

This segment presents an algorithm for the arrangement of :MR.l.s, which depends on the half breed of and PSO. A method for ordering objects in light of the nearest preparing tests in the component space is the k-nearest neighbors' algorithm (kNN). kNN is a kind of lethargic learning, or case based learning, in which all calculation is delayed until grouping and the capability is just privately approximated. Among all AI techniques, the k-nearest neighbor algorithm is quite possibly of the easiest. It orders a thing in view of the larger part vote of its neighbors, relegating it to the class that has the most individuals among its k nearest neighbors (k is a positive whole number, generally little). The article is essentially placed into the class of its nearest neighbor if $k = 1$.

An assortment of things for which the legitimate order is known is utilized to choose the neighbors. Despite the fact that there is no requirement for an unequivocal preparation step, this can be considered of as the algorithm's preparation set. The nearby construction of the information influences the exhibition of the k-nearest neighbor algorithm. A verifiable technique is utilized by earliest neighbor rules to register the choice limit. On the other hand, the choice limit itself can be registered transparently and productively, with the outcome that the computational intricacy relies just upon the boundary intricacy.

The ideal number for k will rely upon the information; as a rule, higher upsides of k diminish the effect of clamor on order yet in addition obscure the lines isolating classes. There are other heuristic techniques for picking a decent k, like cross-approval. The nearest neighbor approach is utilized in the uncommon situation where the class is supposed to be the class of the nearest preparing test (i.e., when $k = 1$). The presence of uproarious or unimportant highlights, or component scales that are conflicting with their significance, can truly impede the kNN algorithm's precision. A ton of study has been finished on include determination or scaling for better classification. PSO has been used in the proposed model to improve the element scaling.

While utilizing a profoundly lopsided dataset for design acknowledgment, there is a risk that the preparation information will prompt a one-sided characterization model that leans toward the greater part class while dismissing tests from the minority class. By either raising the example size of the minority class or diminishing the example size of the greater part class, the information testing approach endeavors to address the skewed class conveyance. Algorithms that use avaricious measures to alter the sample distribution, however, may create unwanted bias. We used a hybrid system based on PSO to apply feature selection approaches to data sampling in this work. Figure depicts the suggested hybrid system's schematic flow.

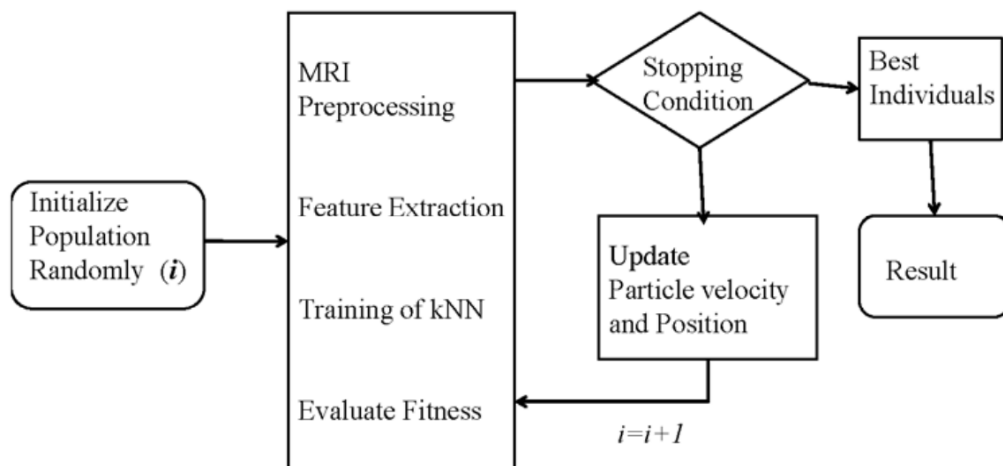


Figure 2: Schematic flow of the proposed hybrid system based on PSO and k

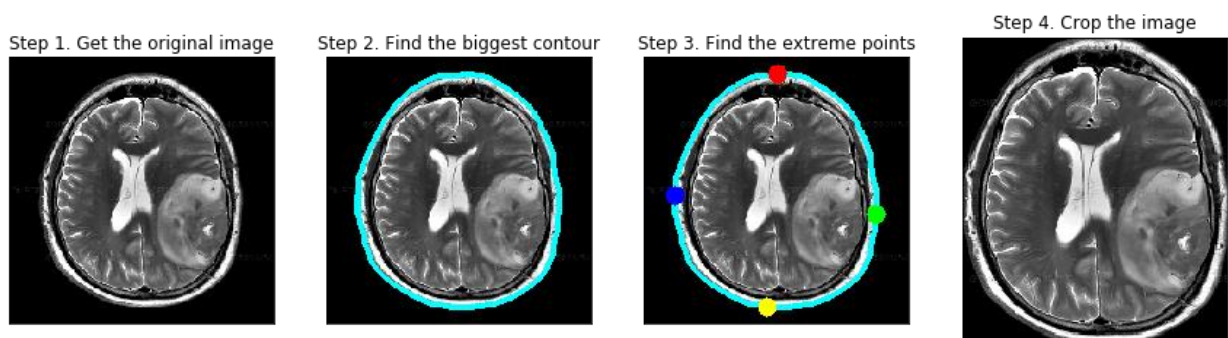


Figure 3: X-ray Imaging of brain

4. Results and Performance Analysis

For the three PSO-based techniques, every image included in the image data set table was used. Figure displays a few of the segmentation findings. The average values of Q_e , d_{max} , and d_{min} for the two PSO models—K-Means

and PSO-K-Means Hybrid—that were utilized for the clustering procedures previously mentioned are listed in Table 2.

Table 2: shows the values of Q_e , d_{max} and d_{min} obtained for GCP SO, K-Means and PSO - K-Means Hybrid.

Algorithm	Q_e	d_{rnax}	d_{rrun}
GCP SO	9.3265	12.2356	20.2356
FDRPSO	8.8862	11.2354	19.8857
K-Means	5.6689	20.2356	12.5742
GCP SO-K-Means Hybrid	5.5246	17.5832	14.2568

Table 2 makes it clear that the K-Means based techniques perform better in terms of Q_e . In contrast, the comparison values d_{max} and d_{min} demonstrate the superiority of PSO-based methods. Table 3 presents a summary of the accuracy, recall, and precision comparison results for each of the three models. Table 3 shows that the PSO-kNN Hybrid model performs far worse overall than PSO and Hybrid PSO kMeans. As a result, the PSO-kNN Hybrid model will no longer be employed in trials.

Table 3: Classification Results for the three proposed algorithms

Classifier	Precision	Recall	Accuracy
GCP SO	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 needs to be adjusted in order to provide the greatest outcomes. In order to do this, different values of the swarm size, velocity, inertia weight, and acceleration constants were used when running the PSO-based clustering algorithms. Figures 4(a), (b), and (c) show the findings obtained for Q_e , d_{max} , and d_{min} versus different values of swarm size, s . The GCP SO and PSO-K-classification accuracy means Plots of hybrid approaches against various swarm sizes and iteration counts are shown in the figures. The figure plots show that optimal performance is achieved when the swarm size is between 35 and 45. Furthermore, the figure makes it clear that a total of 500–700 iterations is necessary to achieve better results. Table 4 lists the different PSO parameter values that were used.

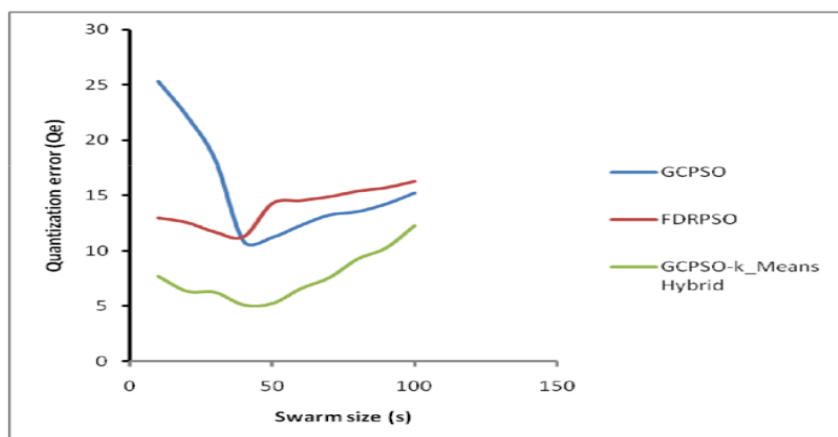


Figure 4 (a): Effect of swarm size on quantization error

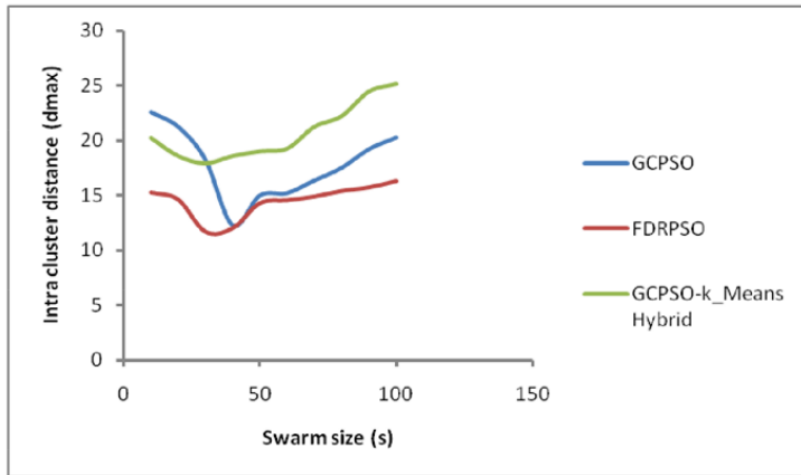


Figure 4 (b): Effect of swarm size on intra cluster distances

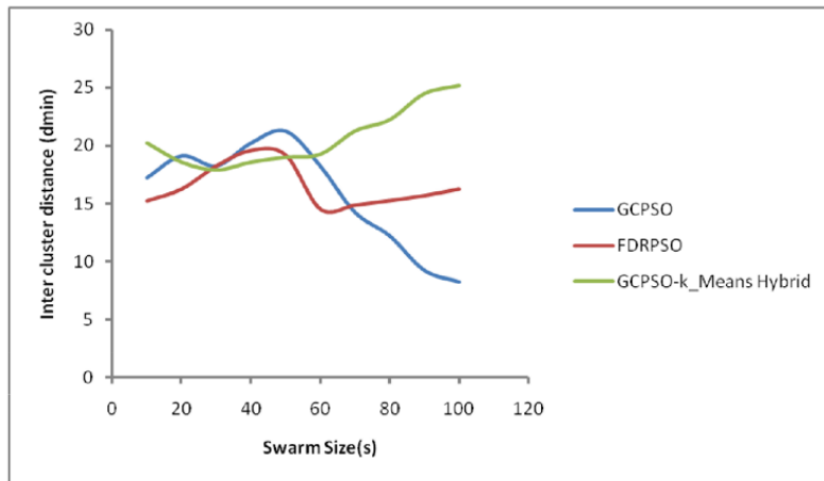


Figure 4 (c): Effect of swann size on inter cluster distances.

Table 4: Parameter Configuration for Particle Swarm Optimization in Brain Tumor Detection

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

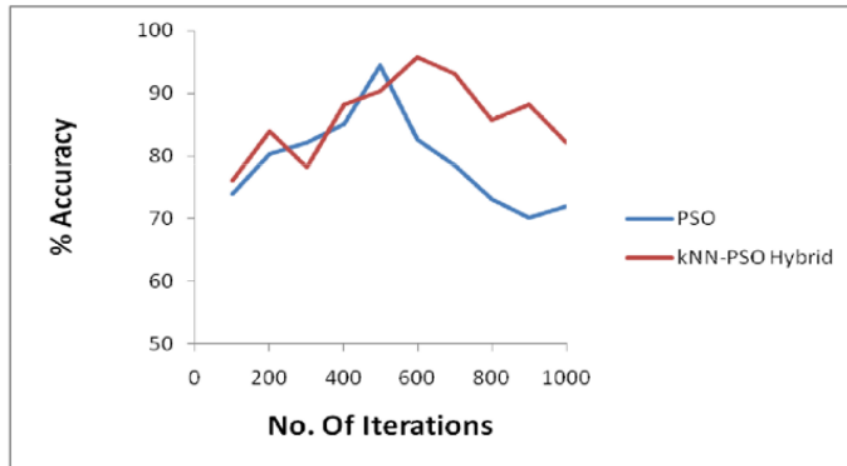


Figure 5 (a): Percentage classification accuracy of PSO and Hybrid PSO against different iterations.

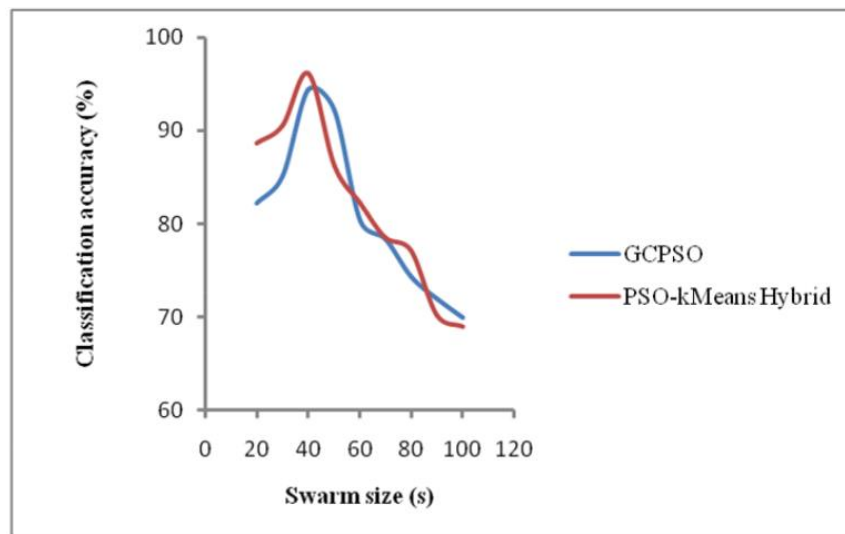


Figure 5 (b): Percentage classification accuracy of PSO and Hybrid PSO against different values of Swarm size.

4.2. Grading of Tumors

The primary challenge in developing an automated tumour grading tool is that conventional MR imaging frequently fails to provide sufficient information to determine the grade of the tumour. Therefore, in order to ascertain the grades of tumours, medical professionals depend on additional investigations like biopsies. In this study, a few attributes of There are several MRI results that could point to a brain tumour of a certain grade. Next, a model for automatically grading tumours is created. To grade the tumours, we take the subsequent actions:

1. Definition of ROI
2. Extraction of features
3. Choosing features
4. Classification using a mix of k-PSO and Leave One Out cross-validation.

In the first place, by blending imaging information from many arrangements, the assorted districts of cerebrum growths are researched. The significance of each element is then assessed as far as arrangement after morphological and textural highlights, for example, pivot invariant surface elements in view of Gabor sifting, are separated. To recognize the three most pervasive kinds of cerebrum growths — glioma (grade II, II, and IV), meningioma (ordinarily grade I), and metastasis — multiclass characterization is utilized.

4.2.1. Feature Extraction:

To start with, the reasonable returns for capital invested were physically picked for include extraction. A few boundaries were picked, like the qualities of the growth's morphology, the image force inside numerous locales of interest, and the Haralick surface elements.

- 1) Shape and statistical characteristics of tumor:
- 2) Image intensity characteristic.
- 3) Haralick textural features.

4.2.2. Grading Implementation and Results

A total of 156 photos were graded, and the needle biopsy procedure was used to confirm the grades for each image. According to WHO guidelines, the brain masses were divided into four categories: grade I, grade II, grade III, and grade IV. Different tumour kinds are displayed in MR scans. The grading outcomes are listed in table 5 below.

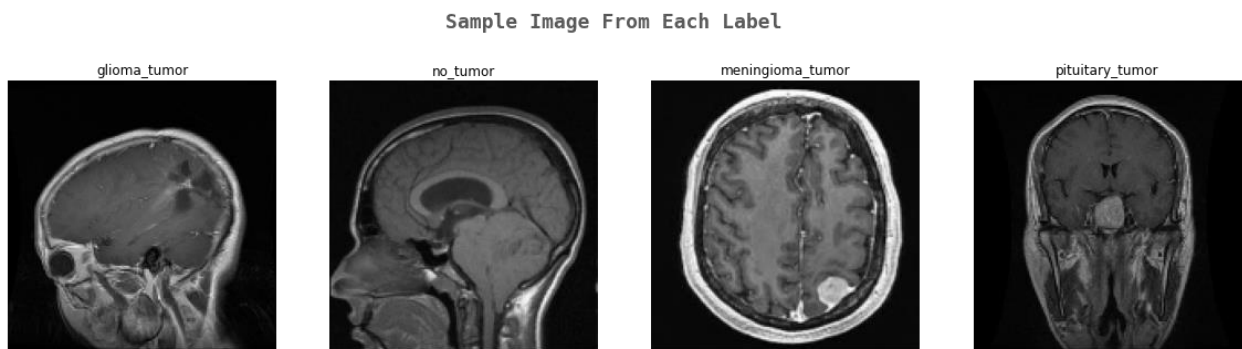


Figure 6: Sample image from each label

Table 5: Performance Metrics for 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

It was investigated how several PSO algorithm versions might be applied to the segmentation and classification of MR images. A PSO-based technique for picture grouping was introduced. For MR image segmentation, a hybrid K-Means/SBM-PSO approach was presented. All of the suggested techniques were put into practice and examined using MR pictures that came from different sources. It was discovered that PSO may be effectively applied to both picture segmentation and K-Means clustering technique optimization. Lastly, a hybrid PSO approach was demonstrated, which was utilized to classify MR images as normal or abnormal based on the presence or absence of brain tumours. In accordance with the WHO classification system for brain tumours, the

PSO-K-Means hybrid model was also employed to grade MR images. The trial discoveries shown that the proposed strategies have more modest intra-group distances and greater between bunch distances generally speaking, with better division results. The trial results recommend that the PSO method can improve the presentation of the K-Means algorithm. PSO and K-Means algorithms worked better together and were more stable than either PSO-based approach or the K-Means algorithm alone. The "not so good" grading findings showed that the current MRI approach is insufficient for grading.

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