CHAPTER 5

ELECTROMAGNETIC LEVEL SET METHOD (ELSM)

In medical field, quantitative analysis of radiological images and other images are performed by CAD tool to detect abnormalities present in the images or to separate a particular region from the images. Each segmented region of the image divulges some information to users about the image. Segmentation techniques vary from image to image and are applied to images, inorder to solve the problem.

Brain is the CNS of the human body, and it plays a key role in many physiological activities. This organ is richly supplied by the blood vessels and is connected to all most all the critical organs including spinal cord, ears, nose and all the nerves present in the human body. Brain tumor is the third most frequently diagnosed tumor worldwide for men and fifth most frequently diagnosed tumor for women. Tumor detection and diagnosis in medical imaging plays an important role not only in diagnosis, but also interventional therapies and surgical planning. MRI imaging technique is a widely deployed clinical methodology due to its high imaging speed, great spatial resolution and maintains minimum cost. Brain tissues have different intensities values which are sometimes similar to the surrounding tissues and outer region of the brain, skull and other regions present in it. Complications related to brain tumor segmentation is because MRI images may vary due to tumor type, pathological stage and contrast substantially at different phases [126].

The quality of the segmented regions depends on the method applied to select the threshold. The use of traditional approach is computationally expensive and they do not have the ability to exploit information related to the characteristics of the images they threshold. They treat all images in the same way, irrespective of the specific nature of the images. When greater accuracy and more consistent performance are required, more information should be used to assist the segmentation. Under such condition, the use of optimisation evolutionary approaches has been extended [45]. Metaheuristic algorithms are used in identifying the optimal solution for the optimisation problem to solve them within a reasonable time. Metaheuristics algorithm attempts to find the best (feasible) solution out of all possible solutions of an optimisation problem, where independent algorithm is unable to find an appropriate solutions for tough problems.
These kinds of algorithms are named as metaheuristics which is inspired by nature to solve the problems by mimicking ontology, biology, or by physics. These evolutionary algorithms are stochastic based, population based or optimisation based algorithms.

The characteristic of this kind of optimisation method is suitable for very difficult problems, which have lots of local optimal solutions. Several nature-inspired algorithms are developed by researchers and widely used presently in different areas of research. For example, GA is based on Darwinian theory of survival, PSO is based on flocking and swarming behavior of birds, differential evolution methods which are similar to GA is based on modified mutation and crossover methods, and harmony search is based on the way musicians change their pitches, harmonies and instruments.

There two types of thresholding, namely, bi-level thresholding and multilevel thresholding, and they can be classified into parametric and non-parametric approaches. For parametric approaches it is necessary to estimate some parameters of a probability density function which models each class. Such approaches are time consuming and computationally expensive. On the other hand, the nonparametric employs several criteria such as between-class variance, the entropy and the error rate that must be optimized to determine the optimal threshold values. These approaches result an attractive option due their robustness and accuracy.

Designed for bi-level thresholding there exist two classical methods, the first maximizes the between classes variance and was proposed by Otsu [96]. The second submitted by Kapur in [71] uses the maximization of the entropy to measure the homogeneity of the classes. Their efficiency and accuracy have been already proved for a bi-level segmentation [31]. Although both Otsu’s and Kapur’s can be expanded for multilevel thresholding, their computational complexity increases exponentially with each new threshold. As an alternative to classical methods, multilevel thresholding problem has also been handled through evolutionary optimisation methods [117]. In general, they have demonstrated to deliver better results than those based on the classical techniques in terms of accuracy, speed and robustness [58].

The main goal of the research work is to combine different complementary segmentation methods into a hybrid approach to avoid many of the disadvantages of each method alone and improve segmentation accuracy. In this thesis a hybrid model
combining EMO algorithm and LSM has been developed to identify the brain tumor affected region accurately from MRI brain images. This chapter introduces a multilevel threshold method based on the Electromagnetism-like algorithm (EMO). This chapter’s main aim is to develop a new hybrid algorithm for MRI brain images to identify the brain tumor affected region accurately. The necessary steps are carried out to achieve this goal and the evolution and characteristics of the newly developed hybrid algorithm are also discussed.

5.1 Introduction

Global optimisation is the biggest area of interest for the researchers and there is more scope in finding new hybrid approaches, which will be used in a wide range of fields. Presently, researchers are developing new models to serve the medical society. Researchers have spent many years in gaining more and more knowledge, since real-time optimisation problems extremely difficult [61]. Developing a new metaheuristic algorithm for MRI brain images is the main aim of this chapter. To develop such an algorithm, the existing two independent methods i.e. EMO method and Level Set method are combined to identify the brain tumor affected region from MRI brain images. This chapter also comprises the results of the new approach and drawbacks of the existing segmentation algorithm techniques.

5.2 Electromagnetic Optimization (EMO)

The study of optimisation algorithm with electromagnet induction and bounded variable was proposed by Birbil and Fang in the year 2003. They developed a new algorithm which combines the basis of electromagnet with the optimisation problem called as Electromagnetic Optimization (EMO) algorithm [65].

The EMO is a global optimisation algorithm that mimics or follows the electromagnetic law of physics. It is also called as population - based method which works on the principle of attraction-repulsion mechanism among the particles i.e., the pixels present in the image. In general, it has an attraction-repulsion mechanism to evolve the members of the population guided by their objective function values. When comparing with the other optimisation algorithms, EMO exhibits interesting search capabilities and maintains low computational overhead.
The idea behind the EMO is to move a particle through the search space following the force exerted by the other particles. Unlike other meta-heuristics such as GA, DE, ABC and Artificial Immune System (AIS), where the population members exchange materials or information between each other, in EMO similar to heuristics such as PSO and Ant Colony Optimisation (ACO), each particle is influenced by all other particles within its population. Although the EMO algorithm shares some characteristics to PSO and ACO, recent works have exhibited its better accuracy regarding optimal parameters, yet showing convergence [45]. Although EMO algorithm is designed to solve optimisation problems with bounded variable, the algorithm works well in handling computational problems. EMO algorithm provides great solution diversity because there are only few overlapped regions and redundant solutions are the highlights of this algorithm [98]. Constrained global optimisation problems are encountered in science and engineering design, VLSI design, economics and management science. In general, optimisation problem can be formulated mathematically as given in equation 5.1.

\[ \min f(X) \text{ subject to} \]

\[ g_k(X) \leq 0, k = 1,2,3, \ldots \ldots \ldots \ldots \ldots \ldots m \]

\[ h_p(X) \leq 0, k = 1,2,3, \ldots \ldots \ldots \ldots \ldots \ldots l \]

\[ X \in [L,U] = \{ X \in \mathbb{R}^n \mid \| x \| \leq u_k, k = 1,2,3, \ldots \ldots \ldots n \} \ldots \ldots \ldots \ldots \ldots \ldots (5.1) \]

Here, \( f, g \) and \( h \) are the real time valued function and the solution vector is represented by \( X = \{ x_1, x_2, x_3, \ldots \ldots \ldots x_n \} \) and \([L,U]\) is the lower and upper bounds in the n-dimensional search space; \( m \) and \( l \) are the number of inequality and equality constraints respectively, \( \varepsilon \) belongs to small positive value. \( \| h(X) \| - \varepsilon \leq 0 \) is the solving condition for optimisation problems [36]. Many clinical and research applications of MRI images rely on the segmentation techniques, inorder to delineate the different intensity values present in the images [143]. EMO algorithm originally came from the electromagnetism theory in physics, which follows the mechanism of electromagnetism by considering each particle is to be an electrical charge. The charge or change of each
particle is determined by its function called fitness function and each particle in the population is based on the degree of attraction or repulsion among them [54].

EMO algorithm interaction is also known by the simulation induced by the electromagnetic force between the electrically charged particles. Due to its effectiveness, EMO algorithm is applied to various optimisation problems such as scheduling, segmentation, vehicle-routing problem, feature selection, clustering and classification, fuzzy neural system and in the designing engineering problems [65]. EMO algorithm is represented mathematically as given in equation 5.2.

\[
\text{Minimize } z = f(x), x = (x_1, x_2, x_3, \ldots, x_n) \in \mathbb{R}^n
\]

\[
\text{subjected to } x \in [L, U] \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots
\]

EMO algorithm solution can be viewed in the search space as a charged particle and its charges are related to its objective function value. EMO was originally designed for solving bounded optimisation problem where \( L \) represents lower bounds and \( U \) represents upper bounds of the decision variable \( x \).

<table>
<thead>
<tr>
<th>Algorithm EMO (m, maxiter, lsiter, ( \delta ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>m : number of sample points</td>
</tr>
<tr>
<td>lsiter : maximum number of local search iterations</td>
</tr>
<tr>
<td>( \delta ) : local search parameters, ( \delta \in {0,1} )</td>
</tr>
<tr>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td>Initialize()</td>
</tr>
<tr>
<td>( i \leftarrow 1 )</td>
</tr>
<tr>
<td>While ( i &lt; \text{max Iter} ) do</td>
</tr>
<tr>
<td>\hspace{1cm} Local(Lsiter, ( \delta ))</td>
</tr>
<tr>
<td>\hspace{1cm} Calculate Forces()</td>
</tr>
<tr>
<td>\hspace{1cm} Move()</td>
</tr>
<tr>
<td>\hspace{1cm} ( i = i + 1 )</td>
</tr>
<tr>
<td>end while</td>
</tr>
</tbody>
</table>

EMO algorithm includes four phases, which comprises three main subroutines and starts after the initialization phase. The second phase is the local search procedure.
and third phase is the calculation of the force extended by each particle and the last
phase is based on the force with which the particles move to a new location. EMO
algorithm is a simple and direct search algorithm which has been inspired by the
electromagnetism phenomenon. It is based on a given population and the optimisation of
global multi modal functions. In comparison to GA, it does not use mutation or
crossover operators to explore feasible regions; in its place it does implement a
collective attraction-repulsion mechanism yielding a reduced computational cost with
respect to memory allocation and execution time. Moreover, no gradient information is
required as it uses a decimal system that clearly is contrast to GA. EMO algorithm can
effectively solve a special class of optimisation problems with bounded variables in the
form of equation 5.3.

\[ f : [l, u] \] \[ \left\{ \begin{array}{l}
\end{array} \right. \]

where \[ [l, u] = \{ x \in R^n | l_d \leq x_d \leq u_d, d = 1,2,3, \ldots, n \} \] and \( n \) being the dimension of the
variable \( x \), \( [l, u] \subset R^n \), a nonempty subset, and a real-value function, \( n \) is the
dimensional size of the problem; \( u_d \) is the highest bound of the \( k^{th} \) dimension; \( l_d \) is the
lowest bound of the \( k^{th} \) dimension; and \( f(x) \) is the function to be minimised. EMO
algorithm comprises four phases: initialisation, local search, computation of the total
force vector and movement.

**Initialisation:** A number of \( m \) particles are gathered as their highest \( (u) \) and lowest limit
\( (l) \) are identified.

**Local search:** Gathers local information for a given point \( g^n, \) where \( p \in (1,2,3,\ldots,m) \).

**Calculation of the total force vector:** Charges and forces are calculated for every
particle.

**Movement:** Each particle is displaced accordingly, matching the corresponding force
vector.

**5.2.1 Initialisation of EMO Algorithm**

First, the population of \( m \) solutions is randomly produced at an initial state. Each
\( n \) dimensional solution is regarded as a charged particle holding a uniform distribution
between the highest \((u)\) and the lowest \((l)\) limits. The optimum particle (solution) is thus defined by the objective function to be optimized. The procedure ends when all the \(m\) samples are evaluated, choosing the sample (particle) that has gathered the best function value [61].

### 5.2.2 Local Search of EMO Algorithm

Local search of the EMO algorithm has very good balance in between the exploitation and exploration of the algorithm. Birbil and Fang proposed two approaches in local search; first one is applied to all particles and the second one is applied to the current best particles [98]. EMO algorithm has the property of global optimisation and rapid convergence. The local search procedure is used to gather local information within the neighbourhood of a candidate solution. It allows obtaining better exploration and population diversity for the algorithm. Local search for all particles can reduce the risk of falling into a local solution; however it is time consuming. According to the experimental results, the algorithm spends 91.84 percent of the computation time in the local search space [98]. However, recent works have shown that eliminating, reducing or simplifying the local search process significantly the convergence, exploration, population diversity and accuracy of the EMO algorithm.

Considering a pre-fixed number of iterations known as ITER and a feasible neighbourhood search \(\delta\), the procedure iterates as follows: Point \(p^g\) is assigned to a temporary point \(t\) to store the initial information. Next, for a given coordinate \(d\), a random number is selected (\(\lambda_1\)) and combined with \(\delta\) as a step length, which in turn, moves the point \(t\) along the direction \(d\), with a randomly determined sign (\(\lambda_2\)). If point \(t\) observes a better performance over the iteration number ITER, point \(g^p\) is replaced by \(t\) and the neighbourhood.

### 5.2.3 Total Force Calculation of EMO Algorithm

This phase is assigning each particle in the population with some electromagnetic charge. Total force vector computation is based on the superposition principle from electromagnetism theory which states that the force exerted on a point through other points is inversely proportional to the distance between the points and directly proportional to the product of their charges. The particle moves following the
resultant Coulomb’s force (force between two or more charged bodies is the force between them due to Coulomb’s law. Coulomb's law states that the magnitude of the electrostatic force of attraction between two point charges is directly proportional to the product of the magnitudes of charges and inversely proportional to the square of the distance between them. The force is along the straight line joining them. If the particles are both positively or negatively charged, the force is repulsive; if they are of opposite charge, it is attractive), which has been produced among particles as a charge like value. In EMO algorithm implementation, the charge for each particle is determined by its fitness value as follows. The charge $q'$ for the particle $x'$ is determined by equation 5.4.

$$q' = \exp \left[ -\frac{f(x') - f(x_{\text{best}})}{\sum(f(x') - f(x_{\text{best}}))} \right]$$

where, $f(x')$– objective value of particle $i$; $f(x^k)$ denotes particle $k$; $f(x_{\text{best}})$ represents the best solution; $m$ represents the population size; $f(x)$- direction of forces between particles; $x_{\text{best}}$ - plays the role of attraction.

The particle that is having the largest charge is known as the optimal particle in the search space. The particle attracts the other particles which having the better fitness values and repels the particles with worst fitness values. According to the electromagnetic theory, force is directly proportional to the product with their changes and inversely proportional to the distance between two particles. The total force in $x'$ is computed by the superposition principle as defined by the equation 5.5 [34].

5.2.4 Movement of EMO Algorithm

The change of d coordinate for each particle $x'$ is computed with respect to the resultant force in equation 5.5.

$$F^i = \sum \begin{cases} 
(x' - x^i) \frac{q'q^j}{\|x' - x^j\|^2}, f(x') < f(x^j) \\
(x' - x^i) \frac{q'q^j}{\|x' - x^j\|^2}, f(x') > f(x^j) 
\end{cases}$$

...
\( f(x') < f(x') \) indicate attraction of particles

\( f(x') > f(x') \) indicate repulsion among particles

\[
X' = \begin{cases} 
X' + \lambda \frac{F_i}{\|F\|} (u_k - x'_k) & jF_k > 0 \\
X' + \lambda \frac{F_i}{\|F\|} (x'_k - l_k) & \text{otherwise}
\end{cases}
\] (5.6)

In equation 5.6, \( \lambda \) is a random step length that is uniformly distributed between zero and one i.e. \( \lambda = \text{random}(0,1), i = 1,2,3,...........m, i \neq \text{best}, k = 1,2,3,..........n \). If the resultant force is positive, then the particle moves towards the highest boundary by a random step length. Otherwise, it moves toward the lowest boundary. The best particle does not move at all, because it holds absolute attraction, pulling or repelling all other particles in the population. The process is ceased when a maximum iteration number is reached, or when the value \( f(g^{\text{best}}) \) is near to zero, or near to the required optimal value. The particle which does not find the best optimum value will update its position according to equation 5.6. The optimal particle does not move because of having the best fitness value and it attracts all other particles [34].

5.2.5 Applications

EMO algorithm has been successfully applied to different engineering problems such as constraints problems, scheduling problems, vehicle routing, array matrix solutions, IP, vehicle routing, pattern optimisation and neural systems [54]. In many recent works, EMO has been used to solve flow shop scheduling, communications, neural network training and medical image segmentation systems [45].

5.3 Level Set Methods (LSM)

LSM for capturing different dynamic interfaces and finding its shapes was introduced by Osher and Sethian in the year 1987. The basic idea of LSM is to represent contour having zero level function with its higher dimension called Level Set Function (LSF). Major ideas in LSM were proposed earlier in the late 1970s by Dervieux and Thomasset; however their work did not pay much attention towards the development of LSM. After the discovery of Osher and Sethian, LSM had far-reaching impact in
various applications, especially, in computer vision. In the field of IP, computer vision applications and image segmentation, active contour models are widely used to represent dynamic parametric contours with spatial parameters. Curve evolution can be expressed by the speed function which controls the motion of the contour [37].

Level set technique is a general framework that track and work on the dynamic interfaces and shapes present in the image. It was first developed as a way to model fluid boundaries like flame front. In pattern recognition and computer vision, LSM had been widely used in segmentation field. The main advantage of LSM is its ability to extract complete complex contours and can easily handle topological changes in the regions such as splitting and merging. LSM belongs to active contour model which is based on the Euclidean framework, i.e., the active contours are based on geometric representation instead of parametric representation. Parametric representation of patterns is based on the Lagrangian framework (Lagrangian specification of the field is a way of looking at fluid motion where the observer follows an individual fluid parcel as it moves through space and time i.e. keeps track of the locations of individual fluid particles). LSM is been widely used in the field of image segmentation because of its intrinsic nature and can handle complex shapes more easily [108].

LSM is well-know and has a wide range of applications since 1990. Curve evolution can be expressed as the speed function which controls the motion of the curve and uses the concept of normal vector to the curve. Curve evolution is expressed in LSM by converting the embedded dynamic contour of the zero level set of time with respect to the parameterised contour models. Embedded LSM takes the negative values when it is inside the level contours and positive value when it is outside the level contour and normal vector can be expressed as the gradient operator. Curve evolution can be converted into PDE which is referred as level set evolution equation. The advantage of LSM is that they represent contours as complex topology and handle topological change in splitting and merging easily in a natural and efficient way. Another desirable feature of LSM is that numerical computations can be performed on a fixed Cartesian grid without having to parameterise the points on contours in parametric active contour models [37].

Intensity inhomogeneity often uses real world images due to various facts such as imperfections of imaging devices and spatial variation in illumination that
complicates several issues in IP. LSM uses have increased rapidly in image segmentation in the last decade. With LSM, image segmentation problem can be represented and solved by mathematical theories including calculus and PDE [39]. Level set formulation of moving fronts i.e., the active contour fronts here is denoted by $c$ and it is defined by moving or tracking the interface regions and it is represented by the zero level set function as given in equations 5.7 and 5.8.

$$c(t) = \{(x, y) | \phi(t, x, y) = 0\}, \phi(t, x, y) = 0$$\hspace{1cm} (5.7)

The evolution of the LSF $\phi$ can be written in the general form as

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0$$\hspace{1cm} (5.8)

The equations 5.7 and 5.8 are level set equations. Speed function is represented by $F$. In image segmentation function $F$ depends on the level set equation $\varnothing$ and the image data $F$. In traditional LSM, $\phi$ denotes the level set function which can develop shocks, flat shapes and very sharp curvature during evolution, which makes further computation in a highly accurate manner.

The function $\phi$ is designed to re-shape the function periodically during the evolution process [38]. Initial position for an interface is defined by the function $F$; initially $F$ is a closed curve and it is a speed function, and $F$ normally moves in positive direction. LSM takes the perspective of zero level set of function $\phi(x, t = 0)$, which is given is equations 5.9 and 5.10, which are

$$\phi + F|\nabla \phi| = 0$$\hspace{1cm} (5.9)

$$\phi(x, t = 0) = \text{given}$$\hspace{1cm} (5.10)

Let $\phi(x, t = 0) \pm d$ where $d$ is the distance from $x$ to $F$ and $+$ symbol denotes the point $x$ outside the initial hyper surface of $F$. Then by using the chain rule from mathematics, interface is defined as in equations 5.8 and 5.9. The initial value of PDE is one higher dimension than its original problem. LSM has a wide range of applications such as image segmentation, computational geometry, fluid dynamics and computer vision [60].
5.4 Proposed Methodology

On the basis of MRI imaging technique, study of cerebral tissues such as white matter and gray matter will be more important and serve the medical field. The main aim is partitioning the intracranial volume into potentially overlapped regions and separate regions, which is very helpful for researchers to study clinical diagnosis. MRI scans the affected region more reliably than CT scan for diagnosing affected regions in the body, and it does not cause any kind of radiation. MRI images have several advantages than CT scan, and it produces high resolution spatial images and acquires good contrast resolution for different tissues.

Numerous techniques related to brain tumor are proposed by many researchers in recent years. Accurate image segmentation plays a major role in anatomic structure inspection, diseases identification, tracking process in the field of biomedical IP and simulation of surgical and treatment planning. Brain is a very complicated and complex structure; therefore, segmentation of tumor, edema and neurosis tissue is a challenging task. This research work’s main aim is to detect brain tumor from MRI brain images. To achieve this objective we develop a hybrid framework that integrates EMO algorithm with LSM. This work also attempts to employ the optimisation concept combining with the level set operations, and form a new hybrid algorithm to obtain the best optimal schedule for MRI brain medical images. This approach achieves converges and diversity effects which are iteratively applied to solve the problem domain. This hybrid algorithm is tested on the MRI brain images taken from previous chapters and the results are discussed and compared in the next chapter.

EMO algorithm and LSM techniques have several drawbacks over MRI brain images in finding the tumor affected region in the images. To overcome the disadvantages, we develop a new algorithm based on the traditional EMO and LSM. ELSM approach is consists of the three steps: one is finding the best fit value for n with EMO algorithm. The second step is to select the correct iteration level value of k by using the level set methods. The last steps in the ELSM algorithm is taking the min and max value from the step 1 and step 2 based on the n and k values, the resultant image is obtained empirically. The main objective of the ELSM algorithm is segmenting the images with the values of n and the resultant image is leveled by boundary detection of the tumor affected region through the numbers of levels based on k values. New EMO
algorithm is been introduced inorder to segment the images based on the intensity of pixels in the image to detect tumor. The EM algorithm is been implemented based on the equation 5.4 in this the value of \( q \) is the charge of each point (pixel) in the image and the power of n denotes the cluster value of segmentation. By calculating the neighbourhood pixel value the \( x^{\text{best}} \) and \( x^{\text{last}} \) values are obtained. With attraction and repulsion mechanism the little contrast intensity values of the images are obtained by the using the cluster values of \( n \) and the best resultant image are evaluated for the enhancement of image.

LSM is combined with the EMO which solves the tumor detection problem. On finding the number of iteration level in detecting the boundary region the value of \( k \) plays a major role. In general boundaries of the pixels are identified by active contours; its computer generated curves that move within the image to find the object boundaries. The intensity of the tumor tissue should take a specific value with physical property. In our hybrid algorithm the EMO algorithm partially segments the tumor with various \( n \) values. The segmented region of tumor is estimated with the active contour, which slowly varies across the image domain with various levels of \( k \). Image intensities are approximately same within each class of tissue. We propose a method which divides this small region pixel intensity separately. The level set functions are evaluated and active contours are applied to detect the affected region separately. The general active contour functions are implemented as a second module of ELSM algorithm.

This research work’s main aim is to detect brain tumor from the MRI brain images with the newly developed hybrid algorithm by enhancing and EMO algorithm and LSM. The proposed hybrid algorithm is the combination of the existing EMO algorithm and LSM. Evolution of EMO algorithm plays a major role in this hybrid approach by highlighting the affected region. The EMO algorithm highlights the pixel that has the same intensity. The LSM segments the affected region separately with the active contour concept. The proposed methodology is applied to the MRI brain images and compared with the standard PSO and FCM segmentation algorithms. The main contribution of this research is to combine the classical EMO algorithm to achieve a better exploration/exploitation trade-off when applied to continuous optimisation problems.
EMO algorithm and the traditional LSM are executed for the MRI brain images taken in this research work. EMO algorithm and LSM are applied to the preprocessed images of the MRI brain images and the results are shown in below figure 5.1. The resultant images from the preprocessing stage are taken as input for implementation of EMO and LSM approaches. The figure 5.1 shows the resultant images of the normal and abnormal images of axial plane and coronal plane in the implementation of EMO algorithm. The figures 5.1 (a), (b), (c) and (d) blurs the image and increases the overall contrast value and also fails to detect the tumor affected region.

![Figure 5.1: Implementation of EMO Algorithm](image)

The figure 5.2 shows the resultant images by implementing the traditional LSM for the MRI brain images. Preprocessed images are subjected to implementation of LSM and the results are shown in figures 5.2 (a), (b), (c) and (d) for both normal and abnormal images of the axial and coronal plane. The results obtained from both axial and coronal plane did not meet the objective of this research work. Traditional LSM fails to detect the contour interface or shapes present in the image. Hence, this work proposes a new hybrid model to solve this optimisation problem and to detect the brain tumor affected region separately from the image.
Segmentation is a difficult task for images with intensity inhomogeneity overlapping with ranges of intensities in the regions to be segmented. This makes it impossible to identify affected regions based on the pixel intensity. In general, intensity inhomogeneity has been a difficult and a challenging task in image segmentation problems [39]. The newly developed hybrid technique is used in clinical and research application of MRI imaging to respond to segmentation, in order to delineate the intensity inhomogeneity values present in the image. MRI signal from the scanner is noted and is mathematically described as given in equation 5.1.

\[ J = I \cdot B + N(I) \]

where, \( J \) is the product of true signal; \( B \) is the spatially varying field factor; \( I \) is generated by the underlying anatomy; and \( N \) is the additive noise [143]. In equation 5.10 MRI brain image acquisition process and noises are expressed mathematically in order to get better understanding of the images. In Chapter 4 we implemented PSO and FCM algorithm to achieve the goal of finding the brain tumor affected region. Both methods were executed and the resultant values were discussed for both segmentation algorithms;
however, they have some major drawbacks. In order to achieve the research goal more accurately we need some other algorithm.

The disadvantage of PSO algorithm is that the method is easily affected by the partial optima solution, which increases the speed and minimises the direction of control and it does not work well on the problem of non-coordinate system. Moreover, it will not lead to accurate results in the energy field and moving rules of the particle in the system. The main problem lies in scattering pixels for finding the optimisation solution of PSO algorithm [23]. FCM has two major drawbacks- one is the absence of any local or spatial information in the FCM measures, which makes the FCM more sensitive and failure to remove noises and image artifacts; and second, the implementation of Euclidean distance is a highly sensitive concept in finding the geometrical shape or cluster in the image [6].

PSO and FCM segmentation algorithms space and time taken is also high. Despite taking more space and time, the results obtained from these algorithms maintain less accuracy when compared with the results of ELSM algorithm which is validated by medical experts. Visually and technically, there is need for development of a new hybrid framework. The newly proposed hybrid algorithm combines the approaches of optimized algorithm with the active contour model LSM. EMO is combined with LSM approach and the new unified hybrid framework is Electromagnetic Level Set Method (ELSM). ELSM is mainly developed to detect the brain tumor affected region from the MRI brain images.

5.4.1 The Algorithm

ELSM algorithm is developed to maintain accuracy and efficiency in predicting brain tumor. ELSM algorithm segments the image based on the intensity present in the image i.e., the intensity inhomogeneity of the image serves as the input for this algorithm. ELSM algorithm is divided into two phase, the first phase is developed with EMO algorithm and the second phase is extended from LSM. The first phase of ELSM algorithm works on the same principle as followed by EMO algorithm and modification in EMO algorithm takes place in the electric charge of each particle and total force calculation. The newly modified equation for electrically changing the particle or pixel present in the images is given in equations 5.12 and 5.13.
\[ q^i = \exp \left[ \sum_{k=1}^{m} f(x^{i-k}) - f(x^{best}) + f(x^{last}) \right] \] 

\[ F^k = \sum \left\{ \frac{x^i q^i q^j - x^i q^i q^j}{(x^i \pm x^j)^2} \right\} f(x^i) > f(x^j) \] 

The total force calculation for the particles or pixels from EMO algorithm is slightly modified as described in equation 5.13. Variables in both equations 5.12 and 5.13 of the ELSM algorithm, follows the same variables as in EMO algorithm. \( q^i \) is the charge of each point in the pixel values, \( n \) represents numbers of segmentation levels, \( x^{best} \) and \( x^{last} \) are calculated with neighbourhood pixels and finding its best value in equation 5.12. \( q^i \) and \( q^j \) represents \( x \) and \( y \) values of the pixels in the image and \( x^i \) represents \( x \) represents the intensity values for the image.

By using the newly modified algorithm for Phase I in ELSM algorithm, we also use the same concept of attraction and repulsion of pixels. Pixels with same intensity are attracted and highlighted. Likewise, the other pixels intensity are repelled and again forms a group of pixels in the image to segment the pixel region. This process is also known as grouping of images based on the intensity present in the images. The different intensity of the image are highlighted, and the resultant image will change based on the segmentation level of the image. The Phase II of ELSM algorithm is taken the input from the Phase I. Segmentation is completely done with the help of LSM. The idea behind this phase is to segregate the highlighted contrast region from phase I images into separate regions. This goal is achieved with the modified LSM as given in equations 5.14 and 5.15.

\[ \frac{\partial \phi(x(t), t)}{\partial t} = 0 \] 

\[ x_i = F(x(t))^k \text{ where } k = \frac{\nabla \phi}{\| \nabla \phi \|} \]

The newly modified LSM is described in the equation 5.13 and 5.14 with the level values denoted by \( k \). The equations are modified with initial \( \phi \) at \( t=0 \), so that it would be possible to know \( \phi \) at any time \( t \) with motion through the numbers of
derivations, value of $x'$ will be represented as in equation 5.15 where $k$ denotes the numbers of iterations(level) in the modified LSM.

**Figure 5.3: Flowchart of the Proposed ELSM Algorithm**

ELSM algorithm works on the principle that Phase I is meant for grouping (partial segmentation) the images i.e. grouping pixels into two or more regions based on the intensity and highlighting the pixel values in the images based on the segmentation level denoted as $n$. Phase II is meant for segmenting, so as to classify the highlighted pixels region in the images into separate images, with continuous iteration of variables. Based on the contour concept the highlighted intensities pixels are separated by the numbers of level values, which are represented by the variable $k$. Phase I is achieved with the modified EMO algorithm and meant for grouping process and Phase II is developed with slight modification to LSM for segmenting pixel values from the image. The flowchart for the ELSM algorithm is shown in figure 5.3.

**Figure 5.4: Overall Architecture of ELSM Algorithm**
ELSM algorithm works on the model developed as given in the flowchart. ELSM algorithm follows the top-down approach in identification of brain tumor from MRI brain images. The preprocessed images are taken as the input for implementation of ELSM algorithm from the preprocessing stage implemented in Chapter 3. The figure 5.4 shows the overall architecture of the ELSM algorithm and the proposed hybrid ELSM algorithm for the MR brain images. The steps in the overall architecture of the ELSM algorithm are explained in the methodology and it is evaluated as follows,

Step 1: Converting the MRI brain images from DICOM file format into standard image file format.

Step 2: Preprocessing the images with Weiner filter for removal of white noises from the images for effectiveness of the resultant image.

Step 3: Implementing the Phase I of the hybrid ELSM algorithm for the images, and producing the grouping results based on the segmentation values of n.

Step 4: With the results from step 3, the newly modified LSM of phase two of the hybrid model is applied to the resultant images of step 3. The purpose of segmentation for identifying brain tumor based on the various level values of k.

Step 5: Using the max and min concepts the best resultant image is observed which separates the brain tumor affected region separately.

Step 6: Computational time, white pixel variation and space complexity of the resultant images are calculated, inorder to find the accuracy and efficiency of ELSM algorithm.

The images are preprocessed with Weiner filter to remove white noises and improve the contrast of the image. The resultant preprocessed images are taken as input for the new hybrid ELSM algorithm. Phase I of the algorithm is the process of grouping pixels based on the inhomogeneity intensity values with the help of modified EMO algorithm, where the segmentation levels are represented by n. Phase II of the ELSM algorithm is based on the segmentation process and the results obtained help in identifying the tumor affected region. The second phase is executed with the help of LSM and the results produced are based on the level values of k. By default, the segmentation value starts with n=2, 3, 4 and 5 in phase I. Phase II of ELSM algorithm
segmentation is based on the level values of $n$. The segmentation phase is executed with the modified LSM. The different iteration level values to segment the highlighted pixels from the grouping are represented by the value of $k$ in the phase II of this hybrid algorithm. For every resultant image obtained from Phase I for $n$ value. It again segments the image based on the level values of $k$ for each every value of $n$. The best resultant image should be identified which segments the brain tumor more precisely. For finding the best resultant image from the various set of $n$ and $k$ values, selection has to be done based on the observation from various resultant images.

Phase I results highlights the intensity values of the pixels in the image. Phase II is mainly developed for finding the curvature and shapes in the resultant clustered or grouped images. For evolution of interfaces, curves and shapes from the images, LSM provides greater contribution. Segmenting the images with different level values of $k$ produces several resultant images for detection of brain tumor from the MRI brain images. Selecting, the best resultant images among the results plays a major role in brain tumor diagnosis from the MRI brain images.

5.4.2 Results and Discussion

In the evaluation of the proposed ELSM algorithm, experiments are carried out on the subset of abnormal images from real patients. The algorithm works on by computing the coefficient of the joint variation of brain tissue, so as to segregate the gray and white matter of the brain. The first stage in the architecture of ELSM algorithm is preprocessing, which is used to remove white noises from the images with the help of Weiner filter. The proposed ELSM hybrid algorithm is implemented using MATLAB R2008a software on Intel core i5 processor with 2.2 GHz, 4GB memory which works on windows 7 operating system. The results discussed here follow the flowchart and architecture of ELSM algorithm for preprocessed images of the axial and coronal plane of the MRI brain images.

The figure 5.5 shows the Phase I results of the ELSM algorithm hybrid approach for AAXI_IMG_02. The input for this hybrid model is from the preprocessing stage done with the Weiner filter. Figure 5.5 shows all the intermediate results for Phase I, the ELSM algorithm with the various segmentation values of $n$. The results in this figure 5.5
are based on the pixels intensity of the preprocessed images. The segmentation values of n and the distinct intensity pixel values are grouped and highlighted.

![Image](image.png)

**Figure 5.5: Phase I of ELSM Algorithm for AAXI_IMG_02**

The above figure 5.5 (a) shows the result when the segmentation value of n=2 and highlights the different intensity in the phase I of ELSM. Figure 5.5 (b) shows the result when the segmentation value of n=3 and the resultant images are shown and the tumor affected regions are highlighted in the image. Figure 5.5 (c) shows the resultant image when the segmentation value of n=4 and figure 5.5 (a) shows the resultant image when the value n=5. If we take bigger value for n say, when the value of n=6 and the resultant image shows the preprocessed input image as its result, so the maximum value of n is 5.

The intermediate results obtained in this stage are taken as the input for the phase II of ELSM algorithm. Based on ELSM, images are partially segmented in phase one, which highlights the pixels intensity in the intermediate results obtained. By increasing the values of n in the images, the resultant images are changed as per its segmentation values. Using this resultant image as input, the phase II of ELSM algorithm is performed. Figure 5.6 shows the resultant image for various segmentation
level values of $k$, when $n=2$. Figure 5.6 (a) shows the resultant image when the value of $k=1$, figure 5.6 (b) shows the resultant image when the value of $k=2$ and figure 5.6 (c) shows the resultant image when the value of $k=3$ on the abnormal axial plane data AAXI_IMG_02.

![Figure 5.6: Phase II of ELSM Algorithm for AAXI_IMG_02](image)

Segmentation of brain tumor is the main objective of this research work, and with the $k$ level values of phase II of ELSM algorithm has been achieved. Selecting among this $k$ level values, the resultant image that identifies brain tumor with more accuracy and efficiency should be selected. The second phase of ELSM algorithm is based on LSM, which identifies contours, shapes or interfaces present in the region. In this ELSM algorithm all the images are segmented based on the pixel intensity the pixels and segmentation levels, and various level values are represented by the values of $n$ and $k$ respectively.

The figure 5.7 (a) shows the resultant image for various segmentation level values of $k$, when $n=3$, where noises and artifacts present in the images are removed in ELSM algorithm. Figure 5.7 (i) shows the resultant image when the value of $k=1$, figure 5.7 (ii) shows the resultant image when the value of $k=2$ and figure 5.7 (iii) shows the resultant image when the value of $k=3$ for the abnormal axial plane image AAXI_IMG_02. Figure 5.7 (b) shows the resultant image for various segmentation level values of $k$, when $n=4$. Figure 5.7 (iv) shows the resultant image when the value of $k=1$, figure 5.7 (v) shows the resultant image when the when the value of $k=2$ and figure 5.7 (vi) shows the resultant image when the when the value of $k=3$ for the abnormal axial plane image AAXI_IMG_02. Figure 5.7 (c) shows the resultant image for various segmentation level values of $k$, when $n=5$. 
Figures 5.7 (vii) shows the resultant images when the value of k=1, figure 5.7 (viii) shows the resultant images when the value of k=2 and figure 5.7 (ix) shows the resultant images when the value of k=3. By increasing the level values, the resultant images obtained are incorrect and the accuracy is minimised. On analysing the resultant images visually, when the values of k increase, the images are corrupted by noises and includes more artifacts details, which increases the space complexity of the resultant image.
Figure 5.8: Top-Down Approach ELSM Algorithm of AAXI_IMG_02
Figure 5.9: Top-Down Approach ELSM Algorithm of NAXI_IMG_01
The overall flow of ELSM algorithm for the abnormal axial plane image AAXI_IMG_02 is shown in figure 5.8 and the overall flow of the coronal plane for NAXI_IMG_01 is shown in figure 5.9. The same procedure is followed for the axial plane image NAXI_IMG_01, is implemented with the hybrid ELSM algorithm and results are analysed. The overall implementation process for the normal axial image in the finding brain tumor is shown in the figure 5.9. The preprocessed image of the NAXI_IMG_01 is taken as the input and for execution of ELSM algorithm. Phase I grouping process, partially segments the image based on the intensity value and the intermediate results are displayed with the various segmentation values of n starting from 2, 3, 4 and 5.

The results are grouped with the pixels intensity, inorder to separately shows the highlighted intensity region values present in the image. By taking this intermediate resultant image pixel value as input of the next phase of the ELSM algorithm, it starts the process of phase II of this algorithm. The segmentation is based on the various level values of k starting from 1, 2 and 3. For every n value of the image the corresponding k values resultant images are shown in the last phase of figure 5.9. For the normal images also the algorithm works more efficiently in identifying the tumor region from MRI brain images. On comparing and examining both the results of the normal and abnormal images, the ELSM algorithm works and follows a same sequential procedure for both the images.

ELSM algorithm is implemented for the MRI brain images and follows the proposed methodology with the preprocessed Weiner filter images. The MRI brain images undergo Phase I and Phase II processes with various levels. In Phase I carries the first level of segmentation level with various n level values and Phase II carries the second level of segmentation with various k level values. The overall implementation process of ELSM algorithm for the normal coronal image in the finding brain tumor is shown in figure 5.10 for NCOR_IMG_03. The figure 5.11 shows the overall implementation process of ELSM algorithm for the abnormal coronal image ACOR_IMG_04.
Figure 5.10: Top-Down Approach ELSM Algorithm of AAXI_IMG_03
Figure 5.11: Top-Down Approach ELSM Algorithm of ACOR_IMG_04
The best resultant image is obtained with the help of n and k values and the results are more accurate. Figure 5.12 shows brain tumor for the normal and abnormal images of both the axial and coronal planes of the MRI brain images used in this research work. Figure 5.12 (a) shows the best resultant image of the normal axial plane NAXI_IMG_01 which segments the brain tumor affected region accurately; figure 5.12 (b) shows the best resultant image of the abnormal axial plane AAXI_IMG_02 which segment the brain tumor affected region accurately. The figure 5.12(c) shows the best resultant image of the normal coronal plane NCOR_IMG_03, which segment the brain tumor affected region accurately, and figure 5.12 (d) shows the best resultant image of the abnormal coronal plane ACOR_IMG_04 which segment the brain tumor affected region accurately. The algorithm does not identify any region for the normal images. Hence, the proposed algorithm works more accurately for all types of images. With the help of the newly proposed ELSM algorithm brain tumor segmentation becomes easier and accurate and it does not need any post processing and extraction techniques. Radiologists and medical experts analysed the results obtained from ELSM algorithm and were convinced that the results obtained were accurate and maintained greater efficiency for the input MRI brain images.

![Image of brain tumor affected region by ELSM Algorithm](image)

*Figure 5.12: Brain Tumor Affected Region by ELSM Algorithm*
Table 5.1: Elapsed Time of ELSM Algorithm

<table>
<thead>
<tr>
<th>Number of Levels n</th>
<th>Values k</th>
<th>Elapsed time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NAXI_IMG_01</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>37.1234</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>36.3456</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>35.4567</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>38.3456</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>39.2345</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>40.3467</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>40.5893</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>41.6358</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>42.2490</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>42.6349</td>
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<tr>
<td></td>
<td>2</td>
<td>43.4086</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>44.4078</td>
</tr>
</tbody>
</table>

Table 5.2: Memory Space of ELSM Algorithm

<table>
<thead>
<tr>
<th>Number of Levels n</th>
<th>Values k</th>
<th>Memory space</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NAXI_IMG_01</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>13.10</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>14.10</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>12.10</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>13.20</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>18.50</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>12.40</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>13.30</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>19.20</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>21.50</td>
</tr>
<tr>
<td>1</td>
<td>21.50</td>
<td>7.44</td>
</tr>
</tbody>
</table>
The above table 5.1 shows the computational time for the resultant images for the MRI brain images for normal and abnormal of both the axial plane and coronal plane. The execution time taken by ELSM algorithm is calculated in seconds and it includes the time of both the phases of ELSM algorithm. The best resultant images are obtained when \( n \) is minimum and \( k \) is maximum \([2, 3]\) based on the observation from several MRI images. The table 5.2 shows the memory space occupied by the resultant images of the MRI brain images and space occupied is represented in kilobytes (KB). The space occupied by the resultant images values does not include the intermediate result space. The best resultant image is obtained when the value of \( n \) and \( k \) is \([2, 3]\); the difference for this value with the minimum value listed in the table is so small, therefore, it is highly negligible.

**Table 5.3: Observation of ELSM Algorithm**

<table>
<thead>
<tr>
<th>Max, Min combinations</th>
<th>Values of ( n ) and ( k )</th>
<th>Results Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>(min, min)</td>
<td>[2, 1]</td>
<td>Small in size</td>
</tr>
<tr>
<td>(min, max)</td>
<td>[2, 3]</td>
<td>Feasible solution</td>
</tr>
<tr>
<td>(max, min)</td>
<td>[5, 1]</td>
<td>Small in size</td>
</tr>
<tr>
<td>(max, max)</td>
<td>[5, 3]</td>
<td>Includes artifacts</td>
</tr>
</tbody>
</table>

By examining several resultant images of the MRI brain images, some results are observed and listed in table 5.3. The observation table is based on analysing several MRI brain image data results. Based on the maximum and minimum concepts, the observations are derived to find the best resultant images from ELSM algorithm for the given MRI brain images, inorder to predict brain tumor. ELSM algorithm works on the input images and our workflow produces nearly 12 resultant images as output in finding the brain tumor affected region for a single MRI brain image. The observation table provides solutions to the problems of choosing the best resultant image. The optimum results are easily achieved by giving the correct parameters for \( n \)
and $k$ values. On studying the values of $n$ and $k$ with the maximum and minimum technique it has four set of combinations, which are

- When both the values are minimum, the resultant image i.e. the brain tumor region is small in size; it does not fully segment the affected region with this $n$ and $k$ values.
- When both the values of $n$ and $k$ are maximum, the resultant images are blurred with noises and include artifacts in the images.
- When the values of $n$ is maximum and $k$ is minimum, it does not segment the entire tumor affected region, i.e., the result of the size of brain tumor is not accurate i.e., small in size.
- When the values of $n$ are minimum and $k$ value is maximum, it fully segments the tumor affected region separately from the MRI brain images more accurately and efficiently.

In the medial field, segmentation of brain tumor or its identification of white matter from brain MRI images is an important and challenging task. By the proposed hybrid ELSM algorithm, it achieves the objectives in a more efficient manner. For any newly developed algorithm, the results obtained are more important, and the time and space occupied by the resultant images also plays a major role in the selection of the algorithm. Time and space complexity are also minimised in this approach. The best resultant images are validated by medical experts and our ELSM algorithm provides around 90 percent accuracy. The efficiency and usability of ELSM algorithm will find its usefulness in the area of image segmentation. The performance of the new hybrid algorithm has more advantages such as random initialisation, fast convergence, robust segmentation, and acquires shorter CPU time.

**5.5 Summary**

This chapter proposes new hybrid ELSM algorithm for the MRI brain images in detecting brain tumor. It also discusses the EMO algorithm and LSM in detail, inorder to develop the new hybrid algorithm. Identification and selection of the tumor affected region is the main objective of this novel approach and it is been achieved by grouping and segmentation process. The resultant images are discussed in this chapter and the efficiency and accuracy of the newly developed hybrid algorithm is calculated for further analysis. The ELSM algorithm proves that
that some characteristics obtained in the resultant images are more precise in the tumor identification.