Performance analysis the of Cerebrospinal Fluid (CSF) Cell Diseases

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Abstract
Medicinal images assume a key part in the diagnosis of tumors as well as Cerebrospinal fluid (CSF) leak. In a similar way, MRI could be the segmentation control regenerative imaging technology, which permits angle sectional perspective of the body which gives convenience to specialists, will inspect the affected person. The image sent by MRI is detailed which enables it to recognize minor improvements of structures throughout the body and is usually a basic part in finding and treatment planning. In this research, the author had endeavored the approach is to classify MRI images (4-Dimensional) either at the beginning of production to have a tumor can be utilized for tumor recognition. The point of the examination is to address the previously mentioned issues related with exactness and increment the productivity of cerebrum disease picture or CSF leakage (discover fluid or liquid within brain). Our aim of this research is to construct a framework that can identify cancer damage area or be isolated from tumors and non-tumors quiet by using 4D image light field segmentation which is followed by MATLAB modelling techniques and to measure the size of brain damage cells deep inside of CSF. Data is usually collected from the SVM Tool by using MATLAB included K-Nearest Neighbor (KNN) Algorithm. The researcher proposes a 4Dimentional modulation method that oversees the light field that can be used for the light editing field. Depending on the input of the user, objective evaluation of each ray is evaluated using the KNN to maintain the 4D frequency (redundancy) light fields. These Methods of light fields can be helpful for improving the quality of application editing segmentation and light field composite pipeline, as they reduce boundary artefacts. the specialist centers on cerebrum tumor and applies a testing for the images of the brain tumor. It at that point goes on depict the arrangement in the therapeutic terms and usage and furthermore gives some forecast about the future created by modified innovation.
Keywords:
Brain Tumor, MRI, Image segmentation, CSF, KNN

1. Introduction

The cerebrospinal fluid (CSF) is the fluid that travels through the brain's ventricles (cavities or voids) and around the surface of the brain and spine. CSF is one of the most challenging neuro chirurgical complications.

CSF leakage is a condition that happens when the CSF leaks through deformity in the dura or head and exits through the nose or ear. CSF leakage is the aftereffect of a gap or tear of the dura that is the most extraordinary layer of meningitis. The purposes behind the hole or tear can damage the head and the medical system of the brain or breast. CSF slots can be produced the same way after the lower back section, also called spinal cord or spinal anesthesia. A CSF leak can occur without restriction in a similar manner without a known cause.

The cells that make up these interfaces are also site s of extensive mechanisms of exchange (transporters) that regulate the brain's entry and exit to a broad spectrum of m olecules.

A significant mechanism for regulating the unique composition of the brain's interstitial fluid is the secretion of cerebrospinal fluid by choroid plexuses that flow throug h the ventricular system and exchange between the cerebro spinal fluid and the brain. Understanding the complexity of barrier mechanisms is necessary to assess the effects of inflammatory conditions on the brain, both in adults and during growth. The Exhaustion of the cerebrospinal liquid may happen by leakage, a shunt, insufficient generation, or exceptionally fast retention. There are additionally some comparable disorders where there is high intracranial consistence; causing comparative side effects when the cerebrum contracts on standing and buoys back upward. Cerebrospinal liquid (CSF) has been widely focused for the recognition of atoms for malignant growth identification. This exploration analyzes the current logical learning about the biochemical components in the CSF that have been accounted for in the literature as brain cancer.

K- Nearest Neighbors, also known as K-NN, is part of the supervised learning algorithms family, which means that the researcher uses a set of tagged data to predict the new category of data points. The K - NN algorithm is a powerful workbook that is often used as a point of reference for more complex ones like the Artificial Neural Network (ANN) or the SVM. The K-NN algorithm can be easily understood and implemented. The K-NN algorithm is read through a complete data set to find the closest neighbors to classify the new data point. Clustering is used as a research

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model. Clustering is a very effective technique used to identify similarity among different clusters or groups. There are many clustering algorithms in which the k-means algorithm is used to identify hidden patterns from the data. In my research, the k-means algorithm explores the unseen information by taking the attribute. It is an unsupervised clustering counts makes a specific number of disjoint level (non-dynamic) assembles. The strategy takes after a clear and basic way to deal with the request a given data set through a particular number of groups. The number of groups (expect k packs) is developed.

K-Means estimations uselessly pick k objects and addressing the k beginning gathering center. The accompanying step is to take each point having a spot with a given data set and accomplice it to the nearest center in perspective of the closeness of the research as shown in fig.1.

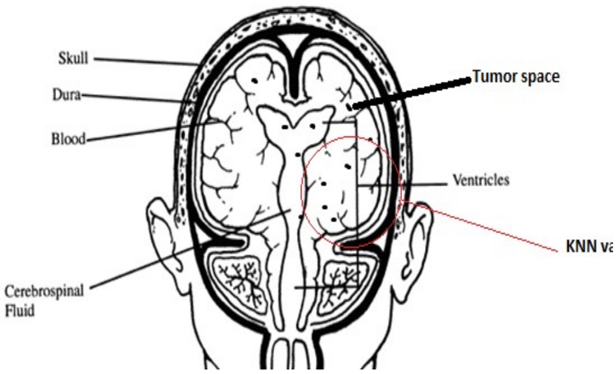


Figure.1: KNN long distance values

This researcher uses Euclidean division and recalculates new k group centers. The strategy is repeated until there is no conformity in k collection centers. This estimation goes for minimizing an objective limit known as squared turn up limit given by the going with. The researcher also uses these 4D-Images of MRI to investigate the life of cancer and how to recover the hidden information of damage cells of brain cancer and CSF with K-NN algorithm.

The selection of 4Dimenstional image segmentation is to find the deepest way to identify cancer with efficacy and accuracy. The cancer is available with a gap or space value and high accuracy with the usage of the latest technology of 4-d using LFT tools. The 4D light fields, by means of a 2D input device, the user selects part of the areas in the 4D light field data. Although the manual selection of a complete region in 4D space remains difficult for users, the functional user interfaces (UI). In the 4D light field, the client must give pointers to determining a locale of interest by entering a name in a segment of the area. The algorithm for the 4D light field decides the significant areas in the 4D light field. One can see that the segmentation results of the 4D light fields can be obtained by applying to each point of view the two - dimensional image segmentation method, and there is no guarantee that the 4D light field frequency (redundancy) will be preserved.

1.1 Problem Statement

The problem associated with the brain cell having an abnormality process due to the more leakage of glucose in terms of low levels of glucose or high levels of protein. When contrasted with the tissues about the backward side of the brain [1]. This is a potentially serious condition that can cause infection in the CSF (meningitis) or the brain itself (brain abscess) [2]. The issue associated with this research is cerebral spinal fluid due to creating by the symptoms of abnormal cells of brain and leakage. The author also focuses on the issue of the K-NN algorithm is highly sensitive to outliers because it simply selects neighbors based on distance criteria. The researcher also uses these 4D-Images of MRI to investigate the life of cancer and how to recover the hidden information of damage cells of brain cancer and CSF with K-NN algorithm. The reason behind the selection of 4Dimenstional image segmentation is to find the deepest way to identify cancer with a space value and high accuracy with the usage of the latest technology of 4-d using LFT tools that will increase the accuracy of K-NN algorithm optimization for the providing the better solution.

2. Literature Review

The researcher explains the method of dividing the tumor in the brain is the partition of the tumor area from the MRI images. There are several ways from the efficient segmentation of brain tumors. In any case, it is a tedious task to recognize the brain tumor from MR images. The procedure of segmentation is the extraction of different tumor tissues. Another case of elements, tumor, debasement, oedema run of the typical tissues of the brain, for example, dark issue (GM) and white issue (WM), notwithstanding cerebrospinal liquid (CSF). As indicated by the survey mull over, most brain tumors are effectively recognized from cerebrum MRI utilizing a district based attractive magnetic resonance imaging technique. However, the level of accuracy required the classification of abnormalities is not surprising [1-4]. The brain tumor segmentation involves many stages. Physical brain segmenting brain images consume a lot, so there are many difficulties in manual segmentation. In this exploratory research, the main goal of this paper is to present half and half of the group. To consisting of the C-Mean Fuzzy Clustering and a set of level strategies (to take care of complex forms) and level set strategy (for taking care of complex shapes) is to identify the correct state of the tumor at an insignificant computational time. Using this methodology, the author felt that for a specific set of images, it takes 0.9412 seconds of time to identify a tumor that is less in contradiction to the existing algorithm, that is, the cross-cross [5-6].

In this research paper, the specialist said that image segmentation is a collection of basic research, as it plays an important role in the investigation and comprehension. Segmenting of images and partitioning the images is one of the most difficult and difficult tasks. Therefore, filtered reports should be split from time to time in advance. Additional beforehand supplementary archive processing methods can be connected, for example, compression or processing pressure or rendering, etc. [7]. The result shows that the fuzzy Level Set Segmentation for a range of levels can segment the tumor if the parameters are correctly configured in the MATLAB condition based on the results; it depends on the fact that when the seed point is selected, the hybrid method is used in a local way A precise tumor at the time of calculation is not significant by improving the correct limit of the tumor in the brain by arranging the tumor pixels using the fuzzy C-Means clustering approach. Segmentation instruments can be used in the health impact images for the programmed splitting of brain tumors. In addition, work can be completed to influence this semi-automatic to automatic segmentation, with the aim that the dimensions of the tumor can also be calculated automatically [8-12].

More importantly, the researcher has shown that the estimated sizes of CSF sequences and the T1 based 3D methods have an excellent relationship. The purpose of the study was to verify the size of the CSF sequence. The researcher mentions future work that can also focus on the processing of additional CSF images in order to identify regional atrophy of the brain. This would allow various types of atrophy in the brain to be discovered. This is a useful addition, as many diseases have different atrophy of the brain e.g. frontal dementia [13-18]. In future studies, the subsequent treatments can also be reduced for one minute to facilitate implementation in clinical practice. The CSF sequence can also be validated in patient cohorts with more brain abnormalities and changes in brain diseases. The CSF sequence provides CSF information. For instance, CSF-T may be related to partial oxygen [19-23]. Finally, for each MRI- CSF sequence has a similar resolution and a very good correlation with the automatic 3D- based segmentation methods created by a segment of the BPV and ICV. However, the short imaging time for the MRI sequence in the CSF exceeds the possible three-dimensional sequence in T1 (3D T1) where the segmentation is performed using specific methods. Both the MRI-CSF sequence contains a similar resolution and a very good correlation with T1: Automatic system-based segmentation methods that are created to partition BPV and ICV. However, the short imaging time of the MRI sequence of magnetic resonance imaging exceeds the 3D-T sequence in which the segmentation is determined by fixed methods [24-25].

In this article, the researcher provides the details of Processing Magnetic resonance imaging (PMRI) treatment which is very complex. The researchers are constantly studying it to give doctors a better ability to diagnose patients. To detect suspicious areas or suspicious tumors automatically as the researcher presents a new method inspired by segmentation of thresholds based on morphological processes in this study [26-28]. The advantages of our approach come from the integration of these two approaches. Morphological processes produce an area of tumors almost and can ultimately affect health. While the threshold segmentation method provides a clear image of the different brain structures and thus these two approaches greatly improve threshold segmentation, detection, and tumor area extraction according to morphology [29-32].

The researcher explains the cerebrum tumor in this article which shows the group of tissues that are distinguished by the slow addition of irregular cells. It happens when the cell includes an abnormal arrangement inside the cerebrum has delayed of turned out to be one of the main sources of death for many people. The significance of a brain tumor is vast among a wide range of disease, so to save lives; quick discovery and treatment ought to be finished. The revelation of these cells is a difficult problem, in light of the development of a malignant form of the cancer cell. It is imperative to compare cerebrum tumor and MRI treatment. A Brain tumor is characterized into three kinds: normal, benign and malignant [33-35]. The neural system used to group the period of the sympathetic or threatening brain tumor or common. To represent by utilizing the Gary Level of Co-Occurrence Matrix (GLCM), the Image acknowledgement and Image pressure are perceived by Principal Component Analysis (PCA) and the vast dimensions of data are decreased. Automatic classification of the phase of cerebrum tumors is performed utilizing a neural network probabilistic (NNP). The segmentation is performed utilizing the K-means clustering algorithm and furthermore distinguishes the territory of the brain tumor. Inadequate cell numbers were found in the spread zone. PNN is the quickest method and furthermore gives a decent evaluating exactness. Simulation is performed utilizing MATLAB [36-39].

The segmentation of the anatomical regions of the brain is the fundamental problem in the analysis of medical images. When examining the literature, it was found that the use of watershed in the MATLAB setting did not work on the segmentation of brain tumors. A method of brain tumor segmentation has been developed in this article and segmentation in 2D and 3D MRI information has been supported. This technique can segment a tumor, provided that the optimal parameters are properly structured. No introduction is required for this method, while the others require initialization within the tumor [40-46]. The visualization and quantity in this article, a supervised three

- dimensional (4D) field segmentation method is described by the researcher using the graph - cutting algorithm. It differs from the ultra - clear 4D storage systems since the 4D light field data contains implicit depth data and a frequency. In order to maintain the frequency, two adjacent (spatial and angular) radios are identified in the light field data. We also design a learning-based option, called objectivity, which uses signs of appearance and variation for a greater resolution of segmentation [47-50]. In this article, we propose a method to divide the supervised 4D photodiode that can be used to edit light fields. Every target is evaluated by SVM depending on the user's input seed. The researcher identifies spatial and angular two neighbors and assesses similarities. The 4D optical field can be divided by a graph-cutting algorithm when you create a 4D structured graph [51].

3. Methodology

3.1 4-Dimentional Light Field Segmentation with Spatial and Angular Consistencies

While there are several ways to represent the segmentation process, in this research for four-dimensional light fields, the researcher has adopted the Lumigraph method to illustrate rays in three-dimensional space [50]. The ray is defined by two intersection points with "u-v" and "x-y" in the three-dimensional coordinates. The ray can be described as a point in a 4D range like p = (u, v, x, y), and p's intensity is displayed. A representation of Lumigraph can be transformed into various depictions containing level of perspective, level of picture, and vice versa. The U-V and X-Y models correspond to the perspective and picture planes respectively in a multi-point perspective. In this study, the investigator describes the easy-to-understand multi-component representation technique [51-53].

3.2. Sampling Techniques

Sampling techniques are usually collected from the 4D light field segmentation process including Lumigraph as well as multi-view representation form. The purpose of this study is to detect brain cancer through MRI in the brain, for example, the supervised machine learning in terms of 4D light field segmentation. SVM Tool for training and testing of datasets. The SVM approach is one of the common ways to meet this requirement. SVMs increase the margin between categories so that the overall performance is generally higher. Regarding the use of multiple categories in SVM, comparability comparison is used. Thus, SVM is used to determine the objectivity of the classifications. KNN-Clustering is used as a research model. Clustering is a very effective technique used to identify similarity among different clusters or groups. There are many clustering algorithms in which the k-means algorithm is used to identify hidden patterns from the data.

4. Tools and Platform

Here are mention the tools of research thesis platform with details which is given below:

4.1 4D Light Field Tool (LFT) Segmentation

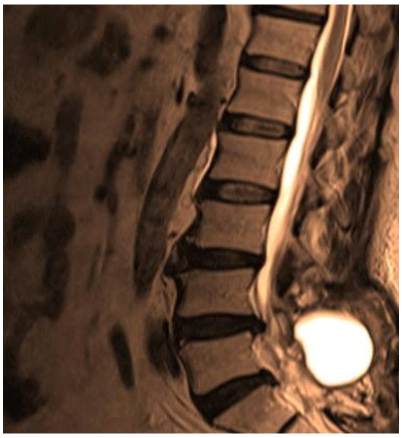
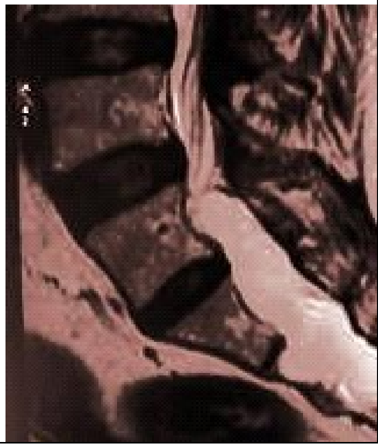
There are several ways to represent the four-dimensional light field segmentation process. The researcher has adopted the Lumigraph method to illustrate rays in three-dimensional space. Two intersection points with "u-v" and "x-y" in the three-dimensional coordinates define the beam (ray). The ray can be represented as a point in a 4D distance such as p = (u, v, x, y), and the intensity of p is represented. A Lumigraph representation can be converted into multiple representations that contain a level of view, an image level, and vice versa. In a multi-point view, the U-V and X-Y models correspond respectively with the view and image planes. In this thesis, the researcher explains the multi-component representation method that is easy to understand.

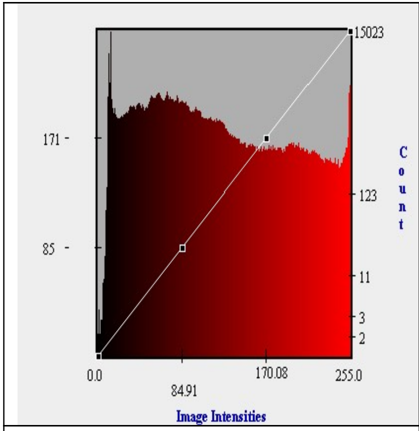
4.2 Description of 4D Light Field Segmentation with Spatial and Angular Consistencies

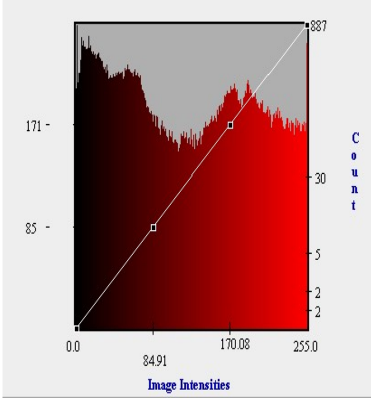
lThis research demonstrates brain cancer by segmenting brain cancer pictures between MRI pictures and using the suggested 4D algorithm. The purpose of this study is to detect brain cancer through MRI in the brain, for example, the supervised machine learning in terms of 4D light field segmentation. The four dimensional light field segmentation techniques use the diagram-cutting algorithm (grab cut). Since the 4D light field information contains verifiable profundity data and contains a recurrence (excess). It varies from the basic 4D estimate size hyper-volume). To look after repetition, the researcher recognizes the two neighboring radios rays (spatial and angular) in light field segmentation. For segmentation goals, additionally a structure of learning-based likelihood and considered objectivity that utilizations indications of appearance and variety. To demonstrate the adequacy of our strategy through numerical assessment and some light field altering applications utilizing artificial light fields (synthetic and true light fields). For example, to represent Lumigraph (v u x y), p = (u, v, x, y) and representation of multiple views. The MRI data is gotten from the Web Brain Database and demonstrates the MRI brain image. In this research work, the analyst deals with these tumor-subordinate images and applies the malignancy segment(counting the leakage of

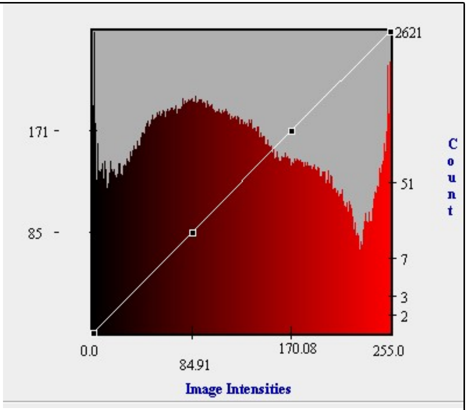
CSF).These images essentially represent the measure of the quantity level of CSF leakage and need to compute the size of cancer as well which estimate the assistance of the MATLAB programming. In this research work, the researcher focuses around the extent of the tumor due to create by CSF leakage and calculate the area of the region from the progression to the last advance to the expanding sizes of cancer cells (cells or damaged tissue). The investigator screened over 200 skull samples using separate instruments that identified the place of brain cancer and also implemented Lumigraph (v, u, x, y), If p= (u, v, x, y) and Multi-view representation. Brain tumors are our primary territory of investigation and precision is the principle instrument for progression, so this survey encourages MRI to get the best images and the highest outcomes.

MRI

IMAGE 1	**IMAGE 2**	**IMAGE 3**
		
		







Size of CSF leakage in Spine	**Size of CSF leakage in Spine**	**Size of CSF leakage in Spine**
max_c =15023	**max_c =887**	**max_c =2621**

Figure 1: CSF mass identification

Figure 1 demonstrates that the initial 3D pictures of the spine cord CSF leakage that are transformed into 4-dimensional pictures and generate the histogram to determine the precision and size of the spine cord CSF leakage. The graphical representation in the wake of programming as should be obvious that the second image of the CSF leak is more prominent than the prior picture in the tumor region. After implementation of the 4d image process, the image concert into grayscale and it clearly appears the size of the CSF tumor which is 0 so it means that the statistical graph shows the size of the tumor is 2550. Here is another value of maximum intensity (max_c) represents the intensity of the CSF-tumor which is 15023 which shows the appearance of CSF leakage. Image.2 show the size of the CSF-tumor which is still in 0 but the value of statistical graph is different which is 2550, so it shows that the situation of CSF leakage which is slowly increasing in the brain and damages the brain cell and the max_c of image.2 is 887. Image.3 also show the size of the CSF- tumor is 0 and the statistical graph shows the size of tumor value is 2550 but the max_c is 2621 which represents the tumor shell in hard form after the deposited of CSF in the brain. This is basically the leakage from initial to final stage of the tumor in spinal cord which is appearing in table.1.

5. Algorithm for detection of area of CSF Leakage in brain

5.1 Algorithm.1

1. Load DICOM Images I1 (MRI).
2. Get Image (MxN).
3. Load DICOM Images I2 (MRI).
4. Get Image (MxN).
5. Applying FILTER for Graph Cutting
6. Select Binary Imaging Tool
7. IMPORT the Binary Imaging Tool
CREATE a two input of segmentation process
8. Load TEXTURE of the segmentation tool
9. SELECT ROI of I1& I2.
Save MI1: = I1 and MI2: = I2
10.Again IMPORT the Binary Imaging Tool
CREATE a two input of segmentation process
Gaussian Filter to un-sharp

A. Applying Multidimensional Image Filtering
Save MI1Filtered: = MI1 and MI2Filtered: = MI2

11. Compare Filtered Images with Original Images
Img1 =img subtract (MI1Filtered, I1)
J1 = Inverse (Img1);
SHOW Image (J1)
SHOW Image (I1)
And
Img2 =image subtract (MI2Filtered, I2)
J2 = Inverse (Img2);
SHOW Image (J2)
SHOW Image (I2)
12. LOOP
SAVE MI1Filtered and MI2Filtered
ImageDiff =image subtract (MI2Filtered, MI1Filtered)
ExactDiff =MAP (ImgDiff, MI2Filtered)
REM: How much change at bit level
CALCULATE

Result=Number of Non Zero (ExtDiff)
CALCULATE PERCENTAGE
[M, N]= Size of Img(Result)
*Percent= (Result/ (M*N))*100*
ELSE
SAVE I1 and I2
ImageDiff =image subtract (I2, MI1)
ExactDiff =MAP (ImgDiff, I2)
REM: How much change at bit level
CALCULATE
Result=Number of Non Zero (ExtDiff)
CALCULATE PERCENTAGE
[M, N]= Size of Img (Result)
*Percent= (Result/ (M*N))*100*
13. SHOW IMAGES
CALCULATE the difference.

Table.1: KNN Testing Result

SNO.	No. of Features	Model Type	Evaluation Criteria	Accuracy	ROC	Sensitivity	Specificity
1	Decision Tree	Preset: Fine Max number of splits: 100 Splits criterion: Diversity Index Surrogate decision splits: off	Training Time Testing Time Prediction Speed	3.533Sec 72.7% 600Obs/Sec	0.83	93%	28%
2	Decision Fine-Tree	Preset: Fine Tee Max number of splits: 100 Splits criterion: Diversity Index Surrogate decision splits: off	Training Time Testing Time Prediction Speed	333.53 Sec 90.9% 59Obs/Sec	0.83	93%	28%
3	Decision Medium-Tree	Preset: Medium Tree Max number of splits: 20 Splits criterion: Diversity Index Surrogate decision splits: Off	Training Time Testing Time Prediction Speed	260.4Sec 90.9% 29Obs/Sec	0.83	85%	60%
4	Coarse Tree	Preset: Coarse Tree Max number of splits: 4 Splits criterion: Diversity Index Surrogate decision splits: Off	Training Time Testing Time Prediction Speed	510.54Sec 90.9% 1600Obs/Sec	0.83	93%	28%
5	Linear Discriminate	Preset: Linear Discriminate Covariance Structure: Full	Training Time Testing Time Prediction Speed	507.42Sec 86.4% 150Obs/Sec	0.91	87%	70%
6	Quadratic Discriminate	Preset: Quadratic Discriminate Covariance Structure: Full	Training Time Testing Time Prediction Speed	510.28Sec 90.9% 180Obs/Sec	0.91	73%	70%
7	Logistic regression	Preset: Logistic regression	Training Time Testing Time Prediction Speed	502.7Sec 86.4% 190Obs/Sec	0.89	73%	70%
8	SVM Linear	Preset: Linear SVM Kernel Function: Linear Kernel Sale: Automatic Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	459.65Sec 93.2% 210Obs/Sec	0.94	92%	60%
9	SVM Coarse	Preset: Coarse SVM Kernel Function: Coarse Kernel Sale: Automatic Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	182.97Sec 86.4% 690Obs/Sec		85%	60%
10	SVM Quadratic	Preset: Quadratic SVM Kernel Function: Quadratic	Training Time Testing Time	458.11Sec 90.9% 710Obs/Sec	0.97	92%	60%

		Kernel Sale: Automatic Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Prediction Speed				
11	SVM Cubic	Preset: Cubic SVM Kernel Function: Cubic Kernel Sale: Automatic Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	457.32Sec 93.2% 710Obs/Sec	0.97	10%	90%
12	SVM Fine Gaussian	Preset: Gaussian SVM Kernel Function: Gaussian Kernel Sale: 0.79 Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	15.624Sec 93.2% 150Obs/Sec	0.91	92%	60%
13	SVM Medium Gaussian	Preset: Medium Gaussian SVM Kernel Function: Gaussian Kernel Sale: 3.2 Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	455.89Sec 93.2% 720Obs/Sec	0.96	92%	60%
14	SVM Coarse Gaussian	Preset: Coarse Gaussian SVM Kernel Function: Gaussian Kernel Sale: 13 Box Constraint Level: 01 Multi-Class Method: One –to-One Standard Data: True	Training Time Testing Time Prediction Speed	455.728Sec 93.2% 1100Obs/Sec	0.91	85%	60%
15	KNN Fine K=1	Preset: Fine KNN Number of Neighbor: 1 Distance Metric: Euclidean Distance Weight: Equal Standard Data: True	Training Time Testing Time Prediction Speed	449.36Sec 90.9% 250Obs/Sec	0.89	92%	60%
16	KNN Medium (Euclidean) K=10	Preset: Medium KNN Number of Neighbor: 10 Distance Metric: Euclidean Distance Weight: Equal Standard Data: True	Training Time Testing Time Prediction Speed	447.88Sec 93.2% 550Obs/Sec	0.94	0%	30%
17	KNN Coarse K =100	Preset: Coarse KNN Number of Neighbors: 100 Distance Metric: Euclidean Distance Weight: Equal Standard Data: True	Training Time Testing Time Prediction Speed	447.48Sec 70.5% 730Obs/Sec	0.44	92%	60%
18	KNN Cosine K=10	Preset: Cosine KNN Number of Neighbour:10 Distance Metric: Euclidean Distance Weight: Equal Standard Data: True	Training Time Testing Time Prediction Speed	447.02Sec 93.2% 220Obs/Sec	0.93	92%	60%
19	KNN Cubic K=10	Preset: Cubic KNN Number of Neighbor: 10 Distance Metric: Minkowski(cubic) Distance Weight: Equal Standard Data: True	Training Time Testing Time Prediction Speed	446.18Sec 93.2% 310Obs/Sec	0.94	92%	60%

20	KNN Weighted K=10	Preset: Weighted KNN Number of Neighbour: 10 Distance Metric: Euclidean Distance Weight: Square Inverse Standard Data: True	Training Time Testing Time Prediction Speed	445.64Sec 93.2% 570Obs/Sec	0.97	0%	30%
21	Ensemble Boosted Tree (ADA Boost)	Preset: Boosted Tree Ensemble Method: ADA Boost Learner Type: Decision Tree Max number of splits: 20 Number of Learner: 30 Learning Rate: 0.1	Training Time Testing Time Prediction Speed	444.81Sec 70.5% 240Obs/Sec	0.96	92%	60%
22	Ensemble Bagged Tree Ensemble method (Decision Tree)	Preset: Bagged Tree Ensemble Method: Bagged Learner Type: Decision Tree Number of Learner: 30	Training Time Testing Time Prediction Speed	441.52Sec 93.2% 80Obs/Sec	0.96	92%	60%
23	Ensemble subspace (Discriminate)	Preset: Subspace Discriminate Ensemble Method: Subspace Learner Type: Discriminate Number of Learner: 30 Subspace Dimension: 5	Training Time Testing Time Prediction Speed	438.77 Sec 90.9% 31Obs/Sec	0.91	85%	60%
24	Ensemble Subspace (KNN)	Preset: Subspace KNN Ensemble Method: Subspace Learner Type: Nearest Neighbor Decision Tree Number of Learner: 30 Subspace Dimension: 5	Training Time Testing Time Prediction Speed	434.28Sec 79.5% 33Obs/Sec	0.91	65%	0%
25	RUS Boost Tree Ensemble method (Decision Tree)	Preset: RUS Boost Tree Ensemble Method: RUS Boost Learner Type: Decision Tree Max number of splits: 20 Number of Learner: 30 Learning Rate: 0.1	Training Time Testing Time Prediction Speed	429.53Sec 90.9% 250Obs/Sec	0.96	85%	60%

5.2. KNN Algorithm (K-Means Clustering)

K- Nearest neighbor, also known as K-NN is part of the supervised learning algorithms family, which means the researcher use a set of tagged data to predict the new category of data points. The K-NN algorithm is a powerful workbook that is often used as a point of reference for more complex ones like the Artificial Neural Network (ANN) or the SVM. The K-NN algorithm can be easily understood and implemented. The K- NN algorithm is read through a complete data set to find the closest neighbors to classify the new data point.

Clustering is used as a research model. Clustering is a very effective technique used to identify similarity among different clusters or groups. There are many clustering algorithms in which the k-means algorithm is used to identify hidden patterns from the data. In this research, the k-means algorithm explores the unseen information by taking the attribute such as image hidden parts, stage of cancer and demographics etc. This model identifies cancer at a very early stage.

6. Result and Discussion

These comparisons are based on semi-supervised machine learning as we work on 4 procedures of segmentation of the Dimensional picture. Because of brain cancer, we concentrate on CSF leakage. The findings of the tests are conducted by a dataset called "Malignant Brain Cancer with CSF Leakage" comprising nine variables with 25 characteristics. The initial information set with 4-dimensional information is then randomly divided into practice and test sets in a proportion of 96.9 percent as shown in this study. Using the training dataset, we trained several supervised machine-learning models namely Decision Tree, Decision Medium-Tree, Coarse Tree, Linear Discriminate, Quadratic Discriminate, Logistic regression, SVM (Linear), SVM (Coarse), SVM (Quadratic), SVM (Cubic), SVM (Fine Gaussian), SVM (Medium Gaussian), SVM (Coarse Gaussian), KNN Fine (K=1), KNN Medium (Euclidean)(K=10), KNN Coarse (K =100), KNN Cosine (K=10), KNN Cubic (K=10), KNN Weighted (K=10), Ensemble Boosted Tree (ADA Boost), Ensemble Bagged Tree, Ensemble subspace(Discriminate), Ensemble Subspace(KNN) and RUS Boost Tree. Once the models are trained, the new data from the testing dataset are predicted. Measuring four Evaluation Metrics (EM), namely sensitivity (sen), specificity (spe) ROC, and precision (Acc), will evaluate the efficiency of the studied techniques. The experimental results are mentioned in Table 10. Among twenty-four machine-learning methods, nine models: SVM (Linear), SVM (Cubic), SVM (Fine Gaussian), SVM (Medium Gaussian), SVM (Coarse Gaussian), KNN Medium (Euclidean)(K=10), KNN Cosine (K=10), KNN Cubic (K=10), KNN Weighted (K=10) and Ensemble Bagged Tree achieved the accuracy of 93.2%. Each classifier's computational time is also calculated to assess their complexity. Table.2 shows each classifier's processing time.

KNN Coarse is comparatively small in computational time, but the practical use satisfies their sensitivity and specificity. The other remaining models: Decision Tree, Decision Medium-Tree, Coarse Tree, Linear Discriminate, Quadratic Discriminate, Ensemble subspace (Discriminate), and RUS Boost Tree are achieved 90.9% accuracy. SVM (Coarse), Logistic Regression and Ensemble Subspace (KNN) are among three techniques that produce 86.40-79.5 percent precision. We also contrasted our outcomes achieved with the outcomes acquired in the literature through associated works. The comparison shows that the KNN (K=1-100) models in our study are superior to the previous works by given 100% accuracy. The biggest advantage of this model is to take shorter time and takes the value for too far distance such as K=100. Our proposed system is better for previous work. These models are improved due to the reason of shorter time period, quickly provide the results, and take longer values. However, the researcher is not meet the 100% accuracy for all models but in 4 dimensional, the KNN give better results as compared to previous work.

7. Conclusion

The proposed 4d method aims at improving the sensitivity of segmentation process to parameter of KNN algorithm techniques and improves efficiency, as well as to increase the long-distance values performance as compared to other comparative methods. KNN significantly enhances the performance of faraway values mainly from two key factors which is brain cancer and CSF leakage. The first improvement resides in the fact that in the KNN algorithm constructs an ensemble of adjacent values with parameters of neighborhood size (K=1-100). These values ensemble building, KNN can obtain the low-dimensional with provide the optimized results. The performance of the studied methods is to focus the measured four Evaluation Metrics (EM) namely sensitivity (sen), specificity (spe) ROC, and accuracy (Acc).The second improvement is that KNN algorithm provides an efficient weighting for all far values which makes the projections much less sensitive to the neighborhood size parameter as compared to previous work. One of the another focus of this research work are increase the efficiency of tumor-dependent images and applies a segmented area to the tumor for the cause of the CSF leakage. These images mainly represent the size of the tumor and need to calculate the cancer shell, frequency, and intensity, the mass of tumor shell) and high accuracy with the usage of the latest technology of 4d using LFT tools of the tumor.

The researcher takes the longer values of KNN (K=1-100) and show their performance for the new proposed model of 4-dimention. The researcher increases the accuracy of missing values of KNN algorithm. The researcher also proposes a 4-Dimensional modulation method that oversees the light field that can be used for the light editing field. Depending on the input of the user, objective evaluation of each ray is evaluated using the KNN algorithm to maintain the 4D frequency (redundancy) light fields. These Methods of light fields can be useful for improving the quality of application editing segmentation and light field composite pipeline, as they reduce boundary artefacts.

Therefore, the proposed KNN algorithm method can be suitable for latest technology of 4d in various tasks, such as image processing, segmentation process, increase the sensitivity with region of curve and various deep learning tasks. In future work we plan to extend ensemble of improve framework to other current work and techniques.

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