Combination of Brain Cancer with Hybrid K-NN Algorithm using Statistical of Cerebrospinal Fluid (CSF) Surgery

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Abstract
The spinal cord or CSF surgery is a very complex process. It requires continuous pre and post-surgery evaluation to have a better ability to diagnose the disease. To detect automatically the suspected areas of tumors and symptoms of CSF leakage during the development of the tumor inside of the brain. We propose a new method based on using computer software that generates statistical results through data gathered during surgeries and operations. We performed statistical computation and data collection through the Google Source for the UK National Cancer Database. The purpose of this study is to address the above problems related to the accuracy of missing hybrid KNN values and finding the distance of tumor in terms of brain cancer or CSF images. This research aims to create a framework that can classify the damaged area of cancer or tumors using high-dimensional image segmentation and Laplace transformation method. A high-dimensional image segmentation method is implemented by software modelling techniques with measures the width, percentage, and size of cells within the brain, as well as enhance the efficiency of the hybrid KNN algorithm and Laplace transformation make it deal the non-zero values in terms of missing values form with the using of Frobenius Matrix for deal the space into non-zero values. Our proposed algorithm takes the longest values of KNN (K = 1-100), which is successfully demonstrated in a 4-dimensional modulation method that monitors the lighting field that can be used in the field of light emission. **Conclusion:** This approach dramatically improves the efficiency of hybrid KNN method and the detection of tumor region using 4-D segmentation method. The simulation results verified the performance of the proposed method is improved by 92% sensitivity of 60% specificity and 70.50% accuracy respectively.

Keywords: *MRI, high dimension segmentation, pre and postoperative surgery, tumor detection*

1. Introduction

The CSF is a fluid that passes through the ve1.ntricular (cavities or holes) of the brain and across the surface of the brain and spine. CSF is one of the most complicated neurosurgery complications. CSF leakage is a condition that happens where the CSF leaks into the deformation of the dura or head and is excreted through the nose or ear. CSF leakage is the result of a puncture or rupture of the upper layer of the dura. The objects behind the hole or fracture can damage the skull and the system inside the brain. CSF openings are usually produced in a similar way of a skull fracture after the leakage of CSF moves from brain to spine, also called spinal cord or spinal anaesthesia. A CSF leak without restrictions can similarly occur without known causes. The cells which make up these interfaces are also sites of integrated exchange mechanisms (vectors) that control the brain's entry and exit
through a wide range of molecules[1-5].

One of the essential mechanisms for regulating the distinctive production of interstitial fluid within the brain is the secretion of cerebrospinal fluid through the chloride plexus, which passes through the ventricular system and transfers materials between cerebrospinal fluid and the brain [6-8]. An understanding of the complexity of the sepal mechanism is necessary to assess the effects of inflammatory conditions in the brain, both in adults and during development. Cerebrospinal fluid depletion can be caused by leaks, bypass, improper production, or very rapid absorption. There are also some similar syndromes in which intracranial compliance is very high; they cause similar symptoms when the brain shrinks. Cerebrospinal fluid is widely targeted in the spinal cord to detect cancer molecules. The above work explores the current scientific knowledge of the biochemical elements in CSF, which is disseminated in the brain cancer literature [9-15], as shown in Fig.1.

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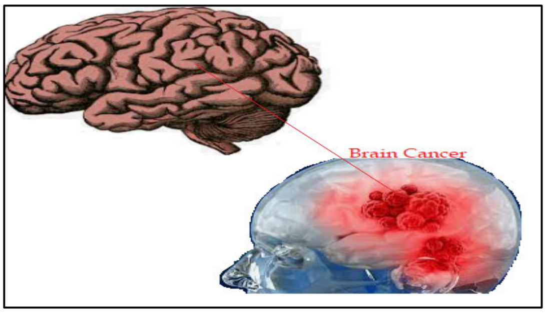

Figure 1: Brain cancer

The brain tumor is an abnormal mass of cells that grows in the brain. The skull is very rigid, closing our brain, as we know that any growth of the cell can cause problems for the limited space inside the brain. Both cancerous cells (malignant) and non-cancerous cells (benign) can be found in brain tumors [13-18]. The cancer cells can increase intracranial pressure when the tumors become benign or malignant. This can cause damage to the brain and endanger life. Brain tumors are classified as primary or secondary [19-20]. There is a large brain tumor in the brain as we can see in Fig.1.

Many primary brain tumors are benign and can quickly be removed from the brain. However, secondary brain tumor, also known as a diffuse brain tumor, develops when other tissues, such as the lung or breast cancer cells, move from the brain to other areas of the body [21-24]. Benign (non-cancer) tumors and malignant (cancer) tumors in most other regions of the body are very difficult to distinguish. Tumors can develop in nearby tissues or spread to distant parts of the human body. One of the key factors for the seriousness of the malignancy is that it will spread across the body. This research also defines L*k*-NN, which is more complicated than the hybrid *k*-NN and must take many of the delays that vary from one variable pair to another into consideration [25-28]. This research created a set of testing and training vectors for each of the delays using the training vector. As this research is based on LPP, LPP is a means of reducing non-linear dimensions; LPP ensures that the closest neighbour's to the original data is maintained in the new space after reducing the dimensions to reduce the missing values of hybrid *k*-NN account allocation values[29-32].

This research focuses on the missing values of KNN using high segmentation method and laplacian transformation. We implement the two techniques to reduce the empty values of KNN and make it convert into non-zero values through Frobenius Matrix of Laplace Transformation. The novelty of this research is based on Frobenius Matrix which is used to reduce the zero values after the usage of partial derivative in terms of derivative form to make it zero values into non-zero values. This method can deal with non-zero values and create the relationship between training and test data points are transformed into partial data points for training to compute the data for the timely response.

Section I provides an overview of brain cancer and CSF details. The challenges of deep learning methods about medical imaging are subject to contemporary immense research. Section II presents the methodology based on the detection of brain cancer through the MRI-4D interface of image segmentation. Sampling techniques and tools generated experimental results after performing statistical analysis. Section III explains the results of the Laplace Transformation method. Section IV describes the method used in the statistical technique. A framework can determine the area of tumors and non- tumors by dividing the 4D field of light. Initially, MRI handled the pre-prepared image method with the ultimate goal of adjusting the image for the rest of the procedures. Section V provides details of the results and discussions while comparing the previous result with the new achievements. Section VI presents the conclusion, describes the contributions made by this study, and suggests future directions.

2. Methodology

The proposed research aims to collect data related to the detection of brain cancer due to the creation of CSF leaks with a high MRI interface. Researchers are discussing injured brain cells due to cell defects. The main objective of our work is to develop a structure that can classify the area of tumors or isolate between tumors and non-tumors. Initially, the sample was provided through MRI images to detect the disease which can be helpful to implement a high-dimensional light field toolbox and its graphical representation.

We practically implementing and simulating experiments (4D image segmentation processes) for tests on random brain tissues samples collected in Pakistan at Neurospinal & Medical Institute (NMI). Our proposed model is to develop a method for can detecting the cerebrospinal fluid loss in the brain during the development of tumor. The data is collected through various sources, which apply the necessary research tools such as hybrid KNN algorithm and laplacian transformation techniques are the main area of research which will train the data and test the original sampling data. There are many clustering algorithms related to the KNN algorithm, but we are focusing k-means algorithm is used to identify hidden patterns from the data such as noisy image hide the small parts of information. This model identifies cancer at a very early stage; it is a supervised count of clustering which makes a specific number of disjoint (non-dynamic) level groups of people data gathered through the hospital sector. The strategy takes a direct and simple approach for the approval of reputed hospitals to gather the data collection only for a certain number of groups which is formed by k-mean to identify the k-distance in terms of cancer and CSF symptoms. Furthermore, the Laplace transformation method used to reduce the missing values of KNN using the Frobenius Matrix for optimization function.

3. Experimental Results of Multidimensional segmentation using Laplace Transformation

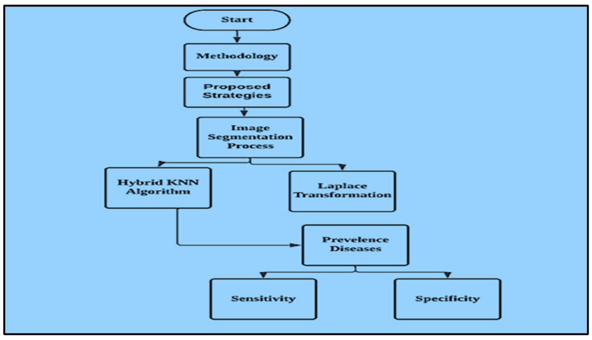

Figure 2: Proposed framework of methodological design

In this research study, we compare the previous work of other researchers and our current work on multi-dimensional segmentation process to check the modification of our work which is focused on MATLAB programming simulation, image processing, interface field, field area, and autocorrelation. These all techniques are not used at the same time and our research motivation is only to the detection of the tumor created by CSF leakage which is still unknown where CSF deposited at the initial level of the brain.We develop solutions to the missing data problem for each calculation model by following the general computation method of Frobenius Matrix, Standard

Frobenius Matrix, Reconstruct Weight Matrix, Relationship between Training Data Points, and test data with rotation parameter optimization function. These methods easily deal with non-zero values, and the relationship between training and test data points is transformed into partial data points for training to demonstrate that optimizing the computed data for identifying method variables is validation related to the test time delay and the training vector resulting from the time delay.

4. Proposed Strategies

Input: Brain Cancer image
Output: User desired images
Step 1: Convert the Images (MRI) into a greyscale image for further processing.
Step 2: Gather the information of brain cancer and hybrid KNN algorithm in tabular form
Step 3: Calculate the histograms for all tabular details of data sets and construct the statistical results
Step 4: Calculate the distance until KNN (1-100) in terms of hybrid KNN algorithm
Step 5: Construct the binary patterns and calculate their histogram
Step 6: Combine the histograms calculated from all data sets.
Step 7: Construct the binary imaging tool and prediction model.
Step 8: Compare the proposed values of hybrid KNN and retrieve the images based on the closest matches.
Step 9: Calculate the sensitivity and specificity.

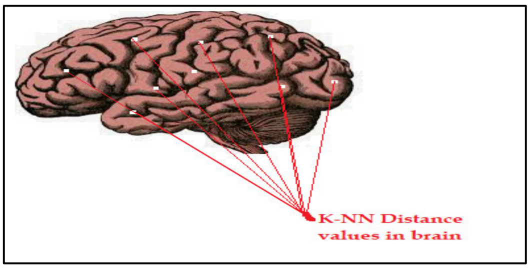

Figure 3: KNN missing values from K=1-100

Fig.4 shows the longest KNN values (K = 1-100) and its high dimensional efficiency for the proposed model. For the hybrid KNN algorithm, we improve the precision of the missing values taking the high results of KNN (1-100) during the calculation of KNN distance measurement of cancer and CSF symptoms. We also suggest a high-dimensional modulation method that monitors the lighting field which can be used in light emission fields and these results can evaluate by using MRI datasets with SPSS significant testing.

Table 1: Statistical results of patients with meningitis

	Bacterial Meningitis	Chemical Meningitis	In determining Cause	P
Temperature	20	28	19	0.51
>37.8 C	6	2	1	0.47
>39.4C	3	0	0	0.06
>40C	6	18	8	0.48

Fever < 7 days	14	23	13	0.74
Headache	7	8	6	0.55
Vomiting	1	1	1	1
Postoperative Seizure, or agitation	8	6	6	0.2
Period of unconsciousness	3	0	1	0.06
Neck Stiffness	9 /16	16/24	13/17	0.53
New Focal Sign	4	0	4	0.02
Rhinorrhea	5	2	1	0.1
CSF	4	0	0	0.21
Wound Drainage	9	2	3	0.004
Purulent	5	0	1	0.007
Wound swelling	2	4	3	0.1

Table.1 shows the records of patient history for the evaluation of the CSF leakage and calculates the level and size of brain cancer.

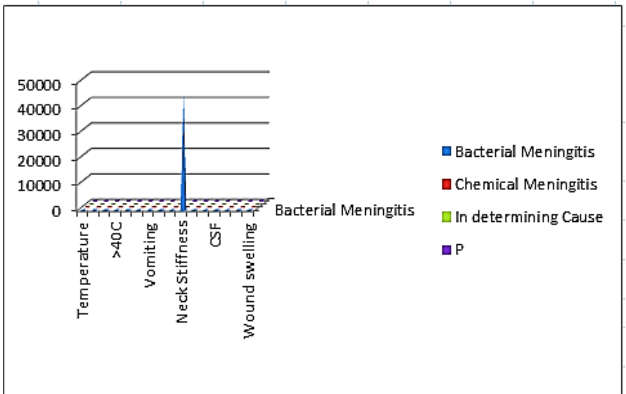

Figure 4: Graph of the statistical results of patients with meningitis neurosurgery (nanometer scale)

Fig.5 shows the graphical results of patient history and symptoms of diseases for the identification of the size of the tumor and stages as shown in Table.3.

Table 2: Results of patients with meningitis

characteristics of patients with meningitis following neurosurgery		
Diagnosis	**Bacterial**	**In determine**
Duration(days)	**Meningitis**	**Cause**
<7	1	8
8 to 10	2	8
11 to 14	4	3
15-21	6	0
22-28	3	1
>28	4	0

Table.2 shows the characteristics of patients with meningitis of neurosurgery in terms of treatment and investigates bacterial meningitis and their causes of brain cancer. This table also calculates the approximate duration of cancer life and size of tumor shell.

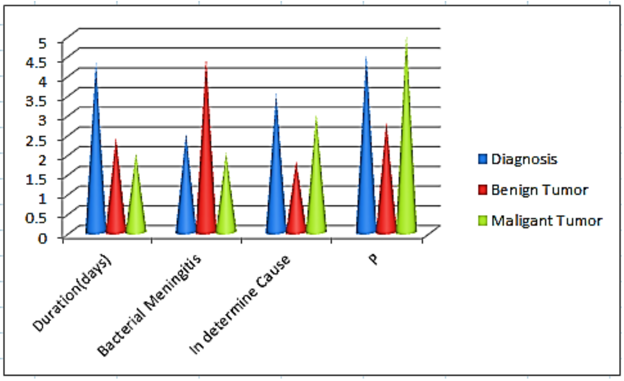

Figure 5: Graph of results of patients with meningitis neurosurgery (nanometer scale)

Fig.6 shows the graphical representation of the treatment of patients with the level of CSF leakage and tumor size and duration of disease identified by hybrid KNN algorithm.

5. Prediction Model using Hybrid K-NN Algorithm

We use clustering as a research model in our study as it is a very effective method used to define similarities between different groups or clusters. There are several clustering algorithms in which the k-means algorithm is used to define hidden patterns of data. In this study, the k-mean algorithm explores invisible information by taking an attribute such as gender recognition, age and type of cancer to identify cancer at a very early stage. Here are the main steps for the k-mean algorithm:

Step 1: Distribute the dataset in cluster K
Step 2(a): For each data point in the data set, calculate the distance of each cluster data point
Step 2(b): Calculate the size of data in the cluster, if the cluster is near the data point, and if we leave it to measure

the distance, move the data point to the nearest point of the cluster.

Step 3: Execute the previous step.2 until any data point moves from one group to another. This stage shows that it is the end of the clustering process and that all groups are stable.

The selection of the primary section can greatly affect the resulting final clusters in the form of holding data together and calculating the distance for groups.

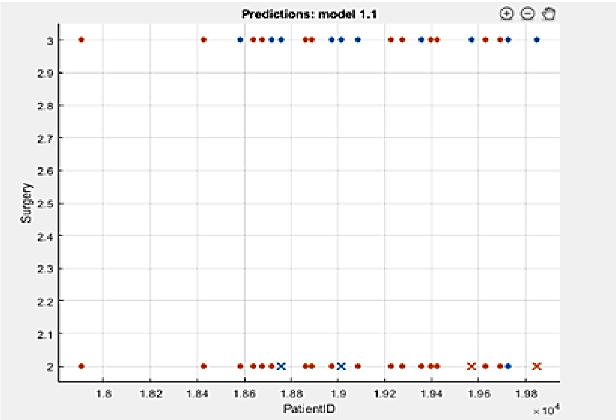

Figure 6: Prediction model of KNN

Fig. 7 shows the prediction model of the KNN algorithm for patient history. This model shows the calculation of the small size of tumor shell and few of CSF leakage inside of the brain. The model is developed by MATLAB tools using significant techniques of KNN using a spreadsheet to cover the patient details which is gathered through the UK National Cancer Research Institute (NCRI) database.

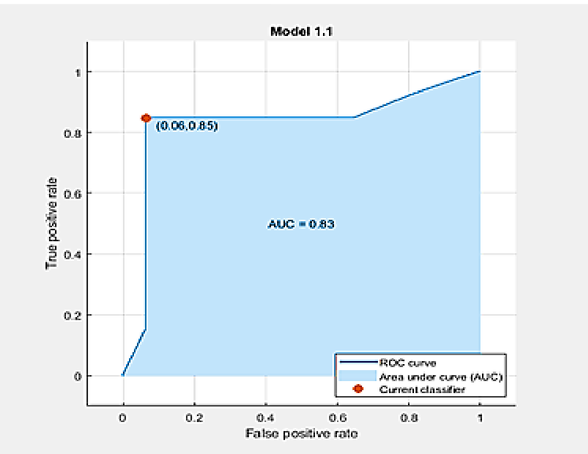

Figure 7: Model of the area under the curve

Fig. 8 shows the accuracy of tools when we investigate the data sets of cancer patients and identify the predictive positive and negative rates of the values to indicate the symptoms of cancer.

Fig.9 shows that the predicted values of the sample population of brain cancer with CSF leakage are used for the study influences the prevalence of calculation through sensitivity and specificity. We calculate the predicted class of each row and column in terms of calculating the values of distance.

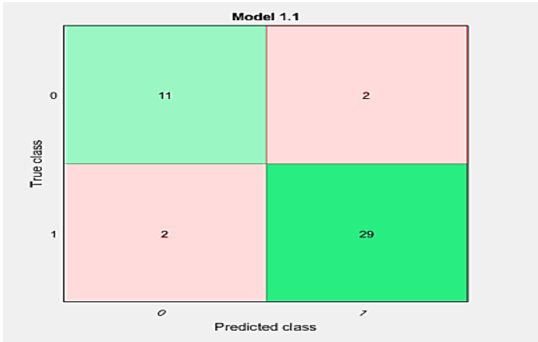

Figure 8: True and false prediction values

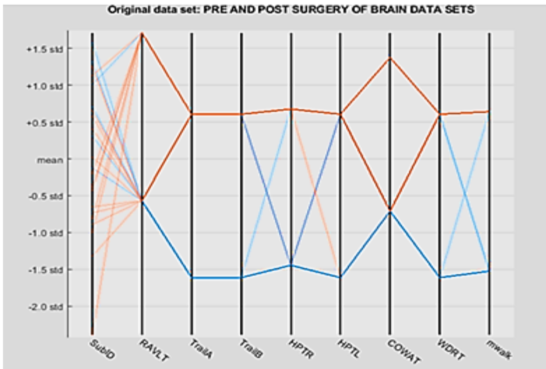

Figure 9: Compiling the data sets of pre and post-surgery of brain cancer

Fig.10 shows the results of patient pre and post-surgery. In this model, we compile the results of the data sets of pre and post-surgery calculating the MRI images generated values.

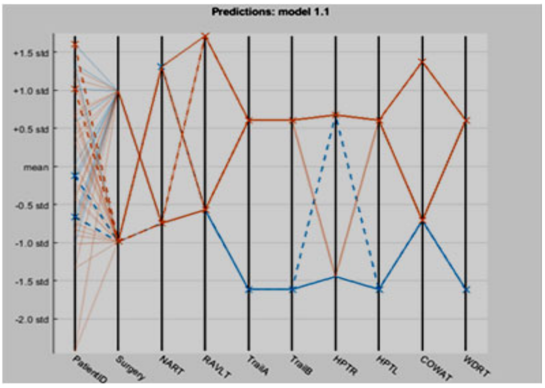

Figure 10: A prediction model

Fig.11 shows the calculation of patient surgery with MRI images results. The X-axis shows the details of MRI techniques and Y-axis shows the distance of datasets values. The range of numbers in the Y-axis shows the distance of tumor samples in a far way inside of the brain. The two columns depending on the actual state of the brain cancer data sets, whether controlled patient or uncontrolled patient. The rows indicate test results, whether positive or negative. Cell A contains real pulses, disease datasets, and positive test results. Cell B identifies people who do not have a disease, but who were tested for brain cancer. Cell C contains negative results for those groups of people who do not have the disease but tested for brain cancer. Cell D datasets show the group of people who do not have the disease but tested positive. Cell A is true- positive, Cell B is true- negative, Cell C is false-negative and Cell D is false- positive. These results come from a population-based sample study and the prevalence can be calculated as follows:

Table 3: Predicted values of CSF and brain cancer

SNO.	Disease	Non- Disease	Total
P *(No.)*	X 10 *(TP)*	Y 40 *(TN)*	$T_{Test\ Positive}$ 50
N *(No.)*	Z 5 *(FN)*	E 45 *(FP)*	$T_{Test\ Negative}$ 50
	T_{Diease} 15	$T_{Non\text{-}Diease}$ 85	Total of 100

Whereas, P: Positive
N: Negative
TP: True Positive
FN: False Negative
TN: True Negative
FP: False Positive

5.1 Sensitivity and specificity are features of the test

Prevalence of Disease=

$$T_{disease}/\ \text{Total} \times 100 \quad (1)$$

The sample population of brain cancer with CSF leakage is used for the study to influence the prevalence of calculation.

The formula for sensitivity is shown in (2) below:

$$\frac{X}{(X+Z)\times 100} \quad (2)$$

Eq.2 shows the calculation of patient diseases in mathematical formulation. Specificity is the disease without a negative test result of the predictive values.

The formula for specificity is shown in (3) below:

$$\frac{E}{(E+Y)\times 100} \quad (3)$$

Eq.3 shows the calculation of patient diseases in the mathematical formulation of predictive values. Equation (2) and (3) show the sensitivity and specificity of the disease result positively and negatively. Here we identify the values of Cell A compared to Cell B and Cell C compared to Cell D. Following are the formulae to calculate across the rows:

Positive predictive value:

$$\frac{X}{(X+Y)\times 100} \quad (4)$$

Negative predictive value:

$$\frac{E}{(E+Z)\times 100} \quad (5)$$

Equations (4) and (5) show the predictive positive and negative values of diseases. The prevalence of brain cancer in the population of the study being analyzed impacts positive and negative predictive values. When we conduct experiments in a highly prevalent setting, people with a positive result are more likely to have the disease than the people with low prevalence.

5.2 Algorithm for selected datasets

1. D(A, B) =$\sqrt{\sum_{i=0}^{n}(Xi - Yi)2}$
2. Where, *A=(a0,a1 a2……,an) and B=(b0, b1,b2…..bn);*
3. Construct KNN classifier is detailed below:
4. Input: D= {(a0, c0),….(an, cn)}
5. a=*(a1,…..,an) new illustration to be categorized*
6. For each labeled illustration *(ai,ci) ;*
7. Calculate *d(ai, a);*
8. Command d(ai, a) from lowest to highest, *(i=0,1,….,N);*

9. Select the K nearest instances to x: Da^K
10. Assign to x the most frequent class in Da^K
11. Train data for the same value of predictor and response
12. Train classifier for a struct containing the train classifier
13. Validate accuracy for a double containing the accuracy in percent
14. Compute (Train classifier, validation accuracy) = Train classifier (T1)
15. Compute yfit = trained classifier .predict Fcn(T2)
16. Extract predictors and response
17. (d) Select Input Table.1 = Training data:
18. *Predictors Names = ('SubID', 'RAVLT', 'TrailA', 'TrailB', 'HPTR', 'HPTL', 'COWAT', 'WDRT', 'mwalk');*
19. Predictors = Input Table.1 (predictor Names);
20. Execute Response = Input Table
21. Execute Categorical Predictors
22. If standardize values are True
23. Compute SVM classifier
24. *Else;*
25. generate zero or empty results
26. Execute Train a classifier
27. Compute Classification SVM = fitcsvm
28. *Compute Kernel Function and linear*
29. *Compute Polynomial Order*
30. *Compute Kernel Scale, auto*
31. *Compute Box Constraint*
32. *If standardize values are True*
33. *Else;*
34. generate zero or empty results
35. Compute Class Names, categorical ({'N'; 'B'}));
36. Compute Predictor Extraction Fcn = @(t) t(:, predictor Names);
37. Compute Tree Predict Fcn = @(x) predict (classification Tree, x);
38. Compute Train classifier: Predict Fcn (predictor Extraction Fcn(x));
39. Compute Train classifier: Required Variables = *{'Patient ID', 'Surgery', 'NART', 'RAVLT', 'Trail A', 'Trail B', 'HPTR', 'HPTL', 'COWAT', 'WDRT'};*
40. Compute Train Classifier CLASSIFICATION TREE
41. Extract predictors and response
42. Compute Input Table = Training data;
43. *Predictors Names = {'Patient ID', 'Surgery', 'NART', 'RAVLT', 'TrailA', 'TrailB', 'HPTR', 'HPTL', 'COWAT', 'WDRT'};*
44. Predictors = input Table (predictor Names);
45. Response = Input Table
46. Execute Categorical Predictors
47. If standardize values are true, compute cross-validation
48. *Else*;
49. Generate zero or empty results
50. Create the result struck with predict function
51. *Compute cross-validation*
52. *Compute validation predictions*
53. *Compute validation accuracy*
54. End if;
55. End Function

6. Result and Discussion

One of the objectives of this research is to increase the accuracy of the missing values for the KNN hybrid algorithm, we take the longest values of KNN (K = 1-100) and show its performance for the proposed new model with a high dimension. We also suggest a high dimensional modulation method that monitors the lighting field that can be used in the field of light emission. Our research goal is to propose a framework that can identify the area of cancer damage or isolate itself from tumors and CSF leaks using KNN classification techniques with Laplace transformation. Using the light field segmentation of a high dimension image in two different ways, we used MRI images for testing a pre-prepared image enhancement method with the final target setting of the image.

We select the damaged cancer and CSF leakage patients' images to compute the set of data to perform the segmentation procedures. We also select brain cancer and CSF patient images to detect the symptoms as a result of the interconnection of the 4D image segmentation process in binary form to overcome the missing values efficiently. The datasets of primary and secondary sources used in this study are implemented by MATLAB software modelling techniques. These results demonstrate the effectiveness of our approach to light editing applications in 4D segmentation. Light field methods can help improve the quality of application-related segmentation and compound light field tubes, as they reduce border artefacts.

Table 4: Comparison of the previous result to the current result

Features	Decision Tree	Linear Discriminate	Quadratic Discriminant	Logistic regression	SVM	KNN Fine	KNN Medium (Euclidean)	KNN
					Linear	K=1	K=10	K =100
Accuracy(C)	90.90 %	86.40%	90.90%	86.40%	93.20%	96.90%	93.20%	70.50%
Sensitivity(C)	93%	87%	73%	73%	92%	92%	0%	92%
Specificity(C)	28%	70%	70%	70%	60%	60%	30%	60%
Accuracy(P)	NA	NA	NA	NA	0.881	0.7143	NA	NA

Sensitivity(P)	NA	NA	NA	NA	NA	NA	NA	NA
Specificity(P)	NA	NA	NA	NA	NA	NA	NA	NA
Accuracy(P)	NA	NA	NA	NA	98.34%	93.34%	NA	NA
Sensitivity(P)	NA	NA	NA	NA	95.23%	90%	NA	NA
Specificity(P)	NA	NA	NA	NA	100%	95%	NA	NA
Accuracy(P)	100%	61.73%	-	100%	100%	91.36%	NA	NA
Sensitivity(P)	100%	84.91	-	100%	100%	96.23%	NA	NA
Specificity(P)	100%	17.86	-	100%	100%	82.14%	NA	NA

Table.4 shows the results of the longest values of KNN (K = 1-100) and the performance of the proposed model with 4-dimension. We implement the statistical results through MATLAB modeling techniques with Laplacian transformation and check the sensitivity and specificity of the selected images. However, the projection model displays KNN's important strategies using a table to cover the specifics of the patient gathered from the database of the UK. National Cancer Research Institute (NCRI). Accuracy strategies demonstrate the accuracy of the instruments as we analyze the cancer patient data sets to assess the statistical positive and negative levels of values that suggest cancer symptoms. Predicted values indicate that the target sample population of brain cancer with CSF leakage is used for the analysis affects the prevalence of estimation by responsiveness and precision and then compiles by two-column methods based on the current status of the brain cancer data sets, whether the patient is monitored or unregulated and The rows indicate test results, whether positive or negative. The performance our research methods are to focus the measured four evaluation metrics, i.e., Sensitivity (Sen), Specificity (Spe) ROC, and accuracy (ACC). The second improvement is that the k-NN algorithm provides an efficient weighting for all far values which makes the projections much less sensitive to the neighborhood size parameter as compared to the previous works.

7. Conclusion

This research concludes with a discussion on the challenges of a deep learning segmentation method on medical imaging. We describe the statistical results of patients with brain cancer due to the MRI-4-dimensional image segmentation interface. We mentioned the details of brain cancer and explained CSF with the concept of cancer treatment that will support the experimental result after performing the segmentation process and T-test for important results. We also mentioned results before and after surgery with the SPSS test and showed the results in detail of the patient's history. Some tumor properties have been revealed that will be useful in medical applications. In this research, we used the segmentation method for utilizing the latest 4-dimension techniques for identifying the symptoms of disease in the initial stages. With general improvement, we raise the missing data issue. This method creates a predictive value optimization problem that explicitly addresses the missing inclusion values and can be used to generate multiple impressions. This paper also describes Lk-NN, which is more complex than k-NN and should take into account many delays that vary from one pair of variants to another. Using a training vector, this investigation generated a set of test and training vectors for each of the delay periods. We provide the closest neighbor with functions derived from the K-algorithm. This perspective of optimization provides a new perspective on the classic data loss problem and leads to new algorithms to improve data accuracy. Our suggested method takes the longest KNN values (K = 1-100), which is illustrated successfully in a 4-dimensional modulation system that measures the illumination field that can be used in light emission fields. This technique significantly increases the 4d segmentation method using the hybrid KNN process and tumor area identification and elimination according to medical procedures. In the end, the performance of the proposed method is improved by 92% sensitivity, of 60% specificity and 70.50% accuracy respectively for using the maximum values intake of KNN.

8. Future Work

We intend to expand the enhancement system of the selected datasets of our research and techniques in future work. The hybrid KNN algorithm method will implement 6D image processing, segmentation procedure, sensitivity increase with curve region and various deep learning tasks and so many other resources for future technologies. The hybrid KNN algorithm will implement not only in software but it will implement a neural network field that will allow us to explore more things such as modeling, operators and correlation techniques. We also suggest a high dimensional modulation method that will monitor the lighting field that can be used in the field of light emission. The objective evaluation of each beam will be calculated using the hybrid KNN algorithm to maintain 6D light fields (repeatability). The future work will also include segmentation and detection of more images to help categorize multiple types of tumors.

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