International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6023
***Article Received**: 10 November 2022 **Revised**: 08 December 2022 **Accepted**: 24 December 2022*

KC Two-Way Clustering Algorithms for Multi-Child Semantic Maps in Image Mining

Saritha Dasari[1], Dr. A Rama Mohana Reddy[2], Dr. B. Eswara Reddy [3]
[1]Research Scholar
JNTUA, Ananthapuramu, Andhra Pradesh, India
e-mail: sarithadasari123@gmail.com
[2]Professor
Department of CSE, S.V.University, Tirupati, Andhra Pradesh, India
e-mail: ramamohansvu@yahoo.com
[3]Professor
Department of CSE, JNTU, Kalikiri, Andhra Pradesh, India.
e-mail: eswarcsejntua@gmail.com

Abstract— Image mining is now a thriving and expanding field of computer science research. Image mining is linked to the advancement of data mining in image preparation. Image mining is used to extract hidden information and in other situations where the photos do not clearly describe the situation. Image mining combines machine learning, data handling, application autonomy, and image preparation concepts. Semantic maps are used to visualize image data stored in image databases. We recommend using Multi-Child Semantic Maps to build semantic maps which fully display the image. In this study, we propose two path clustering on Multi-Child Semantic Maps (MCSM) using the K-C Means Clustering Algorithm, also known as the MCSMK-C algorithm. This algorithm causes image clustering and instructs the mining system to look at the image's top area. When mining, the MCSMK-C algorithm considers the X and Y coordinates. The system looks for groups by examining each object's territory in the database, and it saves a region if it contains more objects than the required number.

Keywords-Spanning Trees, Image Mining, Clustering, Semantic Maps

I. INTRODUCTION

. A common approach for thinking about and gaining specifically from images is called "image mining." It uses computer vision, image processing, picture recovery, data mining, machine learning, databases, and human intelligence. Ordonez et al. subjected huge image databases to a thought-digging process [1]. These are the two most basic systems. The first process involves extracting information from many photographs on its own, and the second methodology involves extracting information from collections of pictures along with associated alphanumeric information. Additionally, Megalooikonomou et al. [2], a separate researcher, suggested using a common mining method to identify connections between the structures and components of human personality. Zaiane et al. [3] presented an image-mining algorithm using a blob to complete the mining of relations within the association of images.

Image mining aims to explain each broad example without knowing the image content, and the example types are clear. Characterization, portrayal, connection, transitory, and geographical instances may be among them. A photo (Image) mining structure by Missaoui et al. [4] covers ordering systems, picture stockpiles, and image recovery in big image datasets. An image mining structure requires merging image recovery, ordering, data mining, and case confirmation methods, making it complicated. A good picture mining system will also identify data outlines and learn beneath image representation, making photo storage easy for consumers. This framework should include picture storage, image management, highlight extraction, image ordering and recovery, and case and learning dissemination.

Image mining begins with division. Image division and gathering are inseparable. Finding clusters in image data is crucial. Pixels with tantamount forces are regions in photographs. The photo also shows weird items. Division divides a picture into areas or parts so that pixels with spots in the same locale are more comparable than pixels with spots in separate zones. These zones must also be connected so that pixels touch. Division systems are endless. These methods use grouping, limit derivation, or locale development. Image division resembles image portrayal. This paper fragments images using two-path grouping. The count enhances classifier performance and reduces components.

Gathering data is a well-known information mining challenge (grouping). Bunching divides a data set into social events (bunches) so that data segments within a gathering are more comparable than those in separate groups [5]. The image mining system structure is shown in Fig. 1. The method uses a predetermined picture trial as data, evacuating photo fragments

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to identify image information swiftly. In addition to the importance of this mining task, a component extraction executive must consider invariance to geometric alterations and power to noise and unique mutilations. Addressing photo content yields the model semantic image illustration. Mining findings are obtained after planning the model depiction with its essential typical portrayal. The typical delineation may be a component or a sequence of components, a verbal representation or expression recalling the underlying purpose to and Feature Extraction Mining Interpretation and Evaluation Knowledge Image Database

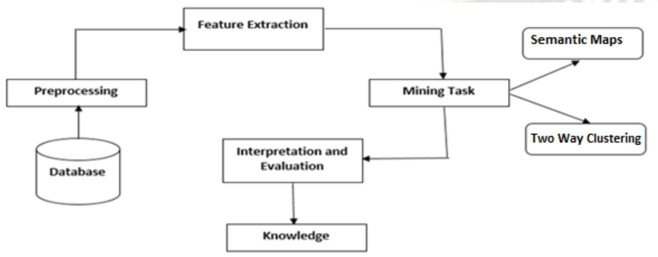

Figure 1. Generalized Architecture for Image Mining

You need to know which category another image (object) belongs to, and you only have a set of predetermined photos to use as a guide. Bunching is an approach to data analysis that uses summaries of related articles to determine the existence of an underlying pattern. In ML, classifying is an example of supervised learning, while identifying patterns requires regulated learning.

II. LITERATURE REVIEW

Highlight subset choice is a technique of finding and discarding as numerous unessential and dreary segments as much as could be normal in light of the current situation. The reason behind this is 1) unimportant components don't compare sounding word use to the insightful exactness, and 2) dreary components give most by far of the information which is starting now introduced in interchange components, so it doesn't redound to getting incredible pointer. Snappy count managing both irrelevant and overabundance segments.

To identify the crucial elements, feature subset determination is typically utilized. Relief is undoubtedly a circumstance that is understood. Lightening only needs to coordinate the time of the number of given parts and plan situations; it is not reliant on heuristics for two perceptive Reliefs with the objective still being unrelated. Without conducting a pair-by-pair close association analysis, the Quick Correlation Based Filter (FCBF) identifies both pertinent and excessive segments. Unlike these figures, the FAST estimate utilizes a collection-based process to select highlights. A technique of word assurance strategy about substance depiction is called different-tiered clustering. There are two categories of frameworks for varying levels of clustering: agglomerative and divisive. To eliminate boring segments, the agglomerative different-tiered gathering was applied. Quick calculations aggregate the components using the Minimum Spanning Tree method.

An approach to area-level semantic mining was put forth by Liu et al. in [6]. Images are divided into two segments using an improved division algorithm, each with homogeneous repulsive and textural features, as it is simpler for users to understand image content by region. Following this, a uniform zone-based representation for each image is created. The Expectation Maximization approach can mine the covered semantic once the probabilistic relationship between the image, range, and hidden semantic is established.

Wang et al. [7] .'s solution to the semantic fissure problem involves mining the entire segment outlines. To mine the undeniable component drawings and develop a rule base to see semantic ideas in photos, fascinating figures are developed. The proposed methodology is more capable than the currently proposed methodologies, according to actual execution research on large image databases with different semantic ideas.

In a photography request method provided by Zhang et al. [8], the semantic link between photos and other low-level visual components is frequently mishandled. It is based on a sequence of semantic phrases representing the classes to be identified with unlabeled photos. At first, a multi-highlight mix model is described for each semantic category using a multi-target enhancement method. By then, a Bayesian learning system had been linked to selecting a model for handling connections between different types of meaning. The final step is employing this association model to label certain objects in photos. A subset of results from a comprehensive test evaluation is displayed to illustrate the efficacy of the methods proposed.

To create the MHBI logic and a combined MHBI-Fish ontology, Abu et al. [9] applied the Taxonomic Data Working Group Life Sciences Identifier vocabulary to our data. Also, they showed a separate vocabulary tailored to commenting on monogenic haptoral bar images (MHBI). These ontologies scored high marks in all five areas of evaluation: clarity; awareness; extendibility; cosmology obligation; encoding slant.

The practice uses the MST grouping calculation. Xu et al. [10] use MSTs to express multidimensional quality expression information. MST-based bunching calculations do not assume that information focuses are assembled around focuses or isolated by a general geometric bend. The calculation is unaffected by bunch limit status. They show three goal capacities and grouping algorithms for determining a traversal tree k-allotment for any predefined $k>0$. The first computation evacuates the $k-1$ longest edges to minimize the k subtree weight. The second goal capacity reduces the aggregate separation between the middle and every information point in a group. K-allotment is made by removing $k-1$ edges from the

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tree. Next, it repeatedly consolidates two adjacent lots to find its perfect 2-bunching configuration. The calculation quickly reaches a local least.

Using an MST, Xu et al. [11] divide a dark-level image into homogeneous regions. The tree apportioning algorithm reduces the variety of dark levels of all sub-trees, and two adjacent sub-trees must have diverse dark levels. Each subtree represents a uniform visual area with a few dim levels. MST grouping calculation is used in image processing [12, 13].

Lopresti et al. [14] suggest a Euclidean least traversal tree for RGB shading grouping. Image shadings are points in the three-dimensional RGB shading space. EMST hubs are all shadings. Edge heaviness is the Euclidean distance between two shading hubs in the tree. After building the EMST, they record edge separation. Thus, edges "longer" than the typical weight by a certain sum is removed from the tree, leaving an arrangement of independent subtrees. Each subtree has shades from a group. The EMST-based shade grouping calculation may fail for surfaces and images with many colours.

Eldershaw et al. [15] examine the limits of many 2D bunching computations that assume groups of a point set are fundamentally circular and give a more extensive definition of a bunch based on transitivity. If two focuses, p1 and p2, are near the same point, p0, they are both from the same group. They create a chart using Delaunay triangulation and remove edges longer than a cut-off point. Next, they use a chart parcelling computation to find the diagram's separated associated portions, which they treat as groups. Unlike Zahn's method, they choose a cut-off point that is the global minimum. Sanjay et al. [16] proposed wavelet-based image mining. The developer suggested wavelet-based picture mining. It uses typical example indistinguishable, design distinguishing proof, and information mining models to classify a real scene/image, aiding various prediction and gauging tools. It involves image, learning, and order. Wavelet change, which uses temporal recurrence affiliation, can replace Fourier change for picture mining. Wavelet change breaks an image into recurring subgroups and uses a small subband for Principal Component Analysis (PCA). Order aids image classification. They created a DWT + PCA-proof model system. Image mining can be used to predict weather events.

Sabyasachi Pattnaik et al. predicted using grouping and information pressure approaches in image mining [17]. Mist satellite photos have a significant role in forecasting climate conditions. The frequency of image acquisition ranges from one image for every instant to the next per hour while considering the climate. These occasions result in a massive gathering and establishment of a hub for the diffusion of visual information. The transmission of images with lasting capacity is a challenging task. Their methodology combines a grouping strategy for information mining with Vector Quantization (VQ) to minimize and group static shading images. Results seem to demonstrate the discoveries both within and externally.

Petra Perner [18] discussed image mining topics such as subjects, structure, a standard instrument, and its application to medical image examination. This author provides a device and a procedure for information mining in image-chronicling frameworks. It is used to determine useful information for image examination and distinguishing proof from the image depiction information base. Learning design techniques generate a list of characteristics for common image portrayals. A specialist creates images based on this list and catalogues them in the database.

III. Proposed Work

The suggested work combines two distinct approaches, yielding effective image mining for the provided image. Multi-Child Semantic Maps develop the context for importing the chosen photos. It uses K-C Clustering methods to draw out specifics from an image.

Phase 1: Multi-Child Semantic Maps

The Multilevel Semantic Map is a split where one parent compares with one child class, the third subtype classes are related namelessly to the swift child guardian class, and the gathering section's forward-looking and backwards-looking usage can be determined.

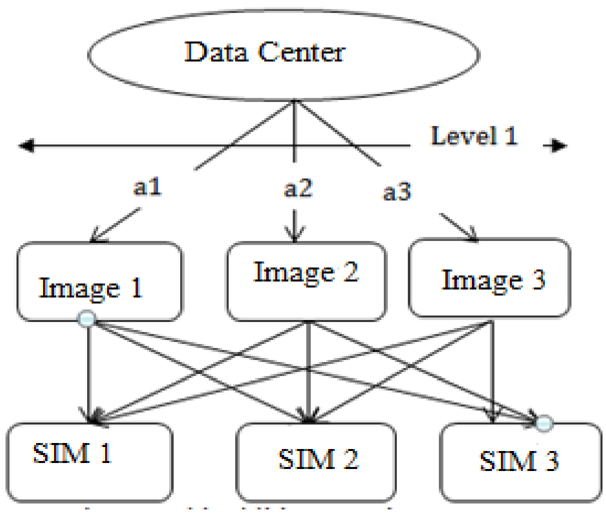

Figure 2. Multi-Child Semantic Map

The multi-child semantic map constitutes the three-factor substitution through which the data relevant to the submitted query will be considered. The mining technique for which the data analysis and extraction are imposed will start the checking process. After the successful verification and extraction, the image relevant to the imposed inputs will be extracted.

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$$A1=\begin{bmatrix} x1 & x2 & x3 \\ x4 & x5 & x6 \end{bmatrix}$$

$$A2=\begin{bmatrix} x7 & x8 & x9 \\ x10 & x11 & x12 \end{bmatrix}$$

$$A_m=\begin{bmatrix} mx1 & mx2 & mx3 \\ mx6 & mx5 & mx6 \end{bmatrix}$$

Where M is the inputted image to which the relevant image is to be extracted.

B= y1

Where N is the image that is to be inputted by the user to verify and extract the information from the set of images A1.

$$A1xB=\begin{bmatrix} y1 \times x1 & y1 \times x2 & y1 \times x3 \\ y1 \times x4 & y1 \times x5 & y1 \times x6 \end{bmatrix}$$

$$A2xB=\begin{bmatrix} y1 \times x7 & y1 \times x8 & y1 \times x9 \\ y1 \times x10 & y1 \times x11 & y1 \times x12 \end{bmatrix}$$

$$A_mxB=\begin{bmatrix} y1 \times mx1 & y1 \times mx2 & y1 \times mx3 \\ y1 \times mx4 & y1 \times mx5 & y1 \times mx6 \end{bmatrix}$$

Every tuple present in the image repository is considered, and the image mining technique is applied to the image available in the repositories.

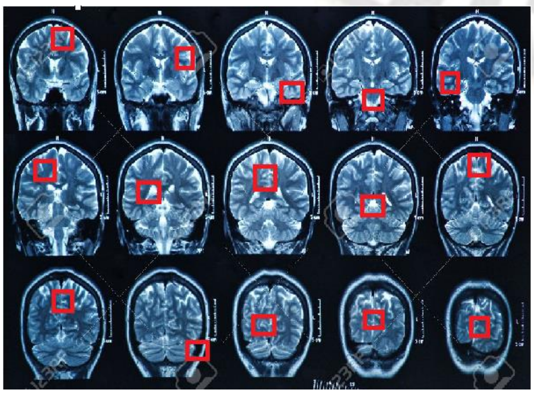

Figure 3. The image-wise segmentation for the selection of appropriate mining image

Various images are taken into consideration. The image relevant to the substituted image will be considered, and the mining technique will be applied to the image to find the relevant proportion.

Phase 2: Ensemble Algorithm for Image Mining

In the second part of the suggested system, the K-means and C-means algorithms are combined to form the K-C Means algorithm, which is then used to process the image obtained from the MCS maps.

a)K-Means Algorithm:-

The K-means clustering algorithm primarily sets the goal to optimize the X-Coordinates that is available in the images that are taken into consideration. The procedure includes the following steps.

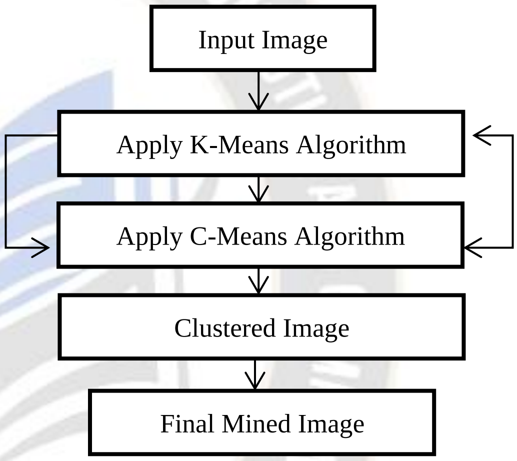

Figure 4. Flow of the algorithm

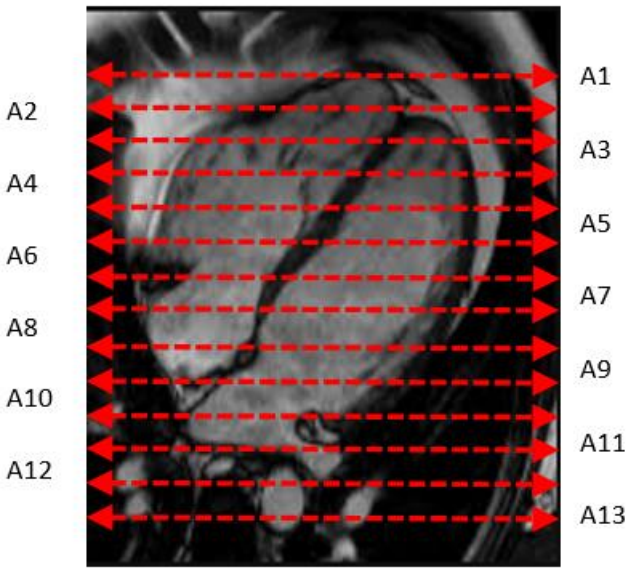

Figure 5. Figure representing the X-Coordinates in the image

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Step 1: Check for the available parameters in the image and randomly generate with the initial population.
Step 2: Find the upper and lower bounds in the X coordinates of the image
Step 3: Initialize the new set of populations using selection, crossover and mutation operators.
Step 4: Obtain the Clustering Results and apply filtering over clustering results
Every Horizontal Coordinate is considered, and the data is traversed in the horizontal form to check for the relevant information to be mined from the image repositories.

b) C-Means Algorithm:

The image is applied with the K-Means clustering algorithm, and the same image is applied with the c-means algorithm to check for the y-coordinates, and the results are obtained. The heterogeneity and homogeneity are applied to get information about the same and different clusters.
Step 1: Choose the Image taken after the application of the K-means Clustering Algorithm (A)
Step 2: Set the rimary Epicenter of the Image as m1,m2……mx
Step 3: Distinguish each vector Z into the closest epicentre mx by using Euclidean Distance:

$$\|zi - mx\| = min\|zi - mx\|$$

Step 4: Re-verify the estimated image centres
Step 5: if no images change, then go to step 3.

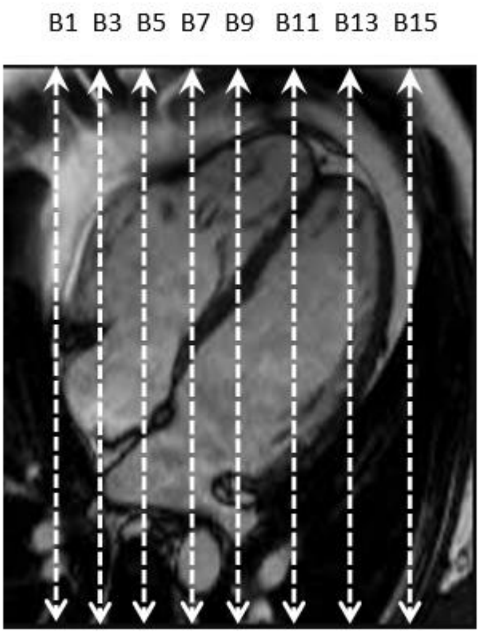

Figure 6. Representing the Y-Coordinates in the Image

Every vertical coordinate is considered, and the data is traversed in the vertical form to check for the relevant information to be mined from the image repositories.

The resultant vector of the K-C Means Clustering Algorithm

The K-C Means Clustering algorithm to be used in the proposed scheme takes charge of using the Horizontal and Vertical Partitions through which the data is traversable. The H represents the Horizontal values, and V Represents the Vertical Values

H=$[A1, A2, A3 \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots An]$

V=$[B1, B2, B3 \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots Bn]$

HxV=$[A1 \times B1, A2 \times B2 \dots \dots \dots \dots \dots \dots \dots . An \times Bn]$

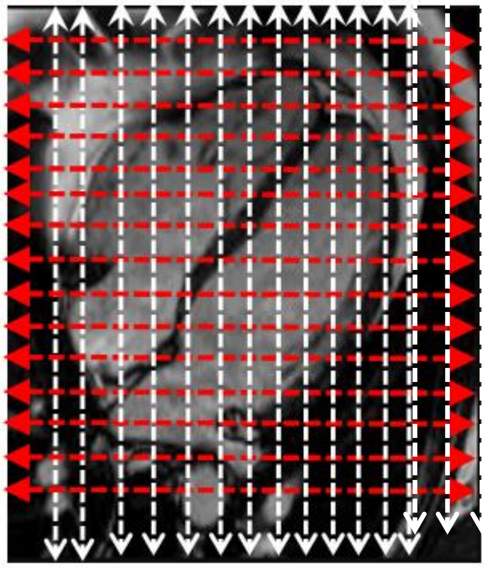

Figure 7. Representation of the X-Y Coordinates after the application of K-C Means Clustering Algorithms.

The resultant vector is achieved after successfully applying the K-C means algorithm and making the image mined.

C) Evolutionary Algorithm for Efficient Scheduling in K-C Means Algorithm

The proposed scheme utilizes the K-C Algorithm to use the clustering in the image mining criteria efficiently. For efficient scheduling, the Evolutionary algorithms are used for the proper scheduling of the K-C Means Algorithm to take place.

T1=Number of Data Clusters
X1=IMmips/T1
Where T1 is the Time
X1 is the Image Line

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IMmips is the number of Clusters in X1

$Dist((a,b),(m,n))=\sqrt{(a-m)^2+(b-n)^2}$

Where x=Task Size

y= Image Clusters

In light of the challenges to approve the outcome in the genuine foundation, we utilized it to assess the trial aftereffect of the proposed work. The proposed booking calculation and Multilevel Need, Based Task Scheduling Algorithm in Image Processing Environment have been contrasted. We assessed our outcome utilizing three unique criteria.

Case 1: The proposed booking calculation diminishes execution time in examining the Multilevel Priority-based Task booking calculation, which appeared. According to the diagram, we can presume that the proposed calculation works better in all criteria with various undertaking rundowns and several Images. If the span of the cloudlet increases, the execution time will diminish.

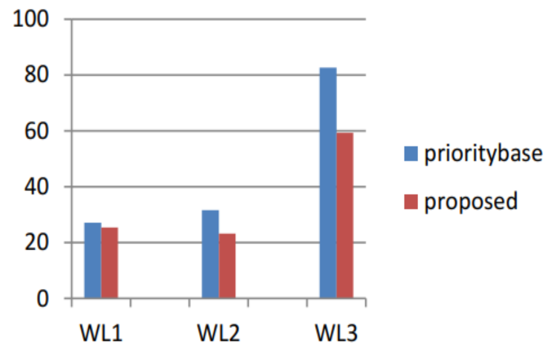

Figure 8 Execution Time with Image

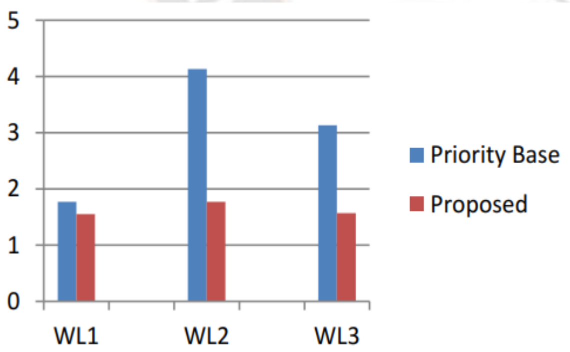

Figure 9. Make Span with Image

Case 2. The close examination of the makespan of both the calculations. According to the chart, we can infer that if no cloudlets increment, then makespan will diminish when contrasted with Multilevel Priority-based calculation. So the execution of the framework will make strides.

IV. EXPERIMENTAL RESULTS

The proposed system is implemented based on the simulation to check whether the mining process is considered. The system is primarily implemented in the MATLAB 2012 Simulink Software to express the mining methodology through the Image Simulation Process.

The continuous image partition is taken into consideration. The image taken into the application is classified with the MCS maps, through which every image is taken and filtered with the relevancy of the images and image repositories. The conditional overflow creates the methodological survey that creates the same image sectors.

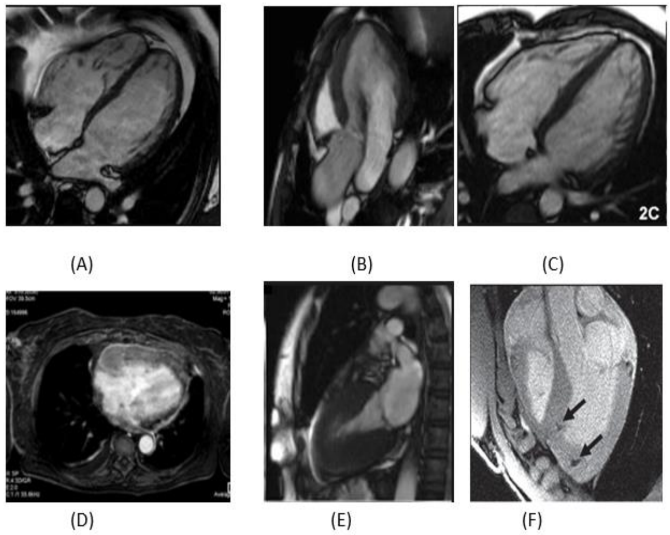

Figure 10. (a)Image taken after the application of MCS-Map (b) The Image taken for the Horizontal Partition using the K-Means Algorithm (c) The Image after the Horizontal partition based on the K-Means Algorithm (d) The Image taken for the vertical partition using the C-means Algorithm (e) The Image after the Vertical Partition using the C-means Algorithm (f)Final Resultant Image after the image mining

Implementing the K-Means algorithm with the image is being too calculated in the X- Coordinates. The X-Partition values are considered and make the image comfortably mined, with the data finally being produced by the system. The implementation calculations make the data to be accurate on the basis of x-axisThe implementation of the C-means algorithm makes the system verify the y-axis and the y-coordinates. The overall image is calculated and made over the system to mine the information that makes the system vertically scan the images concerning the y-values of the images and makes the values accurate based on the y-coordinate.

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The Result generation of this research paper deals with the makeover of the brain tumour detection on the imaginary heart MRI images. The X-axis and Y-Axis coordinates play a vital role in efficiently finding the heart in the brain. The Images are diffused in the X and Y Coordinates, where the systematic diffusion feature evenly diffuses the x and y-axis.

X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
X2	X3	X4	X5	X6	X7	X8	X9	X9	Y1
X3	X4	X5	X6	X7	X8	X9	X10	Y1	Y2
X4	X5	X6	X7	X8	X9	X10	Y1	Y2	Y3
X5	X6	X7	X8	X9	X10	Y1	Y2	Y3	Y4
X6	X7	X8	X9	X10	Y1	Y2	Y3	Y4	Y5
X7	X8	X9	X10	Y1	Y2	Y3	Y4	Y5	Y6
X8	X9	X10	Y1	Y2	Y3	Y4	Y5	Y6	Y7
X9	X10	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8
X10	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9

This exponential table which describes the major portions of the MRI image is disbursed into the various parts of the subspace, which is being created for the efficient finding of the input data set with the specific range of the result generation

Initial step: First, data of the x1 is added for the result found.
Input I=R1
The created checklist which has the efficient dataset from Y={x1,x2,x3………..x10}
Input x1 into the Dataset Y;
Check the Inputted Data with the Dataset,
I=X1{x1,x2,x3…..x10}
{X1→x1,X1→x2,X1→x3……………………………………
….X1→x10}
If X1=x1,x2,x3……………………..x10;
Result: Tumor Location
Else
Result: Change the Log

The X1→R1 for the Image Calculation for both X1 in both the Horizontal and Vertical Plane

Calculation:- ITERATION 2
Iteration 1 has no significance in identifying the tumour; we shift to the second iteration.

Xm→Crm,Crn(Horizontal)
The I2 corresponds to the total data available in the first iterative subspace. This states the following availability of the fixed cue points in the overall image.

Whereas Crm→(Pm,Pn)

Crn→ (Pm, Pn), Iterative Cycle Pointer P=Pm

Pm=With Positive and Negative Approach(Select the Logical Pointer and Check for the Variable Difference)

The horizontal and vertical planes and calculations are shown in APPENDIX.

Rrm→ Pm=1→Xm, Yes
Pn=1→Xn, Yes
Rrn→ Pm=1→Xm, Yes
Pn=1→Xn, Yes
Significance of Tumor : Present

Rrm→ Pm=0→Xm, No
Pn=0→Xn, No
Rrn→ Pm=0→Xm, No
Pn=0→Xn, No
Significance of Tumor : Not Present

In the Conclusion of the Calculation, Tumor Detectable areas based on the Horizontal Biased is
I2= X6{[Cr1(P1,P3)]&&[Cr2(P2,P4)]}
X7{[Cr1(P1,P3)]&&[Cr2{P2,P4)]}
X8{[Cr1(P1,P3)]}
I3= X7{[Cr1(P1)]&&[Cr2(P2)]}
X8{[Cr1(P1)]&&[Cr2(P2)]}
X9{[Cr1(P1)]&&[Cr2(P2)]}
X10{[Cr1(P1)]&&[Cr2(P2)]}

Image mining has the evolution of various other algorithms, namely Vector Machine Algorithm, Data Segregation Algorithm, and KDD Algorithm, efficiently used to find the resultant vector for the user's query execution. The Resultant vector of the existing proposal had the variable difference and maintained a drastic difference in accuracy in finding the Query

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Result. The Two-Way Clustering of the K-Means and C-Means algorithms with effective Horizontal and Vertical Position areas makes the way to exactly where the tumour is situated [16].

Vector Machine Algorithm

The Vector Machine Algorithm which fixes it points towards the uni-vector sequence where the number of iterations is to be performed for finding the proper accuracy

Data Segregation Algorithm

The DSA algorithm segregates the data into multiple units and finds accurate results where multiple iterations are to be needed to perform the adjoined operations

KDD Algorithm

The KDD algorithm only checks the exact data being executed by the user in the form of query where the algorithm doesn't follow the systematic procedure for finding the query. The algorithm's exact path is undesirable and may follow any dimensional systematic approach.

The time consumption cannot be predicted, whereas the KDD uses all the approaches to find and fulfil the complete query analysis for the result. The complete analysis shows up the data taken for the sampling and finding the data, which is better known for the systematic mining of the data, which is being taken into consideration. The finding of the tumour present in the MRI image represents the complete data for the finding of the system [17].

Algorithm /table	VM Algorithm	DS Algorithm	KDD Algorithm	K-C Means Algorithm
Time	High Consumption	High Consumption	High Consumption	Low Consumption
Speed	M X .10 / 256Kbps	M X .10 / 256Kbps	M X .7 / 256Kbps	M X .5 / 256Kbps
Accuracy	Low	Low	Better	High
Data Limit	1024Mb	2Gb	2Gb	2.5Gb
Execution Time	0.5s / 300 Dpi Image	0.48s / 300 Dpi Image	0.78s / 300 Dpi Image	0.36s / 300 Dpi Image
Direction	Unidirectional	Unidirectional	Unidirectional	Bi-Directional
Performance	High	Low	Low	High

V. CONCLUSION

Image mining is, as of now, a developing yet dynamic research centre in software engineering. Image mining is associated with the advancement of data mining inside the field of Image handling. Image mining handles the disguised information extraction and extra cases not clearly described inside the Images. Image mining fuses frameworks like Image Preparation, data taking care of, mechanical autonomy and machine learning. Semantic maps are utilized to imagine the Image data, which is put away in Image databases. To fabricate the semantic maps, we propose Multi-Child Semantic Maps, which display images. We present the two path grouping on Multi-Child Semantic Maps in this study with the K-C Means Clustering Algorithm, also known as the MCSMK-C algorithm. This algorithm bunches the images and directs the mining process to look for the last bit of each image. The MCSMK-C algorithm considers the X and Y coordinates when mining. The addition of evolutionary algorithms allows for the effective scheduling of every cluster. However, it contains more than the base number of items. The computation searches for clusters by examining the region of each item in the database.

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International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6023
***Article Received**: 10 November 2022 **Revised**: 08 December 2022 **Accepted**: 24 December 2022*

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APPENDIX

Horizontal Plane

ITERATION 1

X1		X2		X3		X4		X5		X6		X7		X8		X9		X10	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

ITERATION 2

X2		X3		X4		X5		X6		X7		X8		X9		X10		Y1	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

ITERATION 3

X3		X4		X5		X6		X7		X8		X9		X10		Y1		Y2	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

One the First Iteration on the R1 to R3, The Horizontal Point Scale which is mentioned in the Grey Color states the Fixation point for the monitoring of tumor images.

ITERATION 2

X6→Rr1,Rr2 (Horizontal)	**X7→Rr1,Rr2 (Horizontal)**	**X8→Rr1,Rr2 (Horizontal)**	**X9→Rr1,Rr2 (Horizontal)**
Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X6, No P2=1→X6, YES Rr2→ P3=1→X6, No P4=1→X6, No **Significance: Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X7, Yes P2=1→X7, Yes Rr2→ P3=1→X7, Yes P4=1→X7, Yes **Significance: Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X8, YES P2=1→X8, No Rr2→ P3=1→X8, YES P4=1→X8, No **Significance: Partially Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X9, No P2=1→X9, YES Rr2→ P3=1→X9, No P4=1→X9, No **Significance: Not Present**

ITERATION 3

X7→Rr1,Rr2 (Horizontal)	**X8→Rr1,Rr2 (Horizontal)**	**X9→Rr1,Rr2 (Horizontal)**	**X10→Rr1,Rr2 (Horizontal)**
Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X7, Yes P2=1→X7, Yes Rr2→ P3=1→X7, No P4=1→X7, No **Significance: Partially Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X8, Yes P2=1→X8, Yes Rr2→ P3=1→X8, No P4=1→X8, No **Significance: Partially Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X9, YES P2=1→X9, Yes Rr2→ P3=1→X9, No P4=1→X9, No **Significance: Partially Present**	Rr1→(P1,P2) Rr2→ (P3,P4) Rr1→P1=1→X10, Yes P2=1→X10, Yes Rr2→P3=1→X10, No P4=1→X10, No **Significance: Partially Present**

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6023
***Article Received**: 10 November 2022 **Revised**: 08 December 2022 **Accepted**: 24 December 2022*

Vertical Plane

Iteration I1

X1		X2		X3		X4		X5		X6		X7		X8		X9		X10	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

Iteration I2

X2		X3		X4		X5		X6		X7		X8		X9		X10		Y1	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

Iteration I3

X3		X4		X5		X6		X7		X8		X9		X10		Y1		Y2	
P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4

One the First Iteration on the R1 to R3, The Vertical Point Scale which is mentioned in the Grey Color states the Fixation point for the

ITERATION 2			
X6→Cr1,Cr2 **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→P1=1→X6, Yes P3=1→X6, Yes Cr2→ P2=1→X6, Yes P4=1→X6, Yes **Significance: Present**	**X7→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X7, Yes P3=1→X7, Yes Cr2→ P2=1→X7, Yes P4=1→X7, Yes **Significance: Present**	**X8→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X8, Yes P3=1→X8, No Cr2→ P2=1→X8, Yes P4=1→X8, No **Significance: Partially Present**	**X9→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X9, No P3=1→X9, No Cr2→ P2=1→X9, No P4=1→X9, No **Significance: Present**

ITERATION 3			
X7→Cr1,Cr2 **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X7, Yes P3=1→X7, No Cr2→ P2=1→X7, Yes P4=1→X7, No **Significance: Partially Present**	**X8→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X8, Yes P3=1→X8, No Cr2→ P2=1→X8, Yes P4=1→X8, No **Significance: Partially Present**	**X9→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X9, Yes P3=1→X9, No Cr2→ P2=1→X9, Yes P4=1→X9, No **Significance: Partially Present**	**X9→Cr1,Cr2** **(Vertical)** Cr1→(P1,P3) Cr2→ (P2,P4) Cr1→ P1=1→X9, Yes P3=1→X9, No Cr2→ P2=1→X9, Yes P4=1→X9, No **Significance: Partially Present**

Authors profile:

Saritha Dasari received B.Tech in Computer Science & Information Technology from JNTU Hyderabad in the year 2004, M.Tech (CS) received from JNTU Hyderabad in the year 2006 and Pursuing Ph.DatJNTUAnantapuramu. She is having 16 years of teaching experience in reputed engineering colleges. Her areas of interest are DataMining, Knowledge Engineering, Image Processing and Pattern Recognition.She has published 10 International Journals, 10 International /National Conferences and attended more than 40Workshops /FDP/Seminars etc.,She is a member of ISTE, CSI, IEEE.

Dr. A. Rama Mohan Reddy obtained his Bachelor Degree in Mechanical Engineering and Master's degree in Computer Science and Engineering from NIT Warangal and Ph.D degree from Sri Venkateswara University and at present working as a Professor in Department of Computer Science and Engineering, Sri Venkateswara University College of Engineering. His areas of interest include Software Architecture and data mining. He has more than 27 years of experience in Teaching and Research

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6023
***Article Received**: 10 November 2022 **Revised**: 08 December 2022 **Accepted**: 24 December 2022*

Dr.B. Eswar Reddy obtained his Bachelor Degree in computer science and Engineering From G. Pulla Reddy Engineering College, kurnool and Master's degree in Computer Science and Engineering from Institute of Post Graduate Studies and Research, JNTU Hyderabad and Ph.D (CSE) degree from JNTU, Hyderabad and at present working as Principal and Professor in Department of Computer Science and Engineering, JNTUA College of Engineering, Kalikiri. His areas of interest include Pattern Recognition and Image Analysis, Data Warehousing and Mining and Cloud Computing. He has more than 20 years of experience in Teaching and Research.

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