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Enhanced Ai-Based Machine Learning Model for an Accurate Segmentation and Classification Methods

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Abstract:

Phone Laser Scanner becomes the versatile sensor module that is premised on Lamp Identification and Spanning methodology and is used in a spectrum of uses. There are several prior editorials in the literary works that concentrate on the implementations or attributes of these processes; even so, evaluations of all those inventive computational techniques reported in the literature have not even been performed in the required thickness. At ToAT that finish, we examine and summarize the latest advances in Artificial Intelligence based machine learning data processing approaches such as extracting features, fragmentation, machine vision, and categorization. In this survey, we have reviewed total 48 papers based on an enhanced AI based machine learning model for accurate classification and segmentation methods. Here, we have reviewed the sections on segmentation and classification of images based on machine learning models.

Keywords: Artificial Intelligence, Machine learning, Classification accuracy, Segmentation and classification.

I. INTRODUCTION:

In clinical diagnosis, prominent information about the data and patients was obtained from the image examination [1. 2]. Both classification and segmentation were popularly utilized used image processing methodologies (IPM). To interpret the features, the feature analysis and extraction were dependent upon the image classification as well as segmentation methods in medical image (MI) investigation [3, 4]. The tumor cell classification, blood cell delineation, and tumor location are extensive applications [5, 6].

Till recent times, the research of morphological changes using microscopy (EM) has been frequently limited to subjective depiction owing to technical restrictions that precluded the statistical approach of three-dimensional specimens [7, 8]. The creation is an innovative quantity EM technique. Even so, our capacity to evaluate this info has not progressed in the same way; segmenting EM images continues to be a big and moment painstaking system [9, 10]. As a result, in order to fully realize the explanatory possibility of EM, generally applicable and precise assessment remedies are required [11, 12].

A permeation characteristic specifies the covalent bond inside a sturdy, fluid, as well as fuel, so it allows us to quantify the frequency of the discovered image [13]. Hyperspectral information is routinely made up of 100–200 two hundred pop acts of the spectral range. Introduce a lightweight Multi-view Attention to successfully segment nuclei and category cells in histopathological images to improve network improve operational precision [14, 15].

II. LITERATURE ANALYSIS

In this section, we discussed various kinds of AI oriented machine learning (ML) techniques for accurate classification and segmentation model.

2.1 **Segmentation:**

In this section, different kinds of segmentation techniques such as threshold, multi-level, watershed, cluster based, edge based and region-based segmentation. The splitting of images

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into several tiny images for analyzing purposes is known as image segmentation. This also mitigates the image complexity and is also used for labeling the pixel images. There are several works performed for the exact segmentation of images with machine learning approaches. In this work, we enclose several approaches with their merits and demerits.

2.1.1 Cluster-based segmentation:

The clustering-based segmentation model was suggested by Shukla et al. [16] for the biometric image. The quality segmented binary images were obtained via an effective clustering-based image segmentation model. In the biometric-based identification system, the quality decision was obtained by pre-processing these images. A various number of hand images were received from the biometric data set with the operation and adequate results were achieved. But, the computational complexities are huge.The image clustering model was introduced by Kolluru et al. [17] for learning with fewer images. From the volume, the equally spaced intervals select the initial concept of image choosing. This method demonstrated better and superior sampling performances.

For robust image segmentation, Wu et al. [18] suggested fuzzy clustering and entropy based divergence kernel based on adaptive weighted local information. The alternating iteration of the convergence theorem strictly proves the convergences. Contrasted to the existing methods, this technique demonstrated noisy free clustering and the authors failed to solve the nonlinear model analysis issues. The fuzzy C means clustering model and whale optimization algorithm were introduced by Tongbram et al. [19] for novel image segmentation. Equal numbers of iterations perform both exploitations as well as exploration phases effectively.

2.1.2 Edge based segmentation:

Fang et al. [20] suggested a fuzzy region-based and edge-based active contours-driven method to segment images. Based on the local fuzzy region, the object importance's were hybridized via the fuzzy region. During the curve evolution, the smooth appearance was maintained with the pseudo level set function (LSF) was regularized via edge energy. The better performance with more intensity inhomogeneity and noise were collected.

The edge-based level set model based on a global-to-local region-based indicator embedded was established by Zhou et al. [21]. According to the region information, the active contour curve of bidirectional motion was allowed with the region-based indicator. The one single energy function via both region information and edge information was incorporated with the region-based indicator and it demonstrated higher segmentation outputs.

According to multi-local statistical information, Liu et al. [22] suggested the weighted edge-based level set method. In noisy image segmentation, the traditional edge stop function and regional coefficients with constant length deficiencies were analyzed. Both real and synthetic images were analyzed via the edge-based level set method. Superior segmentation accuracies with fewer standard deviation outputs were achieved.

In a vector image field, Phornphatcharaphong et al. [23] suggested edge-based color image segmentation. The images vector of local color distance was the center-to-centroids collection to create a usual compressive vector meadow. Hamiltonian gradient vector field from vector field analogous were received from the benchmark score. This method offers noise resistance and faster computation time as well as constant length deficiencies.

2.1.3 Region based segmentation:

Region-based homogeneity was suggested by Chen et al. [24] for image segmentation in geodesic paths. The integration of area uniformity characteristics into the metrics under consideration is predicated on an implied portrayal of such characteristics that is a major of this work's contributions. Furthermore, present a method for constructing simply closed contours. The investigational outputs demonstrated current minimum ways oriented image segmentation methods. For image segmentation, the fuzzy region oriented active contour model was examined by Fang et al. [25] via both local and global fitting energy. However, unlike FEAC prototype, which computes the transformation of the external potential pixel by pixel, a forceful formula is used to measure the variation among the old and fresh electricity features inside the image sequence for every iterative process in updating the faux template matching purpose.

Nguyen et al. [26] suggested an unsupervised region-based anomaly detection model. For T1-weighted MRI, the brain tumor segmentation was performed using unsupervised inpainting with a fully automatic oriented brain tumor segmentation model. The regions of the missing healthy brain were reconstructed by training the deep convolutional neural network (DCNN). The new consequences provided a good dice score and standard deviation results with the highest reconstruction loss.

2.1.4 Multi-level set and watershed segmentation approaches:

Segmentation of images is performed to correctly identify the diseases and Kandhasamy et al. [27] stated a novel method

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for the segmentation of Diabetic Retinopathy (DR) for detection of the disease at its early stage. For this, the authors utilized multi-level set segmentation-based SVM for selective features, and for optimization, the author's utilized a genetic algorithm. The stated work diagnoses the diseases effectively at their early stage with the specificity and sensitivity of 98.1%, and 97.56% respectively, however, the segmentation of images with high noises is not accurate and it is difficult to deal with them.

Latif et al. [28] delineated a novel approach for denoising the MR images using the deep Convolutional neural network incorporated with anisotropic diffusion (AD). Henceforth the denoised images are segmented in the timorous region using the watershed transform. The experiment is carried out in BraTS MRI datasets and acquired a specificity of 99.84%, and a dice coefficient of 90.56% respectively with the complexity has been increased.For the effective detection of liver cancer, Das et al. [29] stated a novel method known as Gaussian-based deep learning. To determine liver cancer, the liver portion from the computed tomography has been segmented using the watershed segmentation process and the affected region is separated with the aid of the Gaussian mixture model (GMM) algorithm.

The detection of tumor tissue from the soft tissues in the brain region is a very intricate task and Hasan et al. [30] stated a novel multi-level assessment oriented tumor segmentation approach known as the watershed matching algorithm. In this approach, the authors segmented the tumor portion first from the MR images and the matching of the area is carried out by the algorithm. An automatic scheme has been urbanized for brain tumor detection by Khan et al. [31] and is based on the marker-based watershed segmentation algorithm. The tumor contrast has been performed with the gamma contrast stretching and the chi-square max conditional priority features method has been used for the selection of selective features. The selected features were classified with the usage of SVM methods. The segmentation accuracy is higher with little computational complexity.

To determine brain tumor, Sharma et al. [32] suggested a novel approach the Enhanced watershed segmentation algorithm. This approach maintains the efficacy of computation along with the high-dimensional deep features. The accuracy obtained by this approach is 92%, however, the time complexity is high and also cannot be used to segment multimodal images. The literature review of Multi-level set and watershed-based segmentation approaches is listed in table 4.

<u>2.1.5 Multilevel threshold segmentation algorithm:</u>

Liang et al. [33] stated a novel approach to segment the images using the modified algorithm which is based on the multi-thresholding-based modified grasshopper optimization algorithm. Here the authors utilized the Levy flight algorithm with the grasshopper optimization algorithm. The experiments were conducted for the real-life images and stomata plant images and the segmentation accuracy is higher with increased computational time.

To segment, the grayscale images Abd Elaziz et al. [34] presented a novel approach known as a multi-verse optimization algorithm based on multi-level thresholding. With the maximization of the Otsu and Kapur objective function, the Pareto-optimal sets were created which mitigates the computational complexity and enhances the accuracy of the segmentation of images. Nevertheless, the CPU time increases linearly with the threshold values.

To tackle the issues of ant colony optimizers like the stagnation of local optima Zhao et al. [35] demonstrated a novel random spare strategy and chaotic intensification strategy along with the multi-threshold segmentation of images. The stated approach has been used to improve searchability globally. The outcomes of segmented images using the stated approach can be used to identify any type of disease as well as other applications due to the improved quality. Meanwhile, the parameter sensitivity is higher for the stated approach.

To ensure the efficacy of the multi-threshold image segmentation Mittal et al. [36] stated a novel approach. The optimal threshold has been acquired with the non-local means 2D histogram and the gravitational search algorithm (exponential K-best GSA). The experiments were conducted on datasets like Benchmark (BSDS300) and Berkeley segmentation for both the objective and subjective assessments. The stated techniques can be used to enhance the segmentation accuracy with higher computational time.

1.1 Classification:

Classification is the process of grouping and labeling the pixels based on the special types with one or more spectral and textural features. The classification approaches include two types of methods such as supervised and unsupervised. Here we have reviewed several machine learning approaches such as Support vector machine (SVM) classifier, Logistic regression, Random Forest, and Decision tree.

<u>2.2.1 Random forest and decision tree:</u>

Su et al. [37] presented a random forest method for the classification of the object-based crop. An initial training set

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to train the random forest (RF) classifier and it derives every feature variable. Design the weighted Euclidean distance criterion and the weighting factors with an importance score were treated. For final classification, employ the enlarged training set. Experiment with the Hetao plain of covering apart.

Wang et al. [38] suggested random forest and UAV hyperspectral images based on fine crop classification. The classification accuracy of 97.18% was attained and correlated RF entire classification accuracy. The amount of sample points to the original images affects the image feature transform. But, this method made huge computational difficulties as well as cost.

Oraibiet al. [39] introduced random forests for efficient cell image classification based on deep and local learning features. The local binary patterns and rotation invariant co-occurrence-based information were captured. The VGG-19 image classification network extracts the deep learning features. Based on HEp-2 specimen benchmark dataset, 1000 trees with RF classifier provide five-fold cross-validation outputs.

Charbuty et al. [40] suggested a decision tree classification algorithm. The use of Decision tree classifiers has indeed been proposed in a variety of fields, including diagnosing patients' assessment, text categorization, consumer cell phone categorization and others. This study takes a brief look at decision trees. As a result, the applications of various types of data are debated, and their own results are examined.

Based on GPS signal reception classification algorithm, Sun et al. [41] introduced a gradient boosting decision tree. This model demonstrated superior outputs when compared to the adaptive network-based fuzzy inference system (ANFIS) and distance weighted k-nearest neighbor (KNN) respectively. For COVID-19 diagnosis, Yoo et al. [42] suggested deep learning-based decision-tree classifier. To detect COVID-19, deep learning-based decision-tree classifiers were utilized that provided better feasibility results.

2.2.2 SVM and Logistic Regression:

The classification of mammograms has been performed by Vijayarajeswari et al. [43] with a novel approach known as Hough transform-based Support vector machine (SVM). The features were extracted by using the Hough transform and the extracted features are classified as affected or unaffected by using the SVM approach. The authors tested only about 95 mammogram images and achieved better accuracy. However, the estimation of the classification of images from the large-scale dataset is a complicated process.

To enhance the contrast of mammograms and therein enhances the classification accuracy Bhateja et al. [44] presented a novel approach known as the sigmoidal transformation-based SVM technique. The 14 Haralick features were derived by using the sigmoidal transformation and increased the contrast of ROI and further classification of mammogram images was performed by using the SVM method. The authors stated that the approach enhances sensitivity, specificity, and accuracy to a greater extent. Nevertheless, the adaptability is low and has to be improved.

The cancer disease is classified using the microarray cancer gene expression and Rani et al. [45] presented a novel Spider monkey optimization algorithm for the gene feature selection and SVM-based cancer gene classification. The experiment was carried out with benchmark cancer datasets and thus maximized the classification accuracy. However, only one small-scale dataset is used and hence it is difficult to analyze the large-scale dataset.

To classify the Helitron types Touati et al. [46] delineated a novel approach known as spectral features and support vector machine classification method. The conversion of helitronic DNA to the numerical form is achieved by the FCGS2 coding technique. The derivation of spectral features was performed by the smoothed Fourier transform and the extracted features are classified using the SVM as Helitron1, HelitronY1, HelitronY1A, and HelitronY4 and achieved an accuracy rate of 90.1%. However, the extraction of global Helitron features is arduous and hence needs improvement in the stated approach.

Goudjil et al. [47] demonstrated a novel approach for the classification of text and it relies on the SVM. The authors stated that the work mitigates the labeling effort without reducing the classification accuracy and also chooses the informative samples utilizing the posterior probabilities. These were labeled manually by the expert. However, the label effect should be minimized.

For better classification, Qasim et al. [48] stated a novel particle swarm optimization algorithm-based logistic regression approach is used. Further, the author utilized the Bayesian information criterion (BIC) has also been used for the fitness evaluation. The authors stated that various large-scale datasets have been utilized for the experimental analysis. The authors stated that the fitness evaluation is higher with increased computational time.

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Year	Author	Methods	Advantage	Limitations
Cluster based segmentation				
2021	Shukla et al. [16]	Clustering-based segmentation	Cost effective method	Huge computational difficulties
2021	Kolluru et al. [17]	K-medoids clustering	Good sampling results	Higher cost
2021	Wu et al. [18]	Fuzzy clustering and entropy based divergence kernel based on adaptive weighted local information	Noise-free clustering	Failed to solve the nonlinear model analysis issues
2021	Tongbram et al. [19]	FCM and whale optimization algorithm	Good efficiency and simplicity with a better ability to resolve global optimization issues	Extremely delicate to the effects of noise sources
Edge-based segmentation				
2021	Fang et al. [20]	fuzzy region-based and edge-based active contours driven method	Low computational complexities	More intensity in homogeneity and noise.
2021	Zhou et al. [21]	Edge-based level set model	Good to embed region information	Higher cost and complexities
2019	Liu et al. [22]	Weighted edge-based level set method	Its highly against noises and utilized normalized local entropy	Provides less standard deviation outputs
2020	Phornphatchara phong et al. [23]	Edge-based color image segmentation.	Noise resistance and faster computation time	Constant length deficiencies
Region based segmentation				
2021	Fang et al. [20]	Region-based homogeneity enhancement	Better ability to integrate anisotropic features	Higher computational complexities
2021	Fang et al. [25]	Unsupervised region-based model	Easily balances the significant parameters	More noisy data
2021	Nguyen et al. [26]	Unsupervised region-based model	Good dice score and standard deviation results	Highest reconstruction loss
Threshold based image segmentation				
2020	Kandhasamy et al. [27]	multi-level set segmentation based SVM	Segmentation of images with high noises is not accurate	Diagnoses the diseases effectively at their early stage with the specificity and sensitivity of 98.1%, and 97.56%
2018	Latif et al. [28]	A Deep Convolutional neural network incorporated with anisotropic diffusion (AD) and watershed transform	Increased complexity	Increased specificity of 99.84%, and dice coefficient of 90.56%
2019	Das et al. [29]	Gaussian based deep learning, watershed segmentation, and Gaussian mixture model (GMM) algorithm	Estimation of the volumetric size of the lesion is a complicated task	Increased segmentation accuracy and classification accuracy
2018	Hasan et al. [30]	Watershed matching algorithm	Requires more manual interactions and hence time-consuming	Achieved the accuracy of 98.66%
2019	Khan et al. [31]	The marker-based watershed segmentation algorithm	Computational complexity	Segmentation accuracy is higher
2022	Sharma et al. [32]	Combination of ResNet50 and Enhanced watershed segmentation algorithm	The time complexity is high and also cannot be used to segment multimodal images	The accuracy obtained by this approach is 92%
Random forest and decision tree				
2019	Liang et al. [33]	Multi-thresholding based modified grasshopper optimization algorithm	Increased computational time	Segmentation accuracy is higher
2019	Abd Elaziz et al. [34]	Multi-verse optimization algorithm based on multi-level thresholding	CPU time increases linearly with the threshold values	Acquired uniformity in segmented images with increased quality
2021	Zhao et al. [35]	Random spare strategy and chaotic intensification strategy along with the multi-threshold segmentation of images	Parameter sensitivity is higher	The segmentation quality is higher
2018	Mittal et al. [36]	The gravitational search algorithm (exponential K-best GSA,	Higher computational complexity	segmentation accuracy is maximum
SVM and logistic regression				
2021	Su et al. [37]	Random forest method	Increased accuracy	Segmentation accuracy is higher

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2022	Wang et al. [38]	Random forest and UAV hyperspectral images	Classification accuracy of 97.18%	Huge cost and it make complexities
2018	Oraibiet al. [39]	Random forest method	Less data noise	Provides minimal classification accuracy
2021	Charbuty et al. [40]	Decision tree method	Better robustness and cost-effective	Less reliability
2020	Sun et al. [41]	Gradient boosting decision tree	Superior classification accuracy	Complex to analyze the large scale dataset
2020	Yoo et al. [42]	Deep learning based decision-tree classifier	Better reliability and high robustness	Higher computational cost
Year	Reference	Methods/Algorithm	Limitations	Merits
2019	Vijayarajeswari et al. [43]	Hough transform based Support vector machine (SVM)	Classification of the large-scale dataset is a complicated process	Achieved better accuracy
2018	Bhateja et al. [44]	sigmoidal transformation based SVM technique	Adaptability is low	Sensitivity, specificity, and accuracy are higher
2018	Rani et al. [45]	Spider monkey optimization algorithm for the gene feature selection and SVM based cancer gene classification	Difficult to analyze the large scale dataset	Classification accuracy is higher
2019	Touati et al. [46]	Spectral features and support vector machine classification method, FCGS2 coding technique	The extraction of global Helitron features is arduous	Achieved an accuracy rate of 90.1%
2018	Goudjil et al. [47]	SVM	Labeling effort is high	Higher accuracy
2018	Qasim et al. [48]	particle swarm optimization algorithm based logistic regression utilized Bayesian information criterion (BIC)	Increased computational time	Higher fitness value

Table.1 overall summary of various segmentation techniques

III. DISCUSSION:

How the research papers are taken based on the year is discussed in the section with graphical representation. Figure 1 illustrates the graphical representation with the number of papers published and percentage of papers taken for segmentation and classification. From the years 2013, 2015, 2017 the number of papers taken are 2. The highest number of papers taken from the year 2021 and from 2020 the papers taken are 7, and 2018, and 2019 also hold 8 papers.

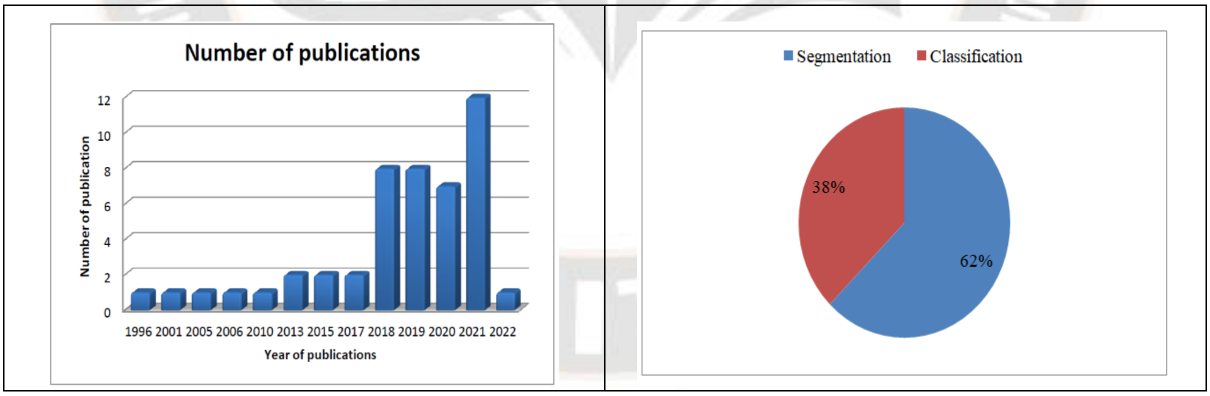

Figure.1 Discussion about the published papers and percentage of papers taken for segmentation and classification

IV. CONCLUSION:

This study reviewed an enhanced Artificial intelligence-based machine learning model for accurate segmentation and classification methods. The segmentation process does have an influence on the accuracy of brain tumor classification based on medical images. The image shape, size, texture and location are all motivated by segmentation. The approach combines three machine vision fiction techniques: image restoration, segmentation techniques, and quasi filtration texture-based and HOG characteristics. Throughout the past few decades, extensive study is in the field of image segmentation and classification. This survey examined AI-based machine learning techniques from both segmentation and classification. A total of 48 papers are used for survey analysis in this investigation. Among these, 20 papers are related to AI-based machine learning literature analysis based on image segmentation, with the remaining literature works related to image classification.

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References:

[1]. Tarabalka, Yuliya, Jocelyn Chanussot, and Jon Atli Benediktsson. "Segmentation and classification of hyperspectral images using watershed transformation." Pattern Recognition 43, no. 7 (2010): 2367-2379.

[2]. Irshad, Humayun, Antoine Veillard, Ludovic Roux, and Daniel Racoceanu. "Methods for nuclei detection, segmentation, and classification in digital histopathology: a review—current status and future potential." IEEE reviews in biomedical engineering 7 (2013): 97-114.

[3]. Grilli, Eleonora, Fabio Menna, and Fabio Remondino. "A review of point clouds segmentation and classification algorithms." The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 42 (2017): 339.

[4]. Grilli, Eleonora, Fabio Menna, and Fabio Remondino. "A review of point clouds segmentation and classification algorithms." The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 42 (2017): 339.

[5]. Farmer, Michael E., and Anil K. Jain. "A wrapper-based approach to image segmentation and classification." IEEE transactions on image processing 14, no. 12 (2005): 2060-2072.

[6]. Tiwari, Arti, Shilpa Srivastava, and Millie Pant. "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019." Pattern Recognition Letters 131 (2020): 244-260.

[7]. Jolly, M.P.D., Lakshmanan, S. and Jain, A.K., 1996. Vehicle segmentation and classification using deformable templates. IEEE Transactions on pattern analysis and machine intelligence, 18(3), pp.293-308.

[8]. Vu, Quoc Dang, Simon Graham, Tahsin Kurc, Minh Nguyen Nhat To, Muhammad Shaban, Talha Qaiser, Navid Alemi Koohbanani et al. "Methods for segmentation and classification of digital microscopy tissue images." Frontiers in bioengineering and biotechnology (2019): 53.

[9]. Khan, Mehshan Ahmed, Muhammad Attique Khan, Fawad Ahmed, Mamta Mittal, Lalit Mohan Goyal, D. Jude Hemanth, and Suresh Chandra Satapathy. "Gastrointestinal diseases segmentation and classification based on duo-deep architectures." Pattern Recognition Letters 131 (2020): 193-204.

[10]. Zhang, T., & Kuo, C. C. J. (2001). Audio content analysis for online audiovisual data segmentation and classification. IEEE Transactions on speech and audio processing, 9(4), 441-457.

[11]. Seidenberg, Julian, and Alan Rector. "Web ontology segmentation: analysis, classification and use." In Proceedings of the 15th international conference on World Wide Web, pp. 13-22. 2006.

[12]. Biljecki, Filip, Hugo Ledoux, and Peter Van Oosterom. "Transportation mode-based segmentation and classification of movement trajectories." International Journal of Geographical Information Science 27, no. 2 (2013): 385-407.

[13]. Xie, Yutong, Jianpeng Zhang, Yong Xia, and Chunhua Shen. "A mutual bootstrapping model for automated skin lesion segmentation and classification." IEEE transactions on medical imaging 39, no. 7 (2020): 2482-2493.

[14]. Tang, Duyu, Bing Qin, Furu Wei, Li Dong, Ting Liu, and Ming Zhou. "A joint segmentation and classification framework for sentence level sentiment classification." IEEE/ACM Transactions on Audio, Speech, and Language Processing 23, no. 11 (2015): 1750-1761.

[15]. Tang, Duyu, Bing Qin, Furu Wei, Li Dong, Ting Liu, and Ming Zhou. "A joint segmentation and classification framework for sentence level sentiment classification." IEEE/ACM Transactions on Audio, Speech, and Language Processing 23, no. 11 (2015): 1750-1761.

[16]. Shukla, Aparna, and Suvendu Kanungo. "An efficient clustering-based segmentation approach for biometric image." Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science) 14, no. 3 (2021): 803-819.

[17]. Kolluru, C., Lee, J., Gharaibeh, Y., Bezerra, H.G. and Wilson, D.L., 2021. Learning with fewer images via image clustering: Application to intravascular OCT image segmentation. IEEE Access, 9, pp.37273-37280.

[18]. Wu, C., & Cao, Z. (2021). Noise distance driven fuzzy clustering based on adaptive weighted local information and entropy-like divergence kernel for robust image segmentation. Digital Signal Processing, 111, 102963.

[19]. Tongbram, Simon, Benjamin A. Shimray, Loitongbam Surajkumar Singh, and Nameirakpam Dhanachandra. "A novel image segmentation approach using fcm and whale optimization algorithm." Journal of Ambient Intelligence and Humanized Computing (2021): 1-15.

[20]. Fang, Jiangxiong, Huaxiang Liu, Liting Zhang, Jun Liu, and Hesheng Liu. "Region-edge-based active contours driven by hybrid and local fuzzy region-based energy for image segmentation." Information Sciences 546 (2021): 397-419.

[21]. Zhou, Zhiheng, Ming Dai, Yongfan Guo, and Xiangwei Li. "Global-to-local region-based indicator embedded in edge-based level set model for segmentation." Digital Signal Processing 114 (2021): 103061.

[22]. Liu, Cheng, Weibin Liu, and Weiwei Xing. "A weighted edge-based level set method based on multi-local statistical information for noisy image segmentation." Journal of Visual Communication and Image Representation 59 (2019): 89-107.

[23]. Phornphatcharaphong, Wutthichai, and Nawapak Eua-Anant. "Edge-based color image segmentation using particle motion in a vector image field derived from local color distance images." Journal of Imaging 6, no. 7 (2020): 72.

[24]. Chen, D., Zhu, J., Zhang, X., Shu, M., & Cohen, L. D. (2021). Geodesic paths for image segmentation with implicit region-based homogeneity enhancement. IEEE Transactions on Image Processing, 30, 5138-5153.

[25]. Fang, J., Liu, H., Liu, J., Zhou, H., Zhang, L., & Liu, H. (2021). Fuzzy region-based active contour driven by global and local fitting energy for image segmentation. Applied Soft Computing, 100, 106982.

[26]. Nguyen, Bao, Adam Feldman, Sarath Bethapudi, Andrew Jennings, and Chris G. Willcocks. "Unsupervised region-based anomaly detection in brain mri with adversarial image inpainting." In 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI), pp. 1127-1131. IEEE, 2021.

[27]. Kandhasamy, J.P., Balamurali, S., Kadry, S. and Ramasamy, L.K., 2020. Diagnosis of diabetic retinopathy using multi level set segmentation algorithm with feature extraction using svm with selective features. Multimedia Tools and Applications, 79(15), pp.10581-10596.

[28]. Latif, G., Iskandar, D.A., Alghazo, J., Butt, M. and Khan, A.H., 2018. Deep CNN based MR image denoising for tumor segmentation using watershed transform. International Journal of Engineering & Technology, 7(2.3), pp.37-42.

[29]. Das, A., Acharya, U.R., Panda, S.S. and Sabut, S., 2019. Deep learning based liver cancer detection using watershed transform and Gaussian mixture model techniques. Cognitive Systems Research, 54, pp.165-175.

[30]. Hasan, S.M. and Ahmad, M., 2018. Two-step verification of brain tumor segmentation using watershed-matching algorithm. Brain informatics, 5(2), pp.1-11.

[31]. Khan, M.A., Lali, I.U., Rehman, A., Ishaq, M., Sharif, M., Saba, T., Zahoor, S. and Akram, T., 2019. Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection. Microscopy research and technique, 82(6), pp.909-922.

[32]. Sharma, A.K., Nandal, A., Dhaka, A., Koundal, D., Bogatinoska, D.C. and Alyami, H., 2022. Enhanced watershed segmentation algorithm-based modified ResNet50 model for brain tumor detection. BioMed Research International, 2022.

[33]. Liang, H., Jia, H., Xing, Z., Ma, J. and Peng, X., 2019. Modified grasshopper algorithm-based multilevel thresholding for color image segmentation. IEEE Access, 7, pp.11258-11295.

[34]. Abd Elaziz, M., Oliva, D., Ewees, A.A. and Xiong, S., 2019. Multi-level thresholding-based grey scale image segmentation using multi-objective multi-verse optimizer. Expert Systems with Applications, 125, pp.112-129.

[35]. Zhao, D., Liu, L., Yu, F., Heidari, A.A., Wang, M., Liang, G., Muhammad, K. and Chen, H., 2021. Chaotic random spare ant colony optimization for multi-threshold image segmentation of 2D Kapur entropy. Knowledge-Based Systems, 216, p.106510.

[36]. Mittal, H. and Saraswat, M., 2018. An optimum multi-level image thresholding segmentation using non-local means 2D histogram and exponential Kbest gravitational search algorithm. Engineering Applications of Artificial Intelligence, 71, pp.226-235.

[37]. Su, Tengfei, and Shengwei Zhang. "Object-based crop classification in Hetao plain using random forest." Earth Science Informatics 14, no. 1 (2021): 119-131.

[38]. Wang, Zhihua, Zhan Zhao, and Chenglong Yin. "Fine Crop Classification Based on UAV Hyperspectral Images and Random Forest." ISPRS International Journal of Geo-Information 11, no. 4 (2022): 252.

[39]. Oraibi, Z. A., Yousif, H., Hafiane, A., Seetharaman, G., & Palaniappan, K. (2018, October). Learning local and deep features for efficient cell image classification using random forests. In 2018 25th IEEE International Conference on Image Processing (ICIP) (pp. 2446-2450). IEEE.

[40]. Charbuty, Bahzad, and Adnan Abdulazeez. "Classification based on decision tree algorithm for machine learning." Journal of Applied Science and Technology Trends 2, no. 01 (2021): 20-28.

[41]. Sun, Rui, Guanyu Wang, Wenyu Zhang, Li-Ta Hsu, and Washington Y. Ochieng. "A gradient boosting decision tree based GPS signal reception classification algorithm." Applied Soft Computing 86 (2020): 105942.

[42]. Yoo, S.H., Geng, H., Chiu, T.L., Yu, S.K., Cho, D.C., Heo, J., Choi, M.S., Choi, I.H., Cung Van, C., Nhung, N.V. and Min, B.J., 2020. Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest X-ray imaging. Frontiers in medicine, 7, p.427.

[43]. Vijayarajeswari, R., Parthasarathy, P., Vivekanandan, S. and Basha, A.A., 2019. Classification of mammogram for early detection of breast cancer using SVM classifier and Hough transform. Measurement, 146, pp.800-805.

[44]. Bhateja, V., Gautam, A., Tiwari, A., Bao, L.N., Satapathy, S.C., Nhu, N.G. and Le, D.N., 2018. Haralick features-based classification of mammograms using SVM. In Information Systems Design and Intelligent Applications (pp. 787-795). Springer, Singapore.

[45]. Rani, R.R. and Ramyachitra, D., 2018. Microarray cancer gene feature selection using spider monkey optimization algorithm and cancer classification using SVM. Procedia computer science, 143, pp.108-116.

[46]. Touati, R., Oueslati, A.E., Messaoudi, I. and Lachiri, Z., 2019. The Helitron family classification using SVM based on Fourier transform features applied on an unbalanced dataset. Medical & biological engineering & computing, 57(10), pp.2289-2304.

[47]. Goudjil, M., Koudil, M., Bedda, M. and Ghoggali, N., 2018. A novel active learning method using SVM for text classification. International Journal of Automation and Computing, 15(3), pp.290-298.

[48]. Qasim, O.S. and Algamal, Z.Y., 2018. Feature selection using particle swarm optimization-based logistic regression model. Chemometrics and Intelligent Laboratory Systems, 182, pp.41-46.